DEPARTAMENTO DE INFORMÁTICA Y AUTOMÁTICA

FACULTAD DE CIENCIAS

VNiVERSiDAD
Đ SALAMANCA

TESIS DOCTORAL

TÉCNICAS DE COMPUTACIÓN SOCIAL E INFORMACIÓN CONTEXTUAL PARA EL DESARROLLO DE ACTIVIDADES DE APRENDIZAJE COLABORATIVO

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DEPARTAMENTO DE INFORMÁTICA Y AUTOMÁTICA

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DOCTORAL THESIS

SOCIAL COMPUTING AND CONTEXT-AWARENESS TECHNIQUES FOR THE DEVELOPMENT OF COLLABORATIVE LEARNING APPLICATIONS

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IALY

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Salamanca, 10 de junio de 2017 Óscar García.

Solicitud de Presentación de Tesis Doctoral

Estimado Coordinador del Programa de Doctorado:

Óscar García García con DNI: 07982656T, y alumno del programa DOCTORADO EN INFORMÁTICA Y AUTOMÁTICA, matriculado en el plan de estudios DP08 INFORMÁTICA Y AUTOMÁTICA (R.D. 1393/2007) y con número de expediente 30,

Solicita que se tenga en consideración la información aportada en este documento con el objetivo de poder presentar la tesis con título *Técnicas de Computación Social e Información Contextual para el Desarrollo de Actividades de Aprendizaje Colaborativo* mediante el formato de compendio de artículos/publicaciones. La información aportada se corresponde con lo establecido en el Procedimiento para la presentación de la Tesis Doctoral en la Universidad de Salamanca en el Formato de Compendio de Artículos/Publicaciones.

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- Autorización de los directores para la presentación de la tesis mediante el formato de compendio de artículos/publicaciones.

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    - Metodología de investigación.
    - Objetivos de la Tesis Doctoral.
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Autorización del Director

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HAGO CONSTAR:
Que como director de la Tesis Doctoral de Óscar García García, con DNI 07982656T, autorizo a presentar la tesis doctoral *Técnicas de computación social e información contextual para el desarrollo de actividades de aprendizaje colaborativo* mediante la modalidad de compendio de artículos al disponer de los siguientes artículos y capítulos de libro publicados:

1. García, Ó., Alonso, R. S., Prieto, J., & Corchado, J. M. (2017). Energy efficiency in public buildings through context-aware social computing. *Sensors*, 17(4):826.

2. Alonso, R. S., Tapia, D. I., Bajo, J., García, Ó., de Paz, J. F., & Corchado, J. M. (2013). Implementing a hardware-embedded reactive agents platform based on a service-oriented architecture over heterogeneous wireless sensor networks. *Ad Hoc Networks*, 11(1):151-166.

3. García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2012). Using ZigBee in ambient intelligence learning scenarios. *International Journal of Ambient Computing and Intelligence (IJACI)*, 4(3), 33-45.

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5. García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2015). CAFCLA: A Framework to Design, Develop, and Deploy AmI-Based Collaborative Learning Applications. *In Recent Advances in Ambient Intelligence and Context-Aware Computing (Ed. Kevin Curran)*, chapter 12, pp. 187-209, ISBN 978-1-4666-7287-1. IGI Global, Hershey, PA, USA.

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Aceptación escrita de los coautores de los artículos presentados

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Ricardo S. Alonso   Javier Prieto   Juan M. Corchado

TÍTULO:
A framework to improve energy efficient behaviour at home through activity and context monitoring.
AUTORES (P.O. DE FIRMA):
Óscar García, Javier Prieto, Ricardo S. Alonso, Juan M. Corchado.
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Javier Prieto   Ricardo S. Alonso   Juan M. Corchado

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Ricardo S. Alonso　　　Dante I. Tapia　　　Javier Bajo

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Ricardo S. Alonso   Dante I. Tapia   Juan M. Corchado

Resumen

La innovación educativa es un campo que ha sido enormemente enriquecido por el uso de las Tecnologías de la Información y las Comunicaciones (TIC) en sus procesos. Gracias a los avances tecnológicos, actualmente es habitual el uso de modelos de aprendizaje donde la información proviene de numerosas y diferentes fuentes. De igual forma, la colaboración estudiante-estudiante, estudiante-dispositivo y dispositivo-dispositivo, proporciona un valor añadido a los procesos de aprendizaje gracias a que, a través de ella, se fomentan aspectos como la comunicación, la consecución de una meta común, o la compartición de recursos. Dentro de la innovación educativa encontramos como un gran desafío el desarrollo de herramientas que faciliten la creación de procesos de aprendizaje colaborativo innovadores que mejoren los resultados obtenidos, respecto a los procesos individualizados, y la fidelidad de los estudiantes al proceso mediante el uso de información contextual. Más aún, el desarrollo de soluciones que faciliten el trabajo a profesores, desarrolladores y técnicos, fomentando la producción de procesos educativos más atractivos para los estudiantes, se presenta como un ambicioso reto en el que las perspectivas de la Inteligencia Ambiental y la Computación Social juegan un papel fundamental. La tesis doctoral aquí presentada describe y evalúa CAFCLA, un framework especialmente concebido para el diseño, desarrollo e implementación de actividades de aprendizaje colaborativo que hagan uso de información contextual basándose en los paradigmas de la Inteligencia Ambiental y la Computación Social. CAFCLA es un framework flexible que abarca todo el proceso de desarrollo de actividades de aprendizaje colaborativo y oculta todas las dificultades que implican el uso e integración de múltiples tecnologías a sus usuarios. Para evaluar la validez de la propuesta realizada, CAFCLA ha soportado la implementación de tres casos de uso concretos y diferentes entre sí. Estos casos de uso experimentales han demostrado que, entre otros beneficios, el uso de la Computación Social personaliza el proceso de aprendizaje, fomenta la colaboración, mejora las relaciones, aumenta el compromiso, favorecen el cambio de comportamiento en los usuarios y mantiene su implicación en el proceso a lo largo del tiempo. Además, con el objetivo de demostrar la flexibilidad del framework, estos casos de uso se han desarrollado en diferentes escenarios (como un museo, un edificio público o el hogar), se han propuesto diferente tipos de aprendizaje (juegos serios, sistema de recomendaciones o WebQuest) y se han elegido diferentes objetivos de aprendizaje (académicos, sociales y de eficiencia energética).

Abstract

Educational innovation is a field in which its processes has been greatly enriched by the use of Information and Communication Technologies (ICT). Thanks to technological advances, the use of learning models where information comes from many different sources is now usual. Likewise, student-student, student-device and device-device collaborations provides added value to the learning processes thanks to the fact that, through it, aspects such as communication, achievement of common goals or sharing resources. Within the educational innovation, we find as a great challenge the development of tools that facilitate the creation of innovative collaborative learning processes that improve the achievement of the objectives sought, with respect to individualized processes, and the fidelity of the students to the process through the use of contextual information. Moreover, the development of these solutions, that facilitate the work of teachers, developers and technicians encouraging the production of educational processes more attractive to students, presents itself as an ambitious challenge in which the perspectives of Ambient Intelligence and Social Computing play a key role. The doctoral dissertation presented here describes and evaluates CAFCLA, a framework specially conceived for the design, development and implementation of collaborative learning activities that make use of contextual information and that is based on the paradigms of Ambient Intelligence and Social Computing. CAFCLA is a flexible framework that covers the entire process of developing collaborative learning activities and hides all the difficulties involved in the use and integration of multiple technologies to its users. In order to evaluate the validity of the proposal, CAFCLA has supported the implementation of three concrete and different use cases. These experimental use cases have shown that, among other benefits, the use of Social Computing customizes the learning process, encourages collaboration, improves relationships, increases commitment, promotes behaviour change in users and enables learning to be maintained over time. In addition, in order to demonstrate the flexibility of the framework, these use cases have been developed in different scenarios (such as a museum, a public building or at home), different types of learning have been proposed (serious games, recommendations system or WebQuest) and different learning objectives have been chosen (academic, social and energy-efficient).

Índice general

1 Introducción

La educación es uno de los pilares básicos sobre los que se sustenta la sociedad. Su influencia en todos los ámbitos requiere que su evelución sea constante, fomentándose continuamente la adquisición de conocimientos y competencias a través de nuevas vías. La Sección 1.1 realiza una introducción del uso de la tecnología en los procesos educativos, a través de los paradigmas de la Inteligencia Ambiental y la Computación Social. La Sección 1.2 motiva el trabajo de la investigación de esta Tesis Doctoral. La Sección 1.3 describe la metodología de investigación que se ha seguido. La Sección 1.4 describe los objetivos de la Tesis Doctoral. La Sección 1.5 describe cómo está estructurado este documento.

1.1. Introducción

A lo largo de la historia la educación, entendida como el proceso mediante el que, a través de la transmisión de conocimientos, los individuos adquirimos habilidades necesarias para nuestro desarrollo personal, profesional y social, ha evolucionado en paralelo al resto de ciencias (Roco and Bainbridge, 2003). La educación y, de forma más concreta, los procesos educativos, se han adaptado a la necesidad de los contextos sociales, experimentando cambios de forma constante a lo largo del tiempo (March, 1991). Son innumerables las formas de aprender y enseñar que conocemos en la actualidad: transmisión de conocimientos de forma oral, la lectura, los juegos, el aprendizaje en grupo, el aprendizaje autodidacta, etc. La continua aparición de nuevas formas de enseñanza y aprendizaje se debe en gran medida al desarrollo de la ciencia y la tecnología (Hendriks, 1999). Al igual que ámbitos como la industria, la agricultura o la medicina se han visto favorecidas por la aparición de nuevas herramientas que mejoran sus niveles de productividad, la educación ha hecho igualmente un uso efectivo de las invenciones del ser humano. De esta forma, la educación se ha visto favorecida por la aparición del papel, por la invención de la imprenta y los libros o por la utilización de pizarras. De forma más reciente, la radio, la televisión y los proyectores permitieron igualmente la aparición de nuevos métodos de aprendizaje. Más aún, estas formas de enseñanza han evolucionado no sólo dentro del aula, sino también fuera de ella. Así, han aparecido procesos de aprendizaje no reglados que pueden ser dirigidos a cualquier público, e incluso a la ciudadanía en general, como por ejemplo aquellos que fomentan un uso más eficiente de la energía a través de diferentes herramientas tecnológicas (contadores inteligentes, aplicaciones móviles, sistemas de recomendación, etc.).

De forma más reciente, hemos sido testigos de la gran aceptación que las Tecnologías de la Información y las Comunicaciones (TIC) han tenido por parte de la sociedad (Stanley, 2009a). Los constantes avances tecnológicos han propiciado la aparición de nuevos dispositivos, protocolos de comunicación o gadgets que hemos incluido en nuestros quehaceres diarios de una forma natural (Cook et al., 2009). En definitiva, el auge de los ordenadores personales, dispositivos móviles e Internet han cambiado nuestro mundo desde el punto de vista político, económico y social (Warschauer, 2004; Dutta and Mia, 2011).

La educación no ha permanecido impasible ante los avances tecnológicos. La tradicional transmisión de conocimientos del profesor a los alumnos ha evolucionado a través del uso de presentaciones en formato electrónico, la utilización ordenadores en clase e incluso integrando plataformas de aprendizaje electrónico tales como Moodle (Rodrigues et al., 2011) o LAMS (Foundation, 2017). Estas herramientas no solo facilitan la transmisión del conocimiento, sino que fomentan tanto la colaboración entre alumnos como la relación profesor-alumno. En este sentido, aparece el enfoque pedagógico CSCL (*Computer Supported Collaborative Learning*) (Koschmann, 1996), que promulga que la tecnología no solo debe mediar entre el estudiante y el conocimiento, sino entre los estudiantes entre sí, con el objetivo de que la interacción entre ellos fomente la creación de nuevo conocimiento (Gómez-Sánchez et al., 2009). Así, el CSCL se ha convertido en un campo de investigación relevante dentro de la educación, pues atrae múltiples intereses, desde los puramente pedagógicos hasta aquellos que se centran en la mejora de las interacciones hombre-máquina (Gómez-Sánchez et al., 2009). En esta visión del proceso de aprendizaje, los participantes realizan actividades que requieren la interacción de los mismos para lograr lo que se denomina un aprendizaje colaborativo. Las aplicaciones basadas en CSCL deben tener en cuenta aspectos relativos al desarrollo de software para el trabajo en grupo, llamado CSCW (*Computer Supported Cooperative Work*) (Ellis et al., 1991), como, por ejemplo, los turnos, las interfaces o problemas de visualización de contenidos en espacios comunes.

Por otro lado, la teoría del aprendizaje constructivista sostiene que el conocimiento es un proceso de interacción entre el sujeto y el medio socio-cultural que lo rodea (Vygotskiĭ and Cole, 1978). En este enfoque pedagógico el profesor acompaña el proceso de aprendizaje actuando como supervisor, mientras que los alumnos disfrutan de una libertad controlada para formar su propio conocimiento. Las características principales de este tipo de aprendizaje son:

- Interdependencia positiva: los participantes en la actividad se necesitan unos a otros para alcanzar el objetivo de la misma. Cada uno de ellos jugará un rol que puede ser adquirido de forma natural o asignado por los educadores.
- Interacción personal: el intercambio de información y opiniones entre los diferentes miembros del grupo afecta al resultado final de la actividad.
- Adquisición de habilidades individuales: el trabajo en grupo fomenta la adquisición de responsabilidades individuales relacionadas con el trabajo a desarrollar por cada alumno.
- Adquisición de habilidades grupales: el trabajo en grupo fomenta el desarrollo de habilidades necesarias para el trabajo en grupo como la capacidad de escucha, la participación, el pensamiento crítico, la coordinación de actividades, el liderazgo, el seguimiento o la evaluación.

Aunando el uso de nuevas tecnologías y la teoría del aprendizaje colaborativo constructivista surge la oportunidad de crear actividades de aprendizaje en las que la colaboración entre alumnos y entre alumnos y contexto sea el pilar fundamental. El aprendizaje colaborativo es un campo en el que los avances tecnológicos han permitido la mejora y la innovación en los métodos de enseñanza y aprendizaje. Un entorno de aprendizaje colaborativo facilita compartir y acceder al contenido de aprendizaje (por ejemplo, texto o imágenes) entre usuarios (por ejemplo, estudiantes o profesores) (Kirschner, 2015). El uso de dispositivos móviles y comunicaciones inalámbricas (Roschelle, 2003) se ha convertido en un tópico de gran interés a través del cual involucrar a los estudiantes en los procesos de aprendizaje y fomentar la colaboración entre ellos (Novak, 2015). Por lo tanto, existen muchas propuestas innovadoras en las que la tecnología apoya el aprendizaje colaborativo, ya sean plataformas de aprendizaje complejas como Moodle, Wiki o LAMS (Cress and Kimmerle, 2008), aplicaciones de aprendizaje que utilizan dispositivos móviles (Melero et al., 2015; Sun and Shen, 2014), herramientas de aprendizaje orientadas al contexto (Hwang et al., 2009a; Park et al., 2007; Laine and Joy, 2009a), plataformas de aprendizaje basadas en localización (Chou and Chanlin, 2014; Ryokai et al., 2013) o aprendizaje basado en juegos (Barzilai and Blau, 2014).

Si además estas colaboraciones y provisiones de información se hacen de forma personalizada, intuitiva y transparente a los usuarios, usando paradigmas como la Inteligencia Ambiental, el proceso de aprendizaje adquiere un atractivo que favorece la creación y adquisición de conocimientos. En este sentido, la Inteligencia Ambiental (AmI - *Ambient intelligence*) (Remagnino and Foresti, 2005) es un área multidisciplinar de importante influencia en la nuevas formas de interacción entre las personas y la tecnología. La Inteligencia Ambiental se define como un modelo de interacción que establece diversas pautas para que la tecnología se integre en la vida diaria de las personas de manera ubicua y que, además, esta se adapte automáticamente a las características del contexto y a las necesidades de los propios usuarios (Cook et al., 2009; Anastasopoulos et al., 2005; Sadri, 2011; Tapia et al., 2010a; Augusto et al., 2010). Así pues, el objetivo final de un sistema basado en la Inteligencia Ambiental es mejorar la calidad de vida de los usuarios a través de dispositivos, servicios o vías de comunicación más eficientes y fáciles de usar. Los conceptos propuestos por la Inteligencia Ambiental pueden facilitar el desarrollo de aplicaciones basadas en el enfoque CSCL, haciendo énfasis en nuevas formas de comunicación e interacción (García et al., 2012c; Basaeed et al., 2007; Laine and Joy, 2009a; Ogata and Yano, 2004; Neyem et al., 2005; Vasiliou and Economides, 2007a).

La utilización de la información contextual posibilita un mejor conocimiento del entorno y a su vez adaptar el proceso educativo al contexto en el que están inmersos los usuarios en un determinado momento, de forma que puedan personalizarse los contenidos que se les proporcionan. Un ejemplo de este uso es el presentado en (García et al., 2011), un escenario educativo en el que en un museo se entregan contenidos personalizados a los alumnos en función de sus necesidades, su ubicación y las pautas que marque su perfil educativo. El uso de información contextual en los procesos de aprendizaje se denomina Aprendizaje Sensible al Contexto (*Context-aware Learning*) (Laine and Joy, 2009a; Ogata and Yano, 2004; Yang, 2006a). El conocimiento de la información contextual puede favorecer la adquisición de conocimientos por parte de los alumnos (Sintoris et al., 2012; García et al., 2015). Sin embargo, la obtención de la información contextual se convierte a menudo en el gran caballo de batalla de estos trabajos (Basaeed et al., 2007; FitzGerald, 2012; Ghiani et al., 2009; Laine and Joy, 2009a; Yang, 2006a). De esta forma, surge otra problemática que motiva el desarrollo de esta investigación: conseguir un modelo de aprendizaje que pueda implementarse en cualquier momento y lugar, personalizado en función de las necesidades del usuario y del entorno que lo rodea.

El modelo de aprendizaje buscado requiere una gestión eficiente de las relaciones entre humanos y entre humanos y máquinas (Curran and Norrby, 2009a; Ghiani et al., 2009; Hsien-Sheng et al., 2010). La Computación Social (*Social Computing*) se considera como un recurso computacional para los estudios sociales, la dinámica social humana y el diseño y uso de las TIC que incluyen la contextualización social (Jin et al., 2010). Este paradigma de la Computación Social requiere la combinación de recursos humanos y TIC (Wang et al., 2007): los seres humanos aportan habilidades, conocimientos y competencias, redes de relaciones sociales y entendimiento de las estructuras sociales; las TIC permiten a los seres humanos buscar y entregar información concreta. Así, los seres humanos pueden confiar en la información exacta de un contexto para alcanzar una meta específica. Cuando este objetivo se refiere a la educación, la Computación Social ofrece un entorno sin precedentes que puede crear experiencias de colaboración para crear un apoyo eficaz al aprendizaje (Musser et al., 2003; Chuang, 2016). Sin embargo, mientras que la Computación Social presenta un gran potencial para cubrir las interacciones sociales y el compromiso grupal (Sinha et al., 2015), solo algunos trabajos aislados han abordado el concepto de aprendizaje colaborativo desde esta perspectiva (Musser et al., 2003).

La aplicación en entornos educativos de las pautas marcadas tanto por la Inteligencia Ambiental como por la Computación Social requieren la utilización de tecnologías que permitan una gestión eficiente de la información. Es aquí donde el uso de Organizaciones Virtuales de agentes juega un papel fundamental para facilitar la gestión del conocimiento, la colaboración y la personalización de sistemas de aprendizaje (Vega et al., 2011; Terzieva et al., 2011). Un agente inteligente puede entenderse como una entidad física o abstracta capaz de recibir datos de su contexto a través de sensores u otras fuentes de información, evaluar estos datos y tomar decisiones a través de razonamientos sencillos (Wooldridge and Jennings, 1995). La utilización de múltiples agentes autónomos que se complementan entre ellos con el objetivo de resolver un problema común es lo que se conoce como un sistema multiagente (Wooldridge, 2009). Los sistemas multiagente presentan importantes características: pueden funcionar sin un sistema de control global, gestionan datos descentralizados y su computación es asíncrona. Esta tecnología ha sido aplicada con éxito en diversos desarrollos basados en la Inteligencia Ambiental, en la Computación Social y en escenarios educativos (Corchado et al., 2008; Tapia et al., 2010b, 2011). Los sistemas multiagente, así como su agrupación en Organizaciones Virtuales de agentes para la resolución de problemas concretos (Vega et al., 2011; Xu et al., 2014), permiten modelar sistemas de e-Learning gracias a su capacidad para personalizar el contenido del proceso de aprendizaje (Arif et al., 2015; Salazar et al., 2015; Xu et al., 2014) y para dotar de inteligencia al mismo (Hwang, 2014; Garcia-Cabot et al., 2015; Salazar et al., 2015).

El objetivo de esta Tesis Doctoral es desarrollar una plataforma de aprendizaje que permita crear procesos educativos inteligentes y autónomos que permitan obtener mayores niveles de personalización de contenidos al alumno y abstraerse de las complejidades implicadas por el uso de distintas tecnologías al profesor. La siguiente Sección aborda de forma más concreta la motivación del trabajo presentado en esta Tesis Doctoral.

1.2. Motivación

Tal y como se desprende del contenido de la sección anterior, las TIC y, de forma más concreta, los paradigmas de la Inteligencia Ambiental y la Computación Social ofrecen un gran potencial innovador al ámbito educativo. Sin embargo, su aplicación práctica requiere tener en cuenta aspectos difíciles de resolver, como son la adaptabilidad, la escalabilidad o la transparencia de las soluciones propuestas. En este sentido, la Tesis Doctoral que se ha desarrollado se basa en tres aspectos fundamentales:

- No existe ningún framework horizontal que permita la adaptación de los procesos educativos a cualquier tipo de entorno, como pueden ser las aulas para fomentar la colaboración, el aprendizaje mediante juegos en un museo para relacionarse con las obras de arte de forma interactiva o en edificios públicos para fomentar el ahorro energético entre sus usuarios, o mediante recomendaciones en el hogar para educar a sus inquilinos en un eficiente de la energía. La estructura en capas del framework que presenta esta Tesis Doctoral, así como la incorporación de Organizaciones Virtuales de agentes lo dotan de una gran escalabilidad y capacidad de adaptación a diferentes entornos y situaciones de aprendizaje.

- De forma habitual, las soluciones tradicionales se han basado en métodos de aprendizaje pasivos donde el usuario era un mero receptor de información. Este rol pasivo de los alumnos no incentiva su motivación, lo que puede fomentar malos resultados en el proceso de aprendizaje. Gracias a la Computación Social y a los modelos de aprendizaje colaborativo, las personas se ven involucradas en la resolución de problemas ya sea por sus propios medios o mediante la colaboración con máquinas o con otras personas. La inclusión de aspectos sociales como la motivación de los alumnos a través de recomendaciones personalizadas y desafíos, así como la colaboración entre alumnos, permite conseguir mejores resultados en el proceso de aprendizaje y, lo que es más importante, mantenerlos en el tiempo.

- El conocimiento de la información contextual que rodea un entorno educativo es utilizado en múltiples propuestas de aprendizaje. Los frameworks y aplicaciones que se han desarrollado hasta el momento y que utilizan información contextual en el proceso educativo han conseguido mejorar tanto los resultados académicos como la fidelidad de los estudiantes al proceso de aprendizaje. Sin embargo, la gestión de la información contextual no ha permitido aprovechar este recurso de forma óptima. Por este motivo, la implementación de técnicas de gestión autónoma de procesos de aprendizaje, así como la dotación de inteligencia a los mismos, permitirán mejorar aún más los procesos diseñados y, en consecuencia, los resultados académicos y la adquisición de competencias de los alumnos.

1.3. Metodología de Investigación

El trabajo de investigación que se ha llevado a cabo para la consecución de esta Tesis Doctoral ha seguido la metodología conocida como *Action-Research*. La base de esta metodología es la identificación de un problema para después formular una hipótesis. El siguiente paso en la investigación que marca la metodología elegida parte de una serie de conceptos definidos dentro del modelo cuantitativo de realidad en el que se desenvuelve el trabajo. A partir de ellos se lleva a cabo una recopilación, organización y análisis de información, para a continuación desarrollar el diseño de la propuesta enfocada a solucionar el problema. La evaluación de los resultados obtenidos de la investigación constituye el paso preliminar a la extracción de las conclusiones de la investigación realizada.

El seguimiento de este modelo de investigación requiere la definición seis actividades que permitan alcanzar los objetivos planteados y la demostración de la hipótesis. A continuación, se desarrolla una breve descripción de cada una de ellas:

- **Problemática:** definición del problema actualmente existente en el ámbito de la educación, de forma más concreta en el uso de las TIC para dar lugar a plataformas de aprendizaje horizontales que cubran varios ámbitos de actuación. Esta definición nos dará lugar a la definición de la hipótesis de trabajo que permitirá solucionar total o parcialmente el problema, así como a la definición y exposición de los objetivos marcados para conseguir solucionarlo.

- **Estado del arte:** revisión del estado del arte la Inteligencia Ambiental, en especial de aquellas soluciones enfocadas a entornos educativos, del aprendizaje colaborativo que hace uso de las TIC, de la Computación Social aplicada a mejorar procesos de aprendizaje y de la sensibilidad al contexto para enriquecer la información de la que dispongan alumnos y profesores. Debe dar lugar a un sólido marco teórico que permita enriquecer el conocimiento y mejorar el proceso de desarrollo.

- **Desarrollo de la propuesta:** diseño gradual e iterativo de un framework que permita la integración de múltiples tecnologías, como redes inalámbricas de sensores y sistemas de localización en tiempo real, que favorezcan el desarrollo de actividades de aprendizaje colaborativas que utilicen información contextual y Computación Social. La información recabada en durante el diseño permite la evolución del modelo de framework propuesto, así como su adaptación al problema planteado.

- **Experimentación:** implementación de diferentes casos de uso (un WebQuest, un juego serio y un sistema de recomendaciones) haciendo uso la solución propuesta formalizará funcionalidades, componentes tecnológicos, comportamientos e interacciones implementados. El uso en escenarios reales controlados, como son un museo, un edificio público y el hogar, permitirá obtener datos que sirvan para evaluar la validez del framework propuesto.

- **Análisis y conclusiones:** los resultados obtenidos durante el desarrollo, tanto de la investigación como en los casos de uso implementados, serán estudiados y comparados con otros obtenidos en estudios similares para poder extraer conclusiones del trabajo, basadas en la hipótesis y objetivos planteados, lo más objetivas posibles. La experimentación se llevará a cabo con usuarios reales, permitiendo así la extracción de conclusiones basadas fundamentalmente en el uso práctico de la solución propuesta, incluyendo, entre otros, análisis de la efectividad de las recomendaciones facilitadas, de la efectividad de los juegos en el aprendizaje o de la mejora de los tiempos de aprendizaje en actividades académicas.

- **Publicación:** puesta en común y presentación de resultados a la comunidad científica. El desarrollo de publicaciones en revistas científicas (como *Sensors* o *Journal of Ambient Intelligence and Humanized Computing*), congresos (como *International Symposium on Ambient Intelligence (ISAmI)* o *IEEE Symposium Series on Computational Intelligence (SSCI)*), talleres (como *Evidence-Based Technology Enhanced Learning (EbTEL)*) u otros medios de difusión del conocimiento dará a conocer resultados parciales y totales de la investigación. Por otro lado, permitirá recibir la realimentación de la comunidad científica experta que permitirá dar validez al trabajo llevado a cabo.

Las actividades anteriormente descritas se llevan a cabo de forma iterativa a lo largo de todo el proceso de investigación.

1.4. Objetivos de la Tesis Doctoral

El propósito último que persigue esta investigación es **diseñar un framework que permita desarrollar aplicaciones de aprendizaje basadas en el enfoque pedagógico CSCL y los paradigmas de la Inteligencia Ambiental y la Computación Social, a través del uso de tecnologías de contextualización, localización y gestión inteligente de la información**. Este framework debe ser capaz de integrar diversas tecnologías sensibles al contexto, de forma que las aplicaciones resultantes sean dinámicas y a su vez fáciles de utilizar por los usuarios participantes en el proceso de aprendizaje. Asimismo, el framework debe permitir el aprendizaje en movilidad a través uso de dispositivos móviles, por lo que su diseño debe ser consciente de las limitaciones de procesamiento, almacenamiento e interfaces de estos dispositivos. Además, el framework requerirá la integración de herramientas que permitan la gestión de las funcionalidades ofrecidas de forma inteligente. Para cumplir este objetivo, se hará uso de Organizaciones Virtuales de agentes que gestionen diferentes tareas de forma autónoma e inteligente. De forma más concreta, los objetivos definidos serán los siguientes:

- **Definir y desarrollar CAFCLA (*Context-Aware Framework for Collaborative Learning Activities*), un framework que se basará en la Inteligencia Ambiental y la Computación Social, como base para crear aplicaciones de aprendizaje basadas en el enfoque CSCL**.

- **Facilitar a educadores y desarrolladores el proceso de diseño y desarrollo de las aplicaciones educativas**, así como la implementación y el despliegue de la infraestructura, abstrayéndoles de la tecnología y ofreciendo herramientas de diseño y configuración intuitivas.

- **Facilitar que actividades de aprendizaje puedan ser personalizadas** en función del estudiante o grupo de estudiantes, así como monitorizadas y gestionadas de forma dinámica por los educadores, disponiendo de información detallada de todo el desarrollo de la actividad que podrá ser analizada a posteriori.

- **Incluir mecanismos que permitan disponer de información contextual** en cualquier momento o lugar en el que se lleve a cabo una actividad, considerando escenarios distribuidos a veces no conectados entre ellos y haciendo especial hincapié en el descubrimiento de servicios, la elección del mejor protocolo de comunicación, o el descubrimiento de posibles colaboradores para llevar a cabo una actividad.

- **Ofrecer la posibilidad de caracterizar un objeto, persona o zona presente en la actividad de aprendizaje**, explotando al máximo las TIC para buscar en todo momento la mejor solución a la contextualización, teniendo en cuenta todas las premisas que afecten a la caracterización en un momento dado.

- **Considerar las diferentes interacciones sociales** que puedan fomentarse o generarse a lo largo del proceso educativo planteado, ya sea entre humanos, entre humanos y máquinas o entre máquinas.
- **Facilitar soporte para facilitar, fomentar y permitir la colaboración de los alumnos** dando sustento a diferentes formas de comunicación y colaboración que permitan la interconexión entre los participantes en la actividad sin que ellos sean conscientes de la complejidad tecnológica implícita.

Para alcanzar los objetivos que se proponen, ha sido necesario analizar el estado del arte de la Inteligencia Ambiental, la Computación Social, la Tecnología de Agentes, los modelos de aprendizaje colaborativo, así como diversas tecnologías de comunicación e información contextual compatibles con tales objetivos. Para alcanzar su consecución, se han planteado a su vez una serie de objetivos a nivel técnico y científico:

- **Desarrollar un framework basado en capas** que integren capacidades como la simplicidad de los sistemas para su uso, la transparencia tecnológica para los usuarios, la eficiencia de los recursos para el desarrollo, la máxima ubicuidad para los servicios ofrecidos, las interacciones para humanos y máquinas, o la incentivación para las relaciones sociales.
- **Definir un modelo de arquitectura basada en Organizaciones Virtuales de agentes distribuida, flexible y adaptable**, que permita cubrir las necesidades de gestión y comunicación exigidas por el framework propuesto.
- **Integrar sistemas de localización en tiempo real**, tanto para entornos de exterior como de interior, que permitan proveer al framework de un alto grado de ubicuidad en lo que respecta a la interacción con los usuarios.
- Integrar diferentes **sistemas de comunicación inalámbrica y redes de sensores** para contextualizar entornos en los que desarrollar actividades de aprendizaje, sin necesidad de que éstas sean desarrolladas en el aula.
- Hacer el **framework interoperable con múltiples tecnologías** que aporten flexibilidad y dinamismo al framework, de forma que éste pueda adaptarse a diversos escenarios de aplicación.
- Diseñar **interfaces intuitivas que permitan un elevado nivel de interacción entre los usuarios y la tecnología**, siguiendo las pautas del framework, de forma que la interacción se realice de forma transparente y ubicua.

- Evaluar de forma empírica el framework mediante su **aplicación a diferentes casos de uso en entornos reales**, cubriendo desde entornos educativos convencionales (por ejemplo, una visita de alumnos a un museo) a escenarios de concienciación general de la sociedad (por ejemplo, educación en eficiencia energética).

1.5. Estructura de la Memoria

El resto de la memoria de esta Tesis Doctoral se estructura en diferentes secciones de la forma que a continuación se detalla.

El Capítulo 2 incluye el estado del arte de los paradigmas y tecnologías que dan sentido a la investigación desarrollada para dar lugar a CAFCLA: Inteligencia Ambiental, CSCL, Computación Social, Sensibilidad al Contexto y Organizaciones Virtuales de agentes.

El Capítulo 3 detalla la contribución que se desarrolla en esta Tesis Doctoral, incluyendo el planteamiento del problema a resolver, la presentación de la solución propuesta y su aplicación a los diferentes casos de uso que se han desarrollado.

El Capítulo 4 presenta los artículos, capítulos de libros y publicaciones en conferencias y workshops que han sido publicados en relación a esta Tesis Doctoral tras su validación por la comunidad científica, así como los proyectos que han dado soporte a la investigación y desarrollo de esta Tesis Doctoral.

El Capítulo 5 incluye las publicaciones originales de los artículos de revista y capítulos de libro más relevantes a los que ha dado lugar esta investigación, antecedidas pos un resumen del contenido, los objetivos buscados y los resultados más relevantes obtenidos en cada una de ellos.

El Capítulo 6 desglosa las conclusiones más relevantes, entre las que se encuentran la mejora de los tiempos de aprendizaje en los alumnos al hacer uso de información contextual en el aprendizaje en museos o la consecución de un mejor uso de la energía en edificios públicos, y el trabajo futuro que dará continuidad al aquí presentado, como puede ser la introducción de localización a través de smartphones o la integración de gadgets de sensorización comerciales en la plataforma.

2 Estado del Arte

Tal y como se ha adelantado en el anterior capítulo, son varios los paradigmas y tecnologías que dan soporte al trabajo realizado en este Tesis Doctoral. El presente capítulo detalla el estado del arte de los paradigmas y tecnologías más relevantes en el ámbito de esta Tesis Doctoral. Así, la Sección 2.1 analiza el papel que el paradigma de la Inteligencia Ambiental juega en el desarrollo de nuestro trabajo, destacando la aportación de premisas como la facilidad de uso, la transparencia o la ubicuidad en las comunicaciones. La Sección 2.2 se centra en el aprendizaje colaborativo y en su evolución durante los últimos años gracias a los avances de las TIC. La Sección 2.3 presenta el paradigma de la Computación Social, el cual realiza una gran aportación en esta Tesis Doctoral gracias a su visión de la relación entre los individuos y los sistemas computacionales. La Sección 2.4 aborda el uso de información contextual en los procesos educativos, identificando sus usos más habituales así como las carencias detectadas que nuestra propuesta resuelve.

2.1. Inteligencia Ambiental - *Ambient Intelligence*

A comienzos de la década de los noventa Mark Weiser plantea el concepto de Computación Ubicua (*Ubiquitous Computing*) en el ámbito científico (Weiser, 1991), intuyendo la integración de todo tipo de dispositivos electrónicos en la vida diaria. Weiser presenta entornos dotados de dispositivos con capacidades de computación y comunicación que proporcionan servicios a los usuarios de forma transparente y ubicua, abstrayendo a estos de cualquier tipo de complejidad tecnológica. A finales de la misma década aparece la Computación Pervasiva (*Pervasive Computing*), la cual focaliza su visión en la movilidad y distribución de los sistemas (Satyanarayanan, 2001), complementado la propuesta anterior de Mark Weiser.

La Inteligencia Ambiental plantea una nueva forma de interacción entre los individuos y la tecnología. En esta visión es la tecnología la que está al servicio de las personas, siendo capaz de adaptarse a sus necesidades en función del contexto en el que estén inmersas en un momento dado (Aarts, 2005). Surgen entonces nuevas formas de interacción y de intercambio de información a través de tecnología embebida, en la que los objetos cotidianos tienen la capacidad de almacenar y procesar datos y de comunicarse entre sí, de forma totalmente transparente a los usuarios. A través de esta nueva visión, los mecanismos tradicionales para la entrada y salida de datos, como son por ejemplo las pantallas o lo teclados, son substituidos por medios de interacción inteligentes que permiten comunicarse con el entorno a través de la voz, el movimiento o con sola presencia del usuario en él (Sadri, 2011). En definitiva, la relación hombre-máquina será intuitiva, natural y transparente, abstrayendo a los usuarios de la complejidad tecnológica. De esta forma se constituirán sistemas de Inteligencia Ambiental que responderán a las necesidades de los usuarios de forma anticipada gracias al conocimiento que tienen de éste y del contexto en el que está inmerso en cada momento.

La educación también se ve beneficiada por la aplicación de técnicas de Inteligencia Ambiental en sus procesos. La educación se trata de uno de los pilares básicos la sociedad y, como tal, no ha permanecido inmune a los cambios que han surgido gracias a los avances tecnológicos. La que ha venido a considerarse como Sociedad del Conocimiento ofrece grandes oportunidades a la Inteligencia Ambiental. El uso de nuevas tecnologías en el aula y fuera de ella ha permitido que los procesos de aprendizaje evolucionen y mejoren facilitando, entre otros aspectos, la adquisición de información, la colaboración entre alumnos, el seguimiento de actividades y su evaluación, etc. Algunas de las influencias que la Inteligencia Ambiental tiene en este campo incluyen el aprendizaje activo. La visión de la Inteligencia Ambiental permite que sean los alumnos los que jueguen el papel más importante en el proceso de aprendizaje, siendo el eje central del mismo. De esta forma, se podrán personalizar los procesos de aprendizaje y los alumnos jugarán un rol activo en el proceso, adquiriendo y generando conocimiento gracias a la realización de diferentes actividades. Por otro lado, el uso de nuevas tecnologías y herramientas ha influido de forma positiva en los cambios que se producen a la hora de aprender y enseñar. El proceso de aprendizaje incluirá la utilización de todo tipo de herramientas para llevar a cabo las actividades. Podrán utilizarse desde las clásicas transparencias o el correo electrónico, hasta dispositivos móviles con los que seguir todo tipo de actividades. De forma más general, puede concluirse que la integración de la tecnología facilita la aparición de diferentes tendencias en el aprendizaje que promulgan la utilización de sistemas colaborativos, la movilidad que proporcionan los nuevos dispositivos y la personalización de contenidos gracias a las tecnologías contextuales. Entre estas tendencias destacan: CSCL (*Computer Supported Collaborative Learning*), m-learning (*Mobile Learning*), u-learning (*Ubiquitous Learning*), Aprendizaje Sensible al Contexto (*context-aware Learning*) y Aprendizaje basado en la Localización (*Location-based Learning*).

Cabe destacar que el aprendizaje, entendido como el proceso en el que se transmite/adquiere el conocimiento, traspasa la barrera de los entornos de enseñanza (por ejemplo, colegios o institutos), y tiene aplicación en otros ámbitos como la formación de trabajadores o la concienciación de la sociedad, donde la tecnología también tiene una fuerte presencia (por ejemplo, no es extraño ver empresas que forman a los trabajadores en prevención de riesgos laborales mediante cursos online). Uno de los ámbitos de aplicación del framework desarrollado en esta Tesis Doctoral, y con ello de la Inteligencia Ambiental, es la educación de trabajadores y consumidores finales en hábitos de consumo energético más eficientes (García et al., 2017; Orland et al., 2014). La Inteligencia Ambiental permite conseguir un uso eficiente de los recursos energéticos a través de redes de sensores y actuadores que permiten optimizar el funcionamiento de los sistemas de calefacción, climatización, iluminación, etc. (Aarts and de Ruyter, 2009a; Gaggioli, 2004; Augusto, 2007; Chong and Mastrogiovanni, 2011). Estas redes se verán complementadas con mecanismos inteligentes determinan el uso de los dispositivos que consumen energía (El Fallah Seghrouchni et al., 2010; D'Oca et al., 2014). Dentro del ámbito profesional, a través de las tecnologías de comunicación y diferentes herramientas de teletrabajo y control a distancia, los hogares pueden convertirse en lugares de trabajo, reduciendo las pérdidas de tiempo por desplazamiento y favoreciendo la conciliación de la vida laboral con la vida personal, gracias a la disponibilidad de horarios flexibles. Más aún, estás mismas herramientas permiten que los usuarios sean capaces de comprobar el estado en el que se encuentra su casa en un momento dado (luces, calefacción, seguridad, etc.) utilizando sistemas de telemonitorización (Lynggaard and Skouby, 2016; Morales et al., 2012; Bhati et al., 2017).

Tanto en entornos de enseñanza, como fuera de estos, el paso del tiempo ha permitido que se hayan introducido múltiples recursos tecnológicos para complementar los métodos tradicionales de enseñanza y aprendizaje (Baylari and Montazer, 2009; Chen and Huang, 2012; Yin et al., 2010; Margetis et al., 2012a). Por lo tanto, la transmisión tradicional de contenido se ha mejorado con la inclusión de presentaciones electrónicas, la utilización de páginas web y el correo electrónico, el uso de plataformas de aprendizaje como Moodle, LAMS o Wikis, o el diseño de actividades colaboración entre los estudiantes (Dimitriadis, 2012; García et al., 2011; Gómez-Sánchez et al., 2009; Martín et al., 2010). De este modo, la tecnología ofrece un amplio abanico de alternativas para mostrar y comunicar el contenido de una actividad de aprendizaje a los estudiantes. De forma general, puede denominarse aprendizaje electrónico, más conocido por su término en inglés *e-learning*, a aquellas iniciativas educativas en las que a partir del uso de tecnología se pretende habilitar y mejorar el aprendizaje (Adelsberger et al., 2002).

Sin embargo, las aplicaciones basadas en el concepto de *e-learning* presentan el contenido generalmente de forma estática, sin tener en cuenta la experiencia y conocimientos previos, así como las habilidades o metas que los estudiantes deben adquirir o alcanzar (Alvarez et al., 2011; Baylari and Montazer, 2009; Echeverría et al., 2006; Martín et al., 2010). En este sentido, la aplicación de los nuevos recursos tecnológicos puede mejorar la gestión de contenido del proceso de aprendizaje, de modo que pueda ser dinámico y personalizable a las necesidades de cada alumno o del escenario en el que se desarrolla la actividad (Baylari and Montazer, 2009; FitzGerald, 2012; Hyndman et al., 2011; Li et al., 2009; Margetis et al., 2012b; Sintoris et al., 2012).

Por otro lado, el uso cotidiano de los dispositivos móviles y gadgets (teléfonos móviles, tablets, etc.) ha permitido que estos sean incluidos en el proceso educativo de forma completamente natural (Echeverría et al., 2011; García et al., 2012b, 2011). Gran parte de los alumnos de todos los niveles educativos disponen de dispositivos móviles (García et al., 2011). Este hecho, unido a la expansión de las tecnologías de comunicación inalámbricas, tales como Wi-Fi, Bluetooth y GPRS/3G, propicia la utilización de los dispositivos en la formación de redes que constituyan parte del escenario educativo, fomentando la colaboración entre alumnos y la comunicación alumno-profesor (Alvarez et al., 2011; Gómez-Sánchez et al., 2009). Esta capacidad de comunicación inalámbrica entre los distintos dispositivos móviles permite a los usuarios crear redes móviles denominadas ad-hoc o MANET (*Mobile Ad-hoc NETworks*). Una MANET es un sistema de nodos móviles inalámbricos que se organizan dinámicamente en topologías arbitrarias temporales. Personas, vehículos y otros objetos en movimiento pueden de este modo interconectarse entre sí sin la existencia de una infraestructura previa o cuando el uso de dicha infraestructura requiere de una extensión inalámbrica (Hu, 2011; Ilyas, 2003; Roy and Roy, 2011). Las redes MANET permiten abrir nuevas puertas tecnológicas como base a formas de aprendizaje (Jorrín, 2006) innovadoras que ayuden a la reproducción de procesos educativos ya aplicados en las aulas o que ayuden a mejorar la educación no presencial (Di Mascio et al., 2012; García et al., 2011; Hu, 2011).

A pesar de lo expuesto, existen limitaciones en la utilización de este tipo de redes, tanto por la propia naturaleza de las MANET, como aquellas inherentes al uso de la tecnología. Entre ellas están (Frohberg et al., 2009; Kakihara and Sorensen, 2002; Kukulska-Hulme et al., 2009; Pachler et al., 2009; Traxler, 2007):

- Falta de interacción directa entre el alumnado y el profesorado al emplearse dispositivos móviles.
- Sensación de control en las interacciones y actividades por parte del alumnado.
- Necesidad de un periodo de formación tecnológica que no todo el profesorado estará dispuesto a asumir y que hay que valorar para cuantificar el beneficio que esta tecnología proporciona.
- Reducción de la socialización de las personas, ya que una excesiva carga tecnológica podría dificultar las relaciones personales.
- Determinación por parte del profesorado que ponga en marcha este tipo de redes a la hora de decidir qué hacer con ellas y cómo hacerlo.

De igual forma, existen autores que defienden el uso de los dispositivos móviles en los procesos educativos (Kukulska-Hulme and Jones, 2011; Roschelle, 2003; Sharples et al., 2009), ya que dan lugar a nuevas oportunidades de enseñanza. No en vano, estos dispositivos están presentes en diversos ámbitos, tanto en entornos personales como en entornos académicos (Bennett et al., 2008; Stanley, 2009b). Además, la capacidad de procesamiento, almacenamiento y comunicación de estos dispositivos aumenta con el paso del tiempo de forma considerable, por lo que las funcionalidades y potenciales aplicaciones que nos ofrecen aumentan de forma notable (Aarts and de Ruyter, 2009b; Helsper and Eynon, 2010).

Más aún, cuando el proceso de aprendizaje se produce fuera del aula, como en el mencionado escenario de educación en eficiencia energética, los dispositivos móviles, sensores y gadgets son capaces de facilitar la movilidad necesaria para trasladar las actividades de un contexto a otro (Sharples et al., 2009, 2010). Tal y como se verá con más detalle en la Sección 2.4, la inclusión de las tecnologías sensibles al contexto (*Context-awareness*) permitirán crear escenarios educativos enriquecidos, ya que se dispondrá de cualquier tipo de información que podrá ser manejada de múltiples formas dentro del proceso de aprendizaje.

La Inteligencia Ambiental enfatiza la transparencia de las tecnologías para los usuarios, de forma que éstas se utilicen para facilitar las tareas ordinarias o mejorar las actividades (Traynor et al., 2010a). En este sentido, los sistemas que combinan diferentes tecnologías raramente facilitan mecanismos para realizar cambios transparentes entre ellas (por ejemplo, protocolos de comunicación diferentes). Del mismo modo, los datos deben gestionarse de una manera inteligente y eficiente, siendo una carencia identificada en la mayor parte de la literatura revisada, utilizando únicamente repositorios de datos estándar que solo consideran la persistencia y la consistencia (García et al., 2011). Funcionalidades como la redundancia de datos para resolver fallos en la red ayudan a hacer que el sistema sea dinámico y beneficie la accesibilidad de los datos con independencia del lugar y del momento.

La aplicación de técnicas de Inteligencia Ambiental en el aprendizaje requiere tener en cuenta algunos aspectos como el diseño de interfaces intuitivas y atractivas o la abstracción de los usuarios finales de la complejidad de la tecnología. Por esta razón, el proceso de diseño debe tener en cuenta, desde un principio, la opinión de todas las partes interesadas: educadores, diseñadores y desarrolladores (Gómez-Sánchez et al., 2009).

A pesar de que es bien conocido que la colaboración beneficia el proceso de aprendizaje (García et al., 2011), la colaboración entre los estudiantes es un tema que no se considera en muchas propuestas (Chen et al., 2007). Incluir dispositivos móviles y protocolos de comunicación inalámbrica en cualquier diseño de aprendizaje que requiera movilidad (como se discute en este documento) es hoy en día necesario. Los dispositivos móviles se conectan fácilmente entre sí, por lo que la colaboración entre los estudiantes es una tarea fácil, aumentando la variedad de actividades y mejorando el proceso de aprendizaje.

A modo de resumen, los aspectos fundamentales en torno a la Inteligencia Ambiental que se investigan en esta Tesis Doctoral son los siguientes:

- Técnicas utilizadas en entornos de aprendizaje colaborativo.
- Transparencia en el uso de diferentes protocolos de comunicación, sistemas de sensori-

zación y sistemas de localización.

- Entrega de contenidos a los usuarios, visualización y realimentación.
- Provisión de inteligencia a las aplicaciones.

La siguiente Sección profundiza en el aprendizaje colaborativo analizando diferentes trabajos que hacen uso de él en el ámbito de esta Tesis Doctoral.

2.2. Aprendizaje Colaborativo Soportado por Ordenador - *CSCL*

Durante los últimos años, el interés por el software educativo (conocido habitualmente como *e-learning*) ha aumentado de forma notable (Gómez-Sánchez et al., 2009). Entre la gran variedad de software educativo disponible se encuentran las aplicaciones de aprendizaje colaborativo o CSCL (*Computer Supported Collaborative Learning*) (Dillenbourg, 1999). Un sistema de aprendizaje colaborativo permite diferentes vías de interacción entre los participantes, que activarán mecanismos de aprendizaje (Koschmann, 1996) a través de una serie de herramientas que faciliten la implementación, desarrollo y despliegue de actividades. CSCL se ha convertido en un importante campo de investigación dentro de la educación que atrae diferentes intereses, desde los puramente educativos hasta los enfocados en mejorar la interacción hombre-máquina (Gómez-Sánchez et al., 2009).

Los dispositivos móviles proveen importantes beneficios al proceso educativo: movilidad, mecanismos de comunicación, incluyendo recolección y provisión de información contextual, así como facilitar una ubicación precisa en cualquier momento. Estos aspectos favorecen además la comunicación, colaboración y compartición de recursos entre estudiantes. El aprendizaje móvil se define como *"los procesos de adquisición de conocimiento a través de conversaciones en múltiples contextos entre las personas y las tecnologías de interacción personal"*(Sharples et al., 2010). Esta definición implica dos ideas importantes: la primera es que la tecnología puede participar en el proceso de aprendizaje; la segunda idea sugiere que el aprendizaje móvil enfatiza la comunicación entre las personas involucradas y su interacción con el contexto (Brown, 2010). Basados en la capacidad de interconectar dispositivos, podemos afirmar que éstos son útiles para fomentar la colaboración entre los estudiantes, es decir, que pueden actuar como una herramienta que apoya CSCL (Koschmann, 1996).

Tal y como se desprende de lo expuesto con anterioridad, este tipo de dispositivos y redes ayudan a mejorar el proceso de Aprendizaje Colaborativo (CL - *Collaborative Learning*) (Koschmann, 1996), más en concreto aquel que hace uso de dispositivos móviles, denominado MCSCL (*Mobile Computer Supported Collaborative Learning*). Este tipo de esquemas de red favorecen la coordinación, las actividades conjuntas y las interacciones sociales que deben producirse en el aprendizaje colaborativo (Cortez et al., 2004). Una actividad colaborativa se define como un compromiso de varios participantes en un esfuerzo coordinado de aprendizaje de objetivos educacionales específicos (Dillenbourg, 1999). Así, al hacer trabajos en grupos, en un contexto de colaboración e intercambio con sus compañeros, los estudiantes obtienen mejores resultados académicos (Johnson and Thomson, 1986; Sharples et al., 2009; Kukulska-Hulme and Jones, 2011), ya que los alumnos pueden aprender más, recordar por más tiempo, desarrollar habilidades de pensamiento crítico o sentirse más valorados y confiados (Evans, 2008). Las propuestas relacionadas con el aprendizaje a través de dispositivos móviles existentes son numerosas. El presente trabajo trata de clasificarlas, de forma cronológica, en función de las diferentes tecnologías que utilizan. De esta forma, el lector puede comprobar cómo a medida que diferentes tecnologías de comunicación o dispositivos adquieren madurez, éstas se integran en el proceso de aprendizaje. Así, el paso más natural para utilizar los dispositivos móviles en herramientas que permitan colaboración dentro de la educación es la adaptación de entornos existentes de *e-learning* (Cobcroft et al., 2006; Fadzil et al., 2012).

Siguiendo esta premisa, Berger *et al.* (Berger et al., 2003), han integrado una herramienta para dispositivos móviles en una plataforma funcional de *e-learning* en la Universidad de Regensburg. Gracias a la nueva funcionalidad aportada por dicha herramienta, los alumnos pueden acceder a la plataforma de aprendizaje a través de cualquier dispositivo móvil. Además de proporcionar movilidad, la solución está enfocada a poder realizar trabajo colaborativo, permitiendo la creación de grupos de trabajo públicos o privados que disponen de diferentes opciones para interactuar (compartición de ficheros o comunicación personal) entre ellos y poder llevar a cabo diferentes tareas. Sin embargo, esta herramienta depende de una infraestructura centralizada que proporciona los recursos a utilizar y que permite la comunicación inalámbrica, por lo que fuera del entorno académico (físico) no puede utilizarse. Por otro lado, con este tipo de soluciones no se fomenta la interacción espontánea entre los alumnos en cualquier lugar, ya que fuera del área que cubre el sistema central la comunicación entre pares no será posible.

El ejemplo expuesto en el párrafo anterior ilustra el clásico sistema de aprendizaje colaborativo a través de dispositivos móviles en el que se adapta el contenido desarrollado para ordenadores personales a las características de los dispositivos móviles. Sin embargo, la capacidad actual de estos dispositivos permite que sean utilizados en un uso más intensivo, dando lugar a tendencias y soluciones con mayor potencial. Los siguientes ejemplos reflejan este potencial en cuatro escenarios habituales de aprendizaje con dispositivos móviles: en el aula (Cortez et al., 2004), en un museo o lugar "bajo techo" fuera del aula (Yatani et al., 2004), en el exterior (Vasiliou and Economides, 2007b) y en cualquier otro lugar (Russell and Pea, 2004). Estas soluciones se aproximan las aplicaciones de aprendizaje que se describen dentro del paradigma de la Inteligencia Ambiental (ISTAG, 2003). Sin embargo, aún no extraen todo el potencial de los dispositivos e infraestructuras de comunicación inalámbricas para proporcionar soluciones cuya transparencia, inteligencia y sensibilidad contextual las permita incluir dentro de la Inteligencia Ambiental.

Yatani describe en (Yatani et al., 2004) una aplicación que permite el aprendizaje colaborativo en museos. El sistema presenta 13 preguntas a responder y los participantes tienen en todo momento una línea de comunicación abierta a través de PDAs y transmisores. La red es centralizada, de forma que el profesor tiene en todo momento conocimiento de qué está pasando en la actividad. El trabajo concluye que los niños son más proactivos en este entorno de aprendizaje, comparten información entre ellos de forma natural y aumentan las peticiones de ayuda hacia los profesores y entre los compañeros.

Russell presenta una aplicación centralizada que pretende aumentar la participación de estos (Russell and Pea, 2004). Los participantes presentan dudas a los profesores de forma anónima y éstos son contestados en tiempo real. El profesor tiene acceso a los comentarios generados por su respuesta, con lo que podrá reaccionar en consecuencia, proporcionando la aplicación cierto nivel de realimentación al profesor.

Cortez *et al.* presentan en (Cortez et al., 2004) una aplicación MCSCL para PDAs y comunicación inalámbrica utilizada para enseñar ciencias. La aplicación es presentada como un juego en el que se plantea una actividad a grupos que requerirá consenso y unanimidad para ser enviada al profesor (nodo central en la infraestructura). El diseño está basado en tres capas: una capa de red que se encarga de las comunicaciones, una capa de actividad que provee las herramientas, y una capa de aplicación que lanza las actividades. Sobre este trabajo se realiza una evaluación cuantitativa y cualitativa, proporcionando resultados entre los que destacan la alta motivación de los alumnos, los mejores resultados académicos obtenidos y la mejora en la resolución de preguntas no explicadas con anterioridad en clase.

Otro ámbito de aplicación diferente es el presentado por Vasiliou *et al.*, al tratar el problema que presentan los escenarios educativos fuera del aula (Vasiliou and Economides, 2007b,c). Para cubrir estos entornos emplean MANETs que utilizan *multicasting*. Los alumnos se dividen en subgrupos que trabajan de forma independiente. La zona de trabajo de cada uno de estos grupos estará cubierta por un nodo móvil, que a su vez se comunicará con la zona desde la que el profesor evalúa la actividad. Esta infraestructura previa es necesaria para que el profesor pueda tener conocimiento del estado de la actividad en cada uno de los grupos. La utilización de envíos *multicast* limita el tráfico generado, al propagarse los mensajes por el árbol creado por los dispositivos, sin necesidad de que los nodos centrales envíen los mensajes a todos los demás. Su uso de describe su uso con tres ejemplos: una visita arqueológica, una visita a un parque natural y una actividad de orientación.

Los anteriores trabajos ilustran cuál es el objetivo principal para la utilización de dispositivos móviles en el proceso de aprendizaje: permite a los alumnos compartir información, coordinar sus tareas y trabajar colaborativamente.

Por lo tanto, la educación puede mejorar sus métodos si los adapta a las características de Inteligencia Ambiental. Li *et al.* (Li et al., 2009) identifican cinco características que distinguen a un sistema de aprendizaje basado en la Inteligencia Ambiental de otros procesos de aprendizaje:

1. El aprendizaje puede llevarse a cabo en cualquier momento y en cualquier lugar.

2. El aprendizaje debe ser sensible al contexto.

3. La interacción entre los usuarios y la tecnología debe ser natural.

4. La colaboración entre los alumnos debe fomentarse y facilitarse.

5. El aprendizaje debe ser continuo, incluso si los estudiantes cambian su ubicación.

Esta Tesis Doctoral se centra en la gestión de la información contextual y de comunicaciones necesaria en un sistema de aprendizaje colaborativo basado en la Inteligencia Ambiental y la Computación Social. Si el contexto en el que se lleva a cabo una actividad de aprendizaje está completamente caracterizado, la actividad es más rica y los educadores son capaces de personalizar los contenidos ofrecidos a los estudiantes en la forma que estimen oportuna. Por lo tanto, el proceso de aprendizaje puede mejorarse si se proporciona información contextual y si se facilita la colaboración y las interacciones entre los estudiantes, así como entre los participantes y el entorno (Brown et al., 2010; García et al., 2012; Li et al., 2012; Peng et al., 2012). Además, la combinación de aprendizaje colaborativo y aprendizaje sensible al contexto lleva naturalmente a pensar en espacios de aprendizaje ubicuos que se caracterizan por facilitar el proceso de identificación de colaboradores, contenidos y servicios en función del tiempo y el lugar en el que se lleve a cabo el proceso de aprendizaje. Para ello, se ha de tener en cuenta el contexto que rodea a los estudiantes, proporcionando, de forma precisa, qué recursos están disponibles y quiénes son los colaboradores que atienden a las necesidades de los alumnos en cada momento (Yang, 2006b).

De forma resumida, los aspectos fundamentales en torno al CSCL que se investigan en esta Tesis Doctoral son los siguientes:

- Uso de información contextual y sistemas de localización en aprendizaje colaborativo.

- Colaboración entre estudiantes a través de dispositivos móviles.

- Inclusión de interacciones hombre-hombre y hombbre-maquina en los procesos de aprendizaje colaborativo.

- Gestión y personalización de los recursos de aprendizaje.

Las siguientes secciones abordan el asunto expuesto en el párrafo anterior de forma más profunda. La Sección 2.3 desarrolla el estado del arte de la Computación Social en el ámbito educativo. La Sección 2.4 hará lo propio pero desde el punto de vista de la información contextual.

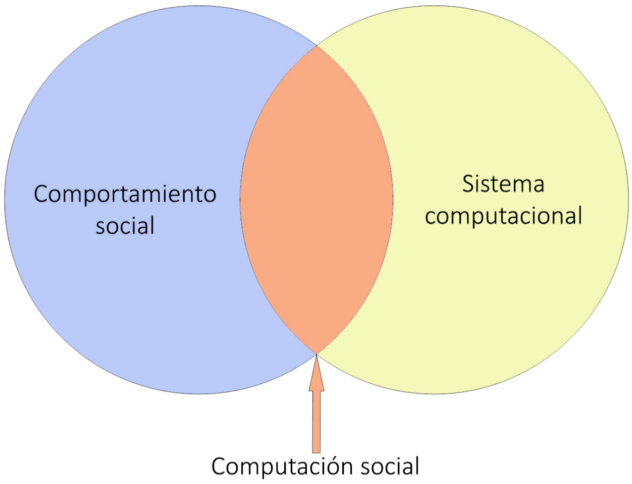

Figura 2.1 – Los estudios de Computación Social se encuentran en la intersección entre la investigación de la ciencia del comportamiento social y los sistemas informáticos.

2.3. Computación Social - *Social Computing*

La Computación Social es un nuevo paradigma centrado en el estudio de la intersección que se produce entre el estudio científico del comportamiento social y los sistemas computacionales (Schuler, 1994). La Figura 2.1 muestra la visión que a través de la cual la Computación Social afronta los problemas a resolver. En esta visión, los problemas se resuelven desde una perspectiva social, en la que tanto los humanos como las máquinas tienen una participación activa[1] (Linden et al., 2003; Von Ahn et al., 2003). Esto requiere resolver nuevos desafíos relacionados con la interacción hombre-máquina, la gestión de organizaciones y la distribución de tareas entre seres humanos y máquinas, que no pueden ser abordadas actualmente por las herramientas existentes.

Este nuevo paradigma está ganando relevancia entre las tendencias en investigación y desarrollo de sistemas software. El gran reto que hoy se plantea es la construcción de máquinas sociales complejas que aporten soluciones eficientes a los problemas sociales, tales como la salud, el turismo, el ocio, el transporte, la comunicación, el aprendizaje, la educación o la respuesta social a emergencias (Robertson and Giunchiglia, 2013). La investigación en esta área debe realizarse sobre la base de mecanismos de inteligencia artificial que construyan sociedades artificiales capaces de resolver problemas de tipo social. Estos mecanismos han de asentarse en una serie de infraestructuras tecnológicas y marcos teóricos como los ilustrados en la Figura 2.2.

En la literatura podemos encontrar algunas referencias que utilizan algunas de estas infraestructuras tecnológicas y marcos teóricos para abordar el aprendizaje colaborativo desde el

[1] Un ejemplo sencillo de esta colaboración humano-máquina es CAPTCHA, donde, para conocer si la persona que está accediendo a una web es humana, la máquina propone un código y el humano lo resuelve.

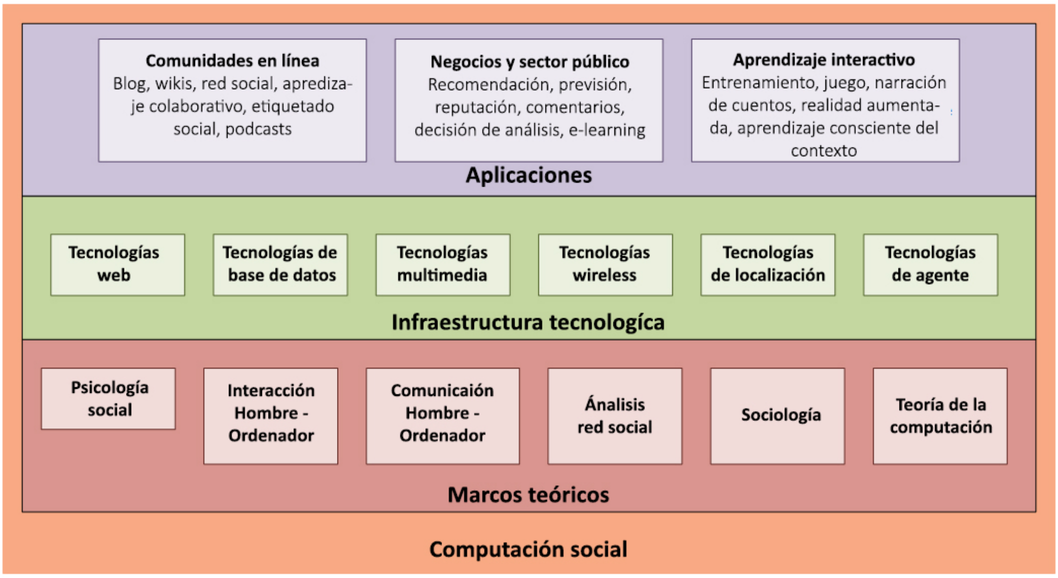

Figura 2.2 – Algunos de los marcos teóricos, infraestructuras tecnológicas o aplicaciones que cubren la Computación Social (Robertson and Giunchiglia, 2013) están directamente vinculados a la educación: interfaz Humano-Ordenador; análisis de redes sociales; tecnologías web; agentes; contexto; colaboración; o *e-learning*.

punto de vista de Computación Social. A continuación se describen las más relevantes.

En (Musser et al., 2003), los autores proponen una arquitectura de Computación Social y colaboración basada en reglas sociales que incluye las siguientes capacidades: representación de la presencia y acciones de los usuarios; representación de localizaciones y lugares; formación y representación de grupos; administración de reglas sociales; comunicación y facilidad de colaboración; notificaciones y acceso ubicuos; elementos de interfaz hombre-máquina; y construcciones de entornos de aprendizaje. Sin embargo, los autores se limitan a presentar la arquitectura de manera teórica sin llegar a desarrollar este framework.

En (Dascalu et al., 2015), los autores presentan un agente recomendador de materiales y herramientas educativas que tiene en cuenta el estilo de aprendizaje, aunque no se refieren explícitamente al paradigma de la Computación Social. Este agente se integra en un entorno de aprendizaje colaborativo virtual en el que los agentes producen dos tipos de recomendaciones: sugerencias y atajos. Sin embargo, el entorno de aprendizaje descrito carece de varios avances tecnológicos (por ejemplo, interoperabilidad con sensores de posicionamiento) que pueden permitir la integración del contexto en la solución del problema social mencionado.

En (Berjón et al., 2015), los autores describen una herramienta que facilita la comunicación para el aprendizaje colaborativo. Aunque el trabajo es muy sensible a las redes sociales, la comunicación y la gestión de usuarios, no profundiza en el proceso educativo porque no tiene en cuenta las actividades a realizar, del mismo modo que no considera aspectos relacionados con la comunicación con otros elementos que pueden participar en el aprendizaje, tales como sensores que caracterizan el contexto en el que se desarrolla o la localización de los participantes en el proceso educativo.

Sin embargo, ninguno de los ejemplos encontrados en la literatura recae en una de las tecnologías con mayor potencial dentro de la Computación Social de entre las mostradas en la Figura 2.2, como son las Organizaciones Virtuales de agentes (Villavicencio et al., 2016). Las Organizaciones Virtuales son sistemas abiertos en los que entidades heterogéneas se agrupan y colaboran para resolver un determinado problema. Algunas de las funcionalidades que avalan su idoneidad son: su capacidad para gestionar el comportamiento de los agentes a través de la inclusión de normas y reglas, su dinamismo a la hora de formar agrupaciones de agentes, su versatilidad para agregar o eliminar componentes, y su capacidad para describir comportamientos funcionales y estructuras (Rodríguez Marín et al., 2016).

Las Organizaciones Virtuales de agentes se usan en aplicaciones de aprendizaje y aprendizaje colaborativo para diferentes propósitos y son comúnmente diseñadas para adaptar la información contextual en los sistemas de aprendizaje orientados al contexto (Yaghmaie and Bahreininejad, 2011) o gestionar el desempeño de las actividades de aprendizaje (Lu et al., 2011; Macarro et al., 2009). Sin embargo, aunque la colaboración entre los agentes se considera en los trabajos anteriores, la colaboración entre los estudiantes no se tiene debidamente en cuenta a la hora de formalizar su diseño.

En (Popescu, 2014), los autores proponen una plataforma de aprendizaje basada en herramientas de medios sociales para fomentar la colaboración entre los estudiantes que integra herramientas Web 2.0 en un solo sistema. La plataforma permite a los profesores crear un entorno de herramientas que facilita funcionalidades como el seguimiento del alumno, monitorización y visualización o clasificación y soporte de evaluación. Sin embargo, eMUSE no da a los estudiantes la libertad de seleccionar herramientas y personalizar su entorno, la plataforma no es flexible (impidiendo la integración de herramientas que aporten información contextual), y el uso de diferentes roles y la gestión de los usuarios no se han tenido en cuenta a lo largo del proceso de aprendizaje.

En (Arif et al., 2015), los autores desarrollan una arquitectura multiagente para ayudar y recomendar a los estudiantes al realizar tutoriales de evaluación. La arquitectura ha sido diseñada para soportar el diseño instruccional, recuperar materiales de aprendizaje relevantes, procesar y analizar datos para permitir recomendaciones significativas de *e-learning* para profesores y estudiantes. A pesar de proveer a la plataforma el nivel de inteligencia que proporcionan los agentes, ésta no tiene en cuenta explícitamente los aspectos de la Computación Social, permitiendo únicamente las interacciones entre los participantes a través de forma asíncrona.

En (Popescu, 2014), los autores presentan una arquitectura de pizarra para la integración y comunicación de componentes distribuidos heterogéneos. Esta propuesta integra diferentes componentes para la construcción de una interfaz de usuario totalmente extensible mediante el uso de espacios de tupla y entornos basados en componentes. A pesar de ser una propuesta interesante en términos de integración de componentes que facilitan la Computación Social, no se ha tenido en cuenta la personalización de los contenidos aprovechando los agentes responsables de la gestión de usuarios, así como tampoco se considera la integración de otros aspectos relevantes de la Computación Social, como los tipos y gestión de la interacción entre estudiantes, y entre profesores y estudiantes.

Resumiendo, tras el análisis de los trabajos presentados a lo largo de esta sección podemos afirmar que las investigaciones no afrontan de forma conjunta el aprendizaje colaborativo, la información contextual y la Computación Social. Además, podemos ver que el enfoque más común en este área está relacionado con el uso de las redes sociales en el proceso, haciendo hincapié en la importancia de las relaciones sociales interpersonales, mientras que las interacciones hombre-máquina, que pueden proporcionar valiosa información contextual para mejorar los entornos de aprendizaje, no se han abordado en profundidad. Los aspectos fundamentales en torno a la Computación Social que se investigarán en esta Tesis Doctoral son los siguientes:

- Sistemas de Computación Social para desarrollas sistemas de aprendizaje inteligentes y adaptativos.
- Utilización de Organizaciones Virtuales de agentes para el desarrollo de herramientas educativas.
- Tipos de interacciones entre personas y entre personas y máquinas, así como su gestión.
- Sistemas de recogida y provisión de información personalizada.

A continuación, la Sección 2.4 profundiza en el uso de la información contextual dentro del ámbito educativo.

2.4. Sensibilidad al Contexto - *Context Awareness*

Según su definición más extendida, proporcionada por Dey en (Dey, 2001), el término *Context-awareness* (Sensibilidad al Contexto en castellano) se refiere a *"cualquier información que se puede utilizar para caracterizar la situación de una entidad"*, mientras que *"una entidad es una persona, lugar u objeto que se considera relevante para la interacción entre un usuario y una aplicación, incluyendo el usuario y las aplicaciones"*. Otros parámetros relevantes que afectan la información contextual son la identificación, el tiempo y la localización (Laine and Joy, 2009b).

En relación con el ámbito educativo, la combinación de aprendizaje colaborativo y sensible al contexto conduce naturalmente a pensar en espacios de aprendizaje ubicuos, caracterizados por *"proveer formas intuitivas para identificar colaboradores, contenidos y servicios correctos en el lugar apropiado y en el momento adecuado, cuándo y dónde están los alumnos (tiempo y espacio), qué recursos y servicios de aprendizaje están disponibles para los alumnos y quiénes son los colaboradores que responden a las necesidades de los alumnos"* (Hwang et al., 2009a).

La inclusión de la información contextual en el proceso de aprendizaje lleva directamente al Aprendizaje Sensible al Contexto (*Context-aware Learning*) (Bruce, 2009). Esta inclusión beneficia al proceso educativo desde diferentes puntos de vista. Por un lado, la caracterización contextual del entorno educativo favorece la flexibilidad del proceso puesto que el aprendizaje puede ser llevado a cabo no solo en las aulas, sino en otros ambientes como museos, zoológicos, etc. (García et al., 2011). Por otro lado, el uso de tecnologías como las Redes de Inalámbricas de Sensores (WSN - *Wireless Sensor Networks*) o los Sistemas de Localización en Tiempo Real (RTLS - *Real Time Localization Systems*) mejora el aprendizaje puesto que facilita la adquisición de información contextual así como el posicionamiento de los elementos involucrados en el proceso educativo (Abowd et al., 2006). Los RTLS son un gran recurso para mejorar la consciencia del contexto en escenarios de aprendizaje, gracias a la gran variedad de tecnologías que se pueden integrar para localizar las diferentes entidades que participan en dicho proceso. Las tecnologías más difundidas para facilitar la localización en tiempo real son GPS (*Global Positioning System*) (Oppermann and Specht, 2000), los sistemas de señalización por Infrarrojo (IR - *InfraRed Systems*) (Curran and Norrby, 2009b), la Identificación de Radio Frecuencia pasiva o activa (RFID - *Radio Frequency IDentification*) (Cheverst et al., 2000), WLANs (Behzadan and Kamat, 2013), BLE (*Bluetooth Low Energy*), Wi-Fi (Prieto et al., 2012), NFC (*Near Field Communication*) (Blöckner et al., 2009), UWB (*Ultra Wide Band*) (Traynor et al., 2010a), o los sistemas inerciales (Prieto et al., 2016).

Una mejor comprensión del entorno a través de la tecnología permite a los educadores para personalizar el contenido proporcionado a los estudiantes. Del mismo modo, la tecnología facilita la interacción con el contexto y entre los estudiantes. Esto debe alcanzarse de una manera tan transparente y natural como sea posible. Son varios los enfoques seguidos en la literatura para la recopilación de información contextual, donde la tecnología empleada para la comunicación entre diferentes dispositivos y la recogida de datos es una piedra angular.

Un primer enfoque para proporcionar información contextual es *etiquetar el contexto*, para lo que se pueden emplear tecnologías como RFID (Blöckner et al., 2009), NFC (Tan et al., 2009a) o códigos QR (Rouillard, 2008). En todos estos casos, tanto la localización como la sensibilidad al contexto están estrechamente relacionadas: conocer con precisión la ubicación de los objetos y las personas permite determinar qué es lo que los rodea y, en consecuencia, caracterizar el contexto en el que están involucrados.

Un segundo enfoque es proporcionar la información contextual en base a la posición absoluta de los objetos/personas. GPS es la tecnología más utilizada para proporcionar localización en el aprendizaje sensible al contexto (Hwang et al., 2009b; Laine and Joy, 2009b). Este sistema de localización proporciona un alto nivel de precisión, estando disponible en la mayoría de teléfonos inteligentes y dispositivos móviles. Estas soluciones se utilizan en diferentes escenarios, como la planificación de rutas (Padovitz et al., 2008a) o la gestión del planificador del estudiante (Driver and Clarke, 2008). Sin embargo, la tecnología GPS no funciona en entornos de interior (los más habituales en procesos de aprendizaje) debido a la visión directa necesaria entre satélites y dispositivos. Para cubrir esta carencia, se utilizan diferentes sistemas de localización basados en RFID activo (Blöckner et al., 2009) o Wi-Fi (Martín et al., 2010), que tratan de replicar el modelo de localización basado en balizas (satélites) del sistema GPS. Este tipo de enfoque tiene limitaciones significativas al desarrollar actividades de aprendizaje sensibles al contexto puesto que la precisión de la ubicación es limitada (en el orden de 3-5 metros). Esta situación presenta un problema importante cuando las áreas donde la información contextual es diferente están cerca (por ejemplo, dos pinturas en un museo).

A las limitaciones de los sistemas de localización se une la carencia en el uso de técnicas de gestión inteligente que permitan personalizar las actividades ofrecidas en el procesa de aprendizaje mediante la predicción, la adaptación y la anticipación a las acciones de los usuarios (Castro et al., 2016). El aprendizaje sensible al contexto debe tener en cuenta no solo las interacciones entre las personas, sino también los elementos tecnológicos del sistema y sus combinaciones. Sin embargo, no existen en la literatura muchos marcos diseñados para implementar actividades de aprendizaje colaborativo que tengan en cuenta la información contextual. A continuación se presentan los ejemplos más completos de los que se han analizado.

En (Castro et al., 2016), los autores presentan la aplicación MOBILEARN. Dicha aplicación se trata de un sistema de aprendizaje móvil basado en el contexto que integra dos módulos: un módulo para el monitoreo del aprendizaje de los estudiantes y otro módulo para ofrecer servicios personalizados a través del uso de redes sociales. El trabajo presenta carencias en cuanto al detalle de tecnologías utilizadas para obtener información contextual. Del mismo modo, no hay ninguna explicación sobre la gestión de contenidos y su personalización antes de ser entregados a los estudiantes.

En (Martin et al., 2010), los autores describen el marco M2Learn, diseñado para desarrollar aplicaciones de aprendizaje colaborativo y social utilizando dispositivos móviles. El marco integra múltiples tecnologías de localización transparentes, identificación de objetos a través de RFID, soporte para sensores de movimiento, interoperabilidad con Moodle y diferentes estándares de aprendizaje. Sin embargo, el no incluye la capacidad de personalizar el proceso de aprendizaje mediante la adaptación dinámica del contenido y la mayor parte del trabajo radica en la integración de tecnologías que proporcionan información contextual, sin describir como se realiza la gestión de usuarios o las interacciones entre ellos.

En (Masud, 2016), los autores proponen un marco para el aprendizaje colaborativo que incluye interoperabilidad de datos semánticos, gestión de metadatos distribuidos y un procesamiento de consultas. El marco permite búsquedas con correspondencia semántica y contextual relacionada con conferencias, temas, formato de conferencia y está basado en agentes para apoyar el intercambio de contenidos de aprendizaje de diferentes sistemas de *e-learning*. Sin embargo, el marco presentado carece de una arquitectura integrada que permita la inclusión de datos procedentes de los sensores relacionados con el contexto, o su adaptación basada en el contenido o en los componentes sociales.

En (Luna et al., 2015), los autores presentan un enfoque basado en ontologías para representar el proceso de interacción entre el perfil de usuario y su contexto de aprendizaje colaborativo. Analizan las asignaciones de funciones, los permisos, las restricciones y la definición de reglas que se aplican al usuario, particularmente en el contexto de aprendizaje colaborativo en el que el sujeto está involucrado. Sin embargo, aunque la ontología se rellena con información recuperada de las redes sociales, la resolución de problemas no se enriquece con las interacciones sociales o entre hombre y máquina.

La revisión de la literatura evidencia algunas carencias en los sistemas de aprendizaje sensibles al contexto que se proponen hasta ahora. En primer lugar, algunos trabajos intentan combinar diferentes tecnologías para cubrir tantas situaciones como sea posible (Martín et al., 2010), la mayoría de ellas solo cubren situaciones de aprendizaje específicas, como aquellas en las que el contexto de marcado con RFID/NFC (Tan et al., 2009b) es necesario o aquellos donde el aprendizaje ocurre al aire libre (Padovitz et al., 2008b). La combinación de ambas situaciones solo es abordada por M2learn (Martin et al., 2010). Sin embargo, esta solución no proporciona sistemas de localización precisos y eficientes ni la posibilidad de integrar redes de sensores inalámbricos, excepto para sistemas RFID.

Por otro lado, los marcos analizados a lo largo de esta sección, podemos observar que hay ciertas carencias en las obras. Entre ellos, la mayoría de estas investigaciones no incluyen un conjunto de tecnologías que permitan la localización en interiores, localización al aire libre, etiquetado y detección a través de sensores físicos simultáneamente. Además, ninguno de los marcos proporciona la gestión del entorno en el que se desarrolla la actividad a diferentes niveles, como la delimitación y caracterización de diferentes áreas o la identificación de objetos de interés. Además, la gestión de contenidos, perfiles de usuario y grupos para personalizar el aprendizaje es inapreciable. Por último, ninguna de ellas aborda explícitamente el problema del aprendizaje colaborativo a través de la informática social, ya sea teniendo en cuenta la perspectiva dual, pedagógica y técnica, al definirlas.

Resumiendo, la presente Tesis Doctoral profundizará en la investigación de los siguientes campos dentro de la sensibilidad al contexto:

- Redes se sensores inalámbricas y sistemas de localización en interiores.
- Algoritmos de localización.
- Gestión inteligente de la información y provisión de contenidos.
- Integración de múltiples tecnologías.

Una vez concluido el estado del arte de esta Tesis Doctoral, el siguiente Capítulo expondrá las contribuciones que el trabajo realizado ha aportado.

3 Contribuciones

Las conclusiones obtenidas del análisis del estado del arte, en conjunto con la motivación de esta Tesis Doctoral, permiten idear CAFCLA, cuyo desarrollo ha propiciado varias contribuciones científicas. A lo largo del presente capítulo se describen las contribuciones que ha aportado esta Tesis Doctoral. La Sección 3.1 plantea el problema e identifican las carencias existentes en la literatura, dando pie a la solución propuesta: el framework CAFCLA. La Sección 3.2 describe cómo se ha diseñado el framework y que potencial tiene para el diseño, desarrollo e implementación de actividades de aprendizaje colaborativo que hacen uso de información contextual. La Sección 3.3 detalla los componentes de CAFCLA desde el punto de vista técnico. La Sección 3.4 detalla la implementación un caso de uso de aprendizaje colaborativo en un museo. La Sección 3.5 describe el caso de uso de un juego serio para fomentar el ahorro energético. La Sección 3.6 presenta un caso de uso en el que se desarrolla un sistema de recomendaciones para fomentar el ahorro energético en los hogares.

3.1. Planteamiento del problema

La innovación educativa se aprovecha en todo momento de la sorprendente evolución tecnológica experimentada en las últimas décadas (Mora et al., 2015; Bosch-Sijtsema and Haapamäki, 2014; Fermoso et al., 2015). Los constantes avances en la electrónica han permitido el desarrollo de dispositivos en los que la capacidad de almacenamiento y procesamiento ha crecido de forma inversamente proporcional a su tamaño. Además de estos avances de hardware, la evolución de los protocolos de comunicación ha sido tan notable que se ha conseguido una conectividad rápida y fiable entre los dispositivos de comunicación que actualmente utilizamos. Así, día a día comprobamos que la capacidad y el número de dispositivos que nos rodea están creciendo continuamente, incluyendo dispositivos móviles que nos permiten comunicarnos en tiempo real con cualquier persona en cualquier lugar, y dispositivos no intrusivos capaces de recoger y almacenar datos ambientales de nuestro alrededor (Meratnia et al., 2007). Esta revolución digital ha generado un gran cambio en la forma en que las interacciones sociales ocurren, lo que ha fomentado un cambio económico, político y social a gran escala al que la educación no ha permanecido inmune (Mora et al., 2015).

La revolución digital ha facilitado la inclusión de los **dispositivos electrónicos** en los procesos de aprendizaje, incluyendo nuevas formas de interacción y comunicación, de forma que han pasado a ser parte activa de la educación y han cambiado la perspectiva en la relación de esta última con las TIC (Jorrín-Abellán and Stake, 2009). En este sentido, los dispositivos móviles y las redes de sensores brindan importantes beneficios al ámbito educativo: movilidad, capacidad de comunicación, provisión de información contextual y localización precisa de usuarios. De esta forma, la adquisición de conocimientos y el aprendizaje pueden fomentarse en múltiples contextos incluyendo interacciones tanto humano-humano como humano-máquina. Por lo tanto, la tecnología participa de forma activa en el proceso de aprendizaje y enfatiza la comunicación entre las personas involucradas y su interacción con el contexto (Brown, 2010). Además, permite la incorporación de dispositivos interconectados que fomentan el aprendizaje colaborativo entre los estudiantes (Koschmann, 1996). Los avances tecnológicos han permitido entonces una mejora e innovación en los métodos de enseñanza que se aplican en el aprendizaje colaborativo. Un entorno de aprendizaje colaborativo facilita compartir y acceder al contenido de aprendizaje (por ejemplo, texto o imágenes) entre usuarios (por ejemplo, estudiantes o profesores) (Masud, 2016). El uso de dispositivos móviles y las comunicaciones inalámbricas (Roschelle, 2003) se han convertido en un ventaja para hacer más atractivo este proceso de aprendizaje y fomentar la colaboración entre los agentes implicados (Gómez-Sánchez et al., 2009).

Los dispositivos móviles ofrecen funcionalidades que facilitan la adquisición de **información contextual**. La información contextual incluye cualquier dato que pueda ser utilizado para caracterizar a una persona, lugar u objeto que se considere relevante para la interacción humano-humano, humano-máquina, o máquina-máquina (Tapia, 2009). La información contextual se enriquece con parámetros como la identificación, el tiempo y la ubicación (Traynor et al., 2010b). Para obtener esta información en el proceso de aprendizaje, se produce un intercambio de información entre la tecnología y los usuarios que permite, no solo contextualizar el entorno en el que se produce el aprendizaje, sino también personalizar el contenido de la actividad, lo que puede entenderse también como una forma de colaboración. Por lo tanto, el aprendizaje sensible al contexto debe tener en cuenta las interacciones entre las personas y los diferentes componentes tecnológicos del sistema en todas sus combinaciones. La tecnología se convierte entonces en un socio indispensable para la adquisición de la información en tiempo real que rodea a los participantes del proceso educativo en todo momento. El diseño, despliegue y uso de sistemas sensibles al contexto permiten determinar qué factores rodean al aprendizaje en un momento dado, incluyendo la localización de los participantes, el uso de instalaciones o dispositivos, o condiciones ambientales a través de información recogida por sensores (temperatura, humedad, tiempo, iluminación, etc.). Las redes inalámbricas de sensores (WSN - *Wireless Sensor Networks*) y los sistemas de localización en tiempo real (RTLS

Real Time Location Systems) se postulan entonces como poderosas herramientas que recogen datos esenciales en este tipo de soluciones (Villarrubia et al., 2014a,b).

Finalmente, la penetración de las **herramientas de interacción social** (redes sociales, sistemas de recomendación, etc.) en nuestra vida cotidiana ha facilitado la apertura de un nuevo campo de acción para lograr la mejora de la conducta de las personas en los procesos de aprendizaje (Chou and Chanlin, 2014). En este sentido, el enriquecimiento del contexto y del proceso de aprendizaje mediante las relaciones e interacciones que se producen entre las personas facilita la personalización del contenido y actividades planteados, donde el paradigma de la Computación Social se postula como la mejor opción para alcanzar esta personalización (Rodriguez et al., 2011). Aparecen entonces soluciones que utilizan herramientas sociales para fomentar el uso de diferentes sistemas, como por ejemplo en el ahorro de energía (Sweeney et al., 2013; García et al., 2017) o en la toma de decisiones (Vassileva and Campillo, 2014; Xu et al., 2015).

A pesar de todo lo anterior, no existe un marco horizontal que permita enriquecer el proceso de aprendizaje con todas las capacidades que ofrecen los dispositivos electrónicos (por ejemplo, smartphones o tablets), los sistemas sensibles al contexto (por ejemplo, redes de sensores o RTLS), o la Computación Social (por ejemplo, redes sociales o sistemas de recomendación). Para cubrir esta brecha, esta Tesis Doctoral presenta el framework CAFCLA (*Context-Aware Framework for Collaborative Learning Activities*) como base para el desarrollo rápido y efectivo de actividades enfocadas a fomentar el aprendizaje colaborativo utilizando información contextual. El framework, diseñado desde la perspectiva de la Computación Social y la Inteligencia Ambiental, dará respuesta al problema planteado:

- Obtendrá información contextual a través de la implementación de redes inalámbricas de sensores que permiten recopilar datos de múltiples fuentes para caracterizar el entorno y de un sistema de localización en tiempo real que permite identificar y rastrear a los usuarios en todo momento. Entre ellos, los sensores que recogen los parámetros ambientales (temperatura, humedad o iluminación) o datos sobre la utilización de dispositivos (encendido o apagado, consumos eléctricos, posición de puertas o ventanas, etc.), mientras que las posiciones de los usuarios permiten identificar patrones de comportamiento (uso de la luz solar, uso de electrodomésticos, temperatura de calefacción), patrones de seguimiento (horarios de trabajo, ausencias prolongadas, horas de sueño, etc.) y ubicaciones (puerta de entrada, salón, cama, etc.) que ayudan a identificar hábitos de comportamiento dentro del aprendizaje.

- Integrará una máquina social que proporciona contenidos personalizados, facilita recomendaciones, gestiona la información contextual y de localización, maneja las relaciones sociales entre los participantes en la actividad, así como gestiona la comunicación, la seguridad, la integridad y la fiabilidad de los sistemas desarrollados bajo su amparo mediante el uso de Organizaciones Virtuales de agentes se proporciona inteligencia al sistema. Posibilitará diseñar y desarrollar diferentes actividades de aprendizaje colaborativo que podrán desarrollarse en cualquier entorno y contexto, con independencia de su ubicación y de los recursos disponibles, gracias a la flexibilidad ofrecida.

- Proporcionará transparencia tecnológica a educadores y alumnos, de forma que estos no deben preocuparte de los problemas que puedan plantearles las TIC, sino solamente de aquellos aspectos que forman parte del proceso educativo y facilitará una API de programación para el diseño y desarrollo de los sistemas, incluyendo la integración de los sistemas de sensorización y localización, la máquina social y las Organizaciones Virtuales de agentes. Desarrollará igualmente las interfaces que sean necesarias para que los usuarios del framework sean capaces de interactuar con él de forma fácil y eficiente.

Una vez propuesto el problema a resolver, así como las directrices para lograrlo, la siguiente sección describe el framework propuesto ahondando en los detalles técnicos y de funcionamiento del mismo.

3.2. Aproximación conceptual de CAFCLA

El framework propuesto en esta sección pretende superar todas las deficiencias mostradas anteriormente, tanto en la sección anterior como en el estado del arte del Capítulo 2, en relación a la Computación Social y al uso de información contextual en el aprendizaje colaborativo. A continuación se describe primero el framework desarrollado y se detallan las capas técnicas subyacentes que constituyen su núcleo.

CAFCLA es un framework cuyo principal objetivo es proporcionar a los profesores una forma fácil de diseñar actividades de aprendizaje colaborativo utilizando información contextual a través de la Computación Social, ya sea dentro o fuera del aula. También pretende simplificar el uso de las interacciones sociales y la obtención de información contextual, permitiendo a los profesores obviar procesos tediosos que no están relacionados con la educación. CAFCLA busca proporcionar a los desarrolladores un conjunto de herramientas para diseñar, desarrollar y desplegar las aplicaciones que implementarán las actividades de aprendizaje diseñadas por los educadores. Asimismo, intenta ayudar a los técnicos en el despliegue de las infraestructuras de comunicación, procesamiento y almacenamiento de datos. CAFCLA quiere mejorar no solo el proceso de aprendizaje individual de los estudiantes, sino también las relaciones interpersonales, el trabajo en equipo y la solidaridad entre ellos.

El proceso de diseño y desarrollo de una actividad de aprendizaje colaborativo a través del framework CAFCLA considera los objetivos del alumno debe alcanzar, los contenidos de aprendizaje, los recursos didácticos, los espacios físicos, los espacios virtuales y las reglas sociales. Para ilustrar los principales componentes, tanto humanos como técnicos, de una actividad de aprendizaje colaborativa específica apoyada por nuestro framework, la Figura 3.1 presenta una actividad hipotética desplegada en el Museo del Prado. Se pueden identificar en ella los diferentes roles manejados, la infraestructura de comunicaciones necesaria o la contextualización del entorno empleado. Esta infografía servirá de base para ilustrar todos los conceptos descritos en las siguientes secciones.

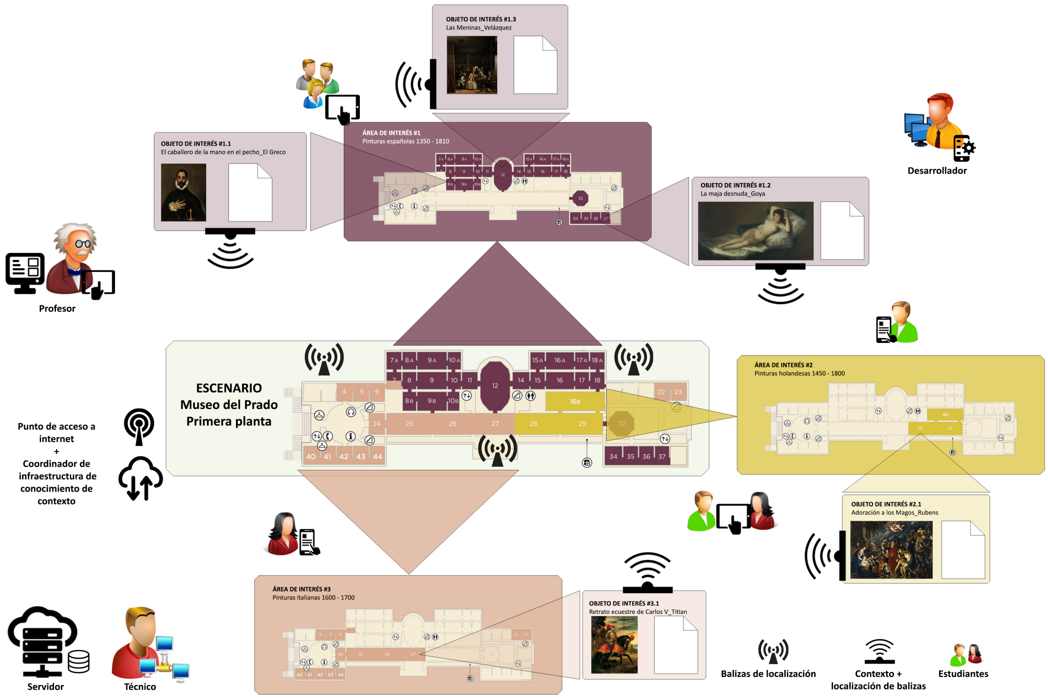

Figura 3.1 – La infografía muestra un ejemplo de despliegue del CAFCLA en el Museo del Prado con los cuatro roles diferentes (profesor, desarrollador, técnico y alumno), la estructura seguida para contextualizar el entorno de aprendizaje (escenario, áreas y objetos de interés) y la infraestructura hardware requerida para ser desplegado (sensores, balizas, puntos de acceso, etc.).

3.2.1. Actores Sociales

Una de las ambiciones de CAFCLA es cubrir todo el proceso involucrado en el desarrollo de una actividad de aprendizaje colaborativo, desde la concepción hasta la ejecución. Por esta razón, aparecen diferentes participantes dependiendo del papel que desempeñen. De forma más concreta, podemos identificar cuatro roles diferentes en el proceso de diseño, despliegue y desarrollo de las actividades consideradas: profesores, desarrolladores, técnicos y estudiantes.

- *Profesor:* es el responsable del diseño de la actividad que se desarrollará y desplegará con CAFCLA. Los profesores tienen un perfil educativo que les permite contextualizar el entorno en el que se desarrolla la actividad. Las tareas que deben realizar los docentes son: el establecimiento de los objetivos de la actividad, la definición del tipo de actividad a desarrollar, la especificación de los alumnos que participan en la actividad, la definición de las colaboraciones entre los alumnos, la definición y descripción de las áreas y objetos de interés, la provisión de los datos que el sistema almacenará para ser entregados durante la actividad y el establecimiento de las reglas sociales.

- *Desarrollador:* es el responsable de desarrollar la aplicación y la infraestructura necesaria que utilizarán estudiantes y profesores, mediante el uso de las herramientas que CAFCLA ofrece para analizar, diseñar, programar, etc., de acuerdo a la actividad ideada por los profesores. Los desarrolladores tienen un perfil técnico orientado a software (aplicaciones). Las tareas que los desarrolladores cumplirán son: diseño de la aplicación, definición de la infraestructura necesaria, programación de la aplicación y ajuste de los diseños y desarrollos basados en la retroalimentación recibida de profesores, técnicos y estudiantes.

- *Técnico:* es el responsable de desplegar la infraestructura tecnológica recomendada necesaria para llevar a cabo la actividad implementada con CAFCLA. Los técnicos tienen un perfil técnico orientado a hardware. Las tareas que se les asignan son: despliegue de la infraestructura de hardware en el sitio y retroalimentación a los desarrolladores para modificar el diseño de la infraestructura de acuerdo con las particularidades del lugar donde se desarrolla la actividad.

- *Estudiante:* es el responsable de realizar la actividad diseñada por el profesor, desarrollada por el desarrollador y desplegada por el técnico. Los estudiantes tienen un perfil de usuario final cuya realimentación puede obtenerse indirectamente. Las tareas que realizan los estudiantes son: acceder a los recursos que ofrece la aplicación a través de diferentes dispositivos móviles, colaborar entre ellos para resolver el problema social, alcanzar los objetivos de la actividad y evaluar la aplicación.

3.2.2. Conceptualización del Contexto

El entorno donde se desarrolla la actividad de aprendizaje colaborativo tiene que crear una rica experiencia social para los estudiantes. Por lo tanto, la información contextual se convierte en fundamental para la construcción de un sistema eficaz que apoye al aprendizaje y fomente la participación de los estudiantes en el proceso. Cualquier lugar o elemento en el entorno de aprendizaje será capaz de proporcionar información relevante para ser utilizado a lo largo de la actividad. Por lo tanto, CAFCLA permite a los profesores describir cualquier lugar o elemento capaz de ser estudiado en la actividad, independientemente de su tamaño y ubicación. Esta descripción puede utilizarse para elementos de diferentes tipos, tales como un lugar particular, una obra de arte en un museo o los datos obtenidos por mediciones recogidas de un sensor de temperatura, entre otros.

Es importante estructurar la información contextual para proporcionarla de manera eficiente a los estudiantes. Por esta razón, CAFCLA define tres niveles de descripción que proporcionan suficiente granularidad a la información requerida por la actividad: escenario, área de interés y objeto de interés.

- *Escenario:* cubre todo el entorno en el que se desarrolla la actividad, siendo el espacio físico completo donde se despliega ésta. De forma general, se trata de la descripción de más alto nivel que se provee. Siguiendo el esquema que muestra la Figura 3.1, el escenario en este caso es el primer piso del Museo, donde se muestran diferentes colecciones de pinturas, organizadas por país de origen del pintor.

- *Área de interés:* espacios dimensionales en los cuales el escenario puede ser dividido y donde se colocan uno o más elementos de estudio para la actividad. Estas áreas suelen agrupar elementos clasificados en el mismo campo. Los profesores identifican, localizan e incluyen la caracterización contextual en ellos, proveen información a los estudiantes dependiendo del diseño de actividad que el profesor haya preparado. En la Figura 3.1 se definen tres áreas de interés: la primera es una zona donde se exponen obras de pintores españoles entre 1350 y 1810, la segunda incluye obras de pintores holandeses entre 1450 y 1800, mientras que la tercera incluye obras de pintores italianos entre 1600 y 1700.

- *Objeto de Interés:* Son el último nivel de detalle dentro de la contextualización del entorno e incluyen la información de un determinado tema de estudio que forma parte de la actividad. Un área de interés puede estar formada por uno o más objetos de interés. Los profesores son responsables de identificar, localizar y caracterizar todos los objetos. Siguiendo el ejemplo simplificado que nos da la infografía de la Figura 3.1, en este caso los objetos de interés son cinco: tres en la primera área de interés correspondiente a los pintores españoles ("El Caballero de la Mano en el Pecho" de El Greco, "Las Meninas de Velázquez" y "La Maja Desnuda" de Goya), uno en el segundo área de interés correspondiente a los pintores holandeses ("Adoración de los Reyes Magos" de Rubens) y uno en el tercer área de interés correspondiente a pintores italianos ("Retrato Ecuestre de Carlos V" de Tiziano).

3.3. Descripción técnica

Los requisitos funcionales del framework diseñado requieren la integración de varias tecnologías. Estas tecnologías serán responsables de apoyar la comunicación, contextualizar el entorno de aprendizaje, agregar inteligencia al sistema o facilitar el trabajo a los desarrolladores. Como se muestra en la Tabla 3.1, CAFCLA ha sido diseñado siguiendo un esquema en capas. Cada una de estas cinco capas interconectadas incluye un conjunto de tecnologías que soportan algunas de las características del framework. El aprendizaje colaborativo basado en la Computación Social requiere una integración efectiva entre todas las tecnologías seleccionadas.

A continuación, ofrecemos una descripción de cada capa y una breve justificación de la elección de cada tecnología para comprender mejor las funcionalidades de CAFCLA que dichas tecnologías cubren.

Tabla 3.1 – Diagrama de capas de CAFCLA.

Capa	Tecnología
Física	Ordenadores personales, tablets, smartphones, sensores, balizas de localización, tags
Comunicación	3G/GPRS, Wi-Fi, ZigBee
Información contextual	Redes Inalámbricas de Sensores, Sistema de Localización en Tiempo Real
Gestión	Computación Social, Organizaciones Virtuales de agentes
Aplicación	API, Actividades de aprendizaje

3.3.1. Capa física

La primera capa es la capa física. La capa física en CAFCLA incluye todos los dispositivos que se pueden utilizar en el framework. Los dispositivos móviles, como tablets, ordenadores portátiles o smartphones, son algunos de los componentes físicos integrados en CAFCLA. Estos dispositivos serán responsables de ejecutar aplicaciones en las que se ejecutarán las actividades de aprendizaje. Del mismo modo, asistirán a los profesores mientras supervisan la actividad desarrollada o a los técnicos para verificar el buen funcionamiento de la infraestructura desplegada en cualquier momento.

Por otra parte, la infraestructura para la adquisición de información contextual también es parte de esta capa. Los sensores, las balizas de localización o las etiquetas de identificación son algunos de los dispositivos que proporcionan información contextual.

Además, las comunicaciones también requieren cierta infraestructura física. En este caso, es necesario utilizar dispositivos tales como puntos de acceso a Internet (Wi-Fi, 3G, Ethernet, etc.), colectores de datos para enviar datos provenientes de la WSN o del RTLS a través de Internet, o balizas para transmitir datos a través de estas redes.

Por último, es necesario un almacenamiento de datos y servidor de aplicaciones.

CAFCLA permite una perfecta integración de las tecnologías antes mencionadas, seleccionando las apropiadas para cada escenario de manera transparente para el profesor y los estudiantes.

3.3.2. Capa de comunicación

La segunda capa es la capa de comunicación. La capa de comunicación en CAFCLA incluye todos los protocolos de comunicación que se incluyen en el framework. Estos protocolos permitirán enviar y recibir información entre dispositivos físicos. También son responsables de transportar la información contextual generada dinámicamente durante el desarrollo de la actividad de aprendizaje, ya sea recolectada por sensores o por cualquiera de los sistemas de localización.

CAFCLA integra los protocolos de comunicación 3G/GPRS, Wi-Fi y ZigBee, siendo utilizados principalmente para el transporte de datos y la comunicación entre dispositivos. Los protocolos Wi-Fi y ZigBee también se utilizan para la contextualización y el transporte de datos de sensores. Finalmente, las características de la señal inalámbrica transmitida se utilizan para calcular la posición de los dispositivos en el RTLS. Además, el framework está abierto a integrar cualquier protocolo adicional que se necesite en el futuro.

3.3.3. Capa de información contextual

La tercera capa es la capa de información contextual. La capa de información contextual en CAFCLA facilita la adquisición de nuevos conocimientos, fomenta la colaboración, involucra a los estudiantes y ayuda a crear experiencias sociales enriquecidas. Además, beneficia el proceso de aprendizaje mediante una mejor comprensión del entorno que lo rodea. Este conocimiento permite adaptar, personalizar y optimizar dinámicamente la información proporcionada a los estudiantes de acuerdo a sus necesidades y requerimientos específicos.

Debido a que las funcionalidades de CAFCLA abarcan el mayor número posible de entornos educativos, se han integrado tres tecnologías sensibles al contexto: una plataforma para implementar WSN, un sistema de localización en exteriores y un sistema de localización en interiores. Estas tecnologías facilitan la identificación, caracterización y localización de cualquier objeto o lugar que sea de interés en la actividad de aprendizaje:

- *Plataforma de sensorización:* CAFCLA integra la plataforma n-Core (Nebusens, 2016), la cual permite la implementación de un gran número de sensores (por ejemplo, iluminación, temperatura o humedad). Los sensores forman una red mallada usando el protocolo ZigBee para comunicarse entre ellos y con el resto de los dispositivos del sistema. El modo de funcionamiento más común es sencillo: los datos recopilados se envían a un colector de datos que a su vez los envía al servidor de datos de CAFCLA a través de Internet. Al diseñar la actividad de aprendizaje, los educadores deciden el tipo de sensor a integrar, su ubicación y la frecuencia con la que se transmiten sus mediciones.
- *Localización en exteriores:* CAFCLA integra también el sistema de posicionamiento GPS, la solución más extendida, que está totalmente integrada en la mayoría de los dispositivos móviles actualmente en el mercado. Esta tecnología facilita la inclusión de esta funcionalidad en actividades de aprendizaje e integra la plataforma de mapas Google Maps. Al diseñar la actividad los profeores determinan las áreas en las que se proporcionarán contenidos de aprendizaje.
- *Localización en interiores:* CAFCLA integra un RTLS basado en n-Core Polaris (Nebusens, 2016), un sistema que utiliza el protocolo de comunicación inalámbrica ZigBee y que determina la posición de los usuarios con una precisión de hasta 1 metro. Para obtener la ubicación de los usuarios en interiores, el área donde se desarrolla la actividad está equipada con un conjunto de balizas llamadas n-Core Sirius RadIOn. Estas balizas transmiten la ubicación de un estudiante a un colector de datos que transmite la información

al servidor de datos a través de Internet. Cada estudiante tiene que usar un dispositivo ZigBee llamado n-Core Sirius Quantum para ser localizado. Este dispositivo se comunica con sus balizas más cercanas que recogen diferentes medidas de señales enviadas por los dispositivos Sirius Quantum y las envían al colector de datos. Una vez que la información está en el servidor de datos, el motor de localización calcula la posición del estudiante. Otros sistemas de localización en interiores han sido descartados porque no cumplen con los requisitos que CAFCLA necesita. Por ejemplo, la localización mediante Wi-Fi no proporciona la misma precisión de localización que ZigBee (García et al., 2012b); la localización mediante ultrasonidos requiere visión directa con las antenas (De Marziani et al., 2009); y la navegación mediante sensores inerciales implica llevar sensores en partes específicas del cuerpo para evitar el error de deriva (Prieto et al., 2016; Zampella et al., 2013). De igual modo que para la localización en exteriores, al diseñar la actividad los profesores determinan las áreas en las que se proporcionarán contenidos de aprendizaje.

En el diseño de una actividad, los profesores delimitan un espacio en el mapa de interior o al aire libre e incluyen toda la información contextual relacionada con este espacio que se puede definir como un área o un objeto de interés. En esta inserción de datos también se incluyen diferentes versiones de la información que se utilizará, con el fin de personalizar la información proporcionada de acuerdo con los requisitos de los estudiantes o de las interacciones sociales. Mientras la actividad se está realizando, los estudiantes usan un dispositivo móvil con GPS integrado y/o un tag ZigBee que transmite su posición continuamente. Tan pronto como el estudiante cruza un área de interés o se acerca a un objeto de interés, la información contextual establecida por el diseño de la actividad será entregada a través del dispositivo móvil.

3.3.4. Capa de gestión

La cuarta capa es la capa de gestión. La capa de gestión en CAFCLA integra la máquina social y es responsable del funcionamiento efectivo, predecible y distribuido de la capa de información contextual y de la capa de comunicación. El desarrollo de los sistemas de Computación Social es una tarea compleja que requiere coordinación y comunicación entre las entidades participantes, ya sea humano o máquina (Rodriguez et al., 2011). Las tendencias actuales recomiendan el uso de Organizaciones Virtuales (VO - *Virtual Organizations*) para estas tareas.

Las Organizaciones Virtuales puede considerarse como un conjunto de instituciones y personas que necesitan coordinar servicios y recursos a través de los límites institucionales (Boella et al., 2005; Jennings, 1999). De aquí en adelante, consideraremos una organización virtual como un sistema abierto compuesto de entidades heterogéneas, agrupadas y colaborando entre sí, y entre las cuales hay una separación de forma y función que requiere definir cuál será el comportamiento de cada uno (Boella et al., 2005).

La Organización Virtual de Agentes es una tecnología general de sistemas software que ha motivado preguntas de investigación en relación a la autonomía, la cooperación, la formación o la gestión de comunicaciones grupales, entre otros (Villarrubia et al., 2014b). Esta tecnología permite la formación de organizaciones de agentes dinámicos y es especialmente útil para sostener el framework de aprendizaje colaborativo presentado. El uso de VOA permite describir comportamientos funcionales, tales como tareas, planes o servicios, y describir estructuras lógicas, como roles, grupos, patrones de interacción o relaciones. De manera similar, la organización puede incorporar estándares que permitan el control del comportamiento de un agente, la composición dinámica de grupos de agentes o la creación dinámica de componentes, sobre modelos de organización, sobre la Teoría de la Organización Humana, sobre las topologías estructurales, sobre la representación de las normas o sobre planteamientos institucionales.

El objetivo de la capa de gestión es implementar la máquina social sobre la base de una VOA que apoya el aprendizaje colaborativo basado en el contexto. La Figura 3.2 muestra las diferentes organizaciones que integran la arquitectura propuesta:

- *Organización de recogida de datos:* esta organización gestiona las fuentes que suministran datos al sistema. Estos datos son tan diversos como las fuentes que los generan, por lo que es necesario un control exhaustivo de los mismos. Las redes de sensores, los sistemas de localización, los propios profesores cuando crean contenido o información pública consultada, son algunos de los orígenes de estos datos.

- *Organización de gestión de datos:* esta organización mantiene la integridad de los datos durante el proceso de aprendizaje. Decide qué datos deben almacenarse y entregarse en todo momento. La disponibilidad de datos durante el desarrollo del proceso es crucial ya que el rendimiento de la actividad depende de ello. Se relaciona con la organización de recogida de datos que recopila nueva información y con la organización de la actividad que decide la información que debe almacenarse o los datos específicos que deben solicitarse. También clasifica la información que es entregada dependiendo del contexto y la información social que rodea al estudiante en un momento determinado durante el desarrollo de la actividad.

- *Organización de contexto:* esta organización controla la información recogida por la red de sensores. Debe coordinarse con la organización de gestión de datos para mantener actualizada la información de cualquier servicio físico implementado por la red de sensores.

- *Organización de actividad:* esta organización coordina toda la actividad. Recibe toda la información de la máquina social (perfiles, datos contextuales, colaboraciones, etc.) y decide qué información se proporciona a cada estudiante dependiendo del modelo de aprendizaje seleccionado y del estado en el que se desarrolla la actividad implementada.

- *Organización de la máquina social:* esta organización realiza varios análisis para extraer información socialmente relevante de la interacción entre los agentes correspondientes:
  - *Agente de estudiante:* almacenan el perfil de los estudiantes y toda la información relacionada con el proceso de actividad, agrupándose en organizaciones. Esta organización permite la interacción estudiante-estudiante y estudiante-máquina.
  - *Agente de profesor:* establece las reglas sociales que subyacen a la organización de la máquina social. Este agente crea, modifica y monitoriza el desarrollo de una actividad, agrupándose en organizaciones.
  - *Agente de colaboración:* monitoriza todo el proceso de comunicación con la organización Activity y la organización Context. Esta organización permite gestionar todas las relaciones existentes en la actividad.
  - *Agente de configuración:* crea, modifica y monitoriza el desarrollo del juego. Este agente establece las reglas sociales de la organización de la máquina social.
  - *Agente de preferencias:* analiza la información almacenada por la capa de gestión de datos. Este agente identifica y clasifica las preferencias de cada usuario de la actividad.
  - *Agente de reputación:* gestiona la reputación de las acciones llevadas a cabo durante la actividad teniendo en cuenta la fiabilidad (si ha implicado utilidad) y la fidelidad (si se han continuado con el tiempo). Este agente recomienda las acciones más reputadas.
- *Organización de objetivo y recomendaciones:* controla los desafíos y recomendaciones realizados por la máquina social. Esta organización produce acciones personalizadas y atractivas para que los estudiantes alcancen los objetivos establecidos en la organización de la actividad.

La implementación de la organización virtual se ha desarrollado utilizando la plataforma JADE (*JAVA Agent DEvelopment Framework*) y la herramienta Jadex (Bellifemine et al., 1999), una extensión que proporciona una arquitectura BDI (*Belief-Desire–Intention*) a los agentes JADE. Así, los agentes de Jadex trabajan con conceptos tales como creencias, metas y planes. Jadex tiene la ventaja de permitir al programador introducir sus propios mecanismos deliberativos. La plataforma permite una fácil implementación de Organizaciones Virtuales de agentes abiertas mediante el uso de diferentes herramientas para crear, gestionar y controlar Organizaciones Virtuales, incluyendo aspectos organizativos.

3.3.5. Capa de aplicación

La quinta capa es la capa de aplicación. La capa de aplicación en CAFCLA apoya las actividades de aprendizaje colaborativo a desarrollar y, por lo tanto, proporciona las interfaces entre los usuarios con un papel educativo (profesores y estudiantes) y el resto de los componentes

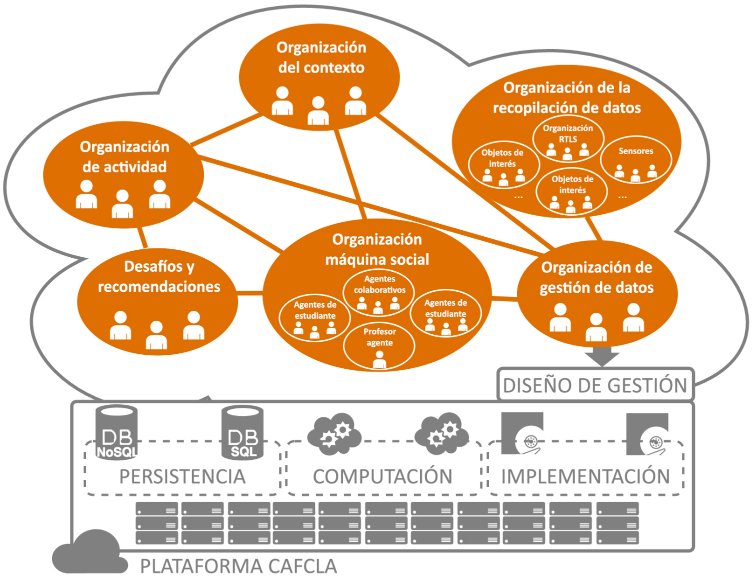

Figura 3.2 – La abstracción del problema social del aprendizaje colaborativo como una Organización Virtual de agentes permite implementar el framework CAFCLA de forma adaptativa y efectiva.

del framework. En esta Tesis Doctoral, se ha seguido un enfoque educativo y social para la elección de las funcionalidades proporcionadas por esta capa y, por lo tanto, de las tecnologías integradas que satisfacen estas necesidades. Por lo tanto, en primer lugar se han definido las actividades de aprendizaje colaborativo social que se pueden ejecutar a través de CAFCLA, y luego, se han elegido las tecnologías que mejor se adaptan a los requisitos de cada uno.

Se han predefinido cuatro tipos de actividades de aprendizaje colaborativo social que pueden ser fácilmente diseñadas y desarrolladas usando CAFCLA, sin perjuicio de que puedan definirse otros tipos de actividades, ya sean regladas o no. A continuación se presenta un resumen del funcionamiento y los objetivos de cada tipo de actividad.

- *Aprendizaje basado en retos:* en esta práctica de aprendizaje los estudiantes trabajan individualmente o en grupos pequeños para resolver un reto generado por la máquina social basado en las reglas establecidas por el profesor. Los estudiantes son responsables de su propia organización mientras se desarrolla la actividad, pero siempre son apoyados por el profesor, que actúa como facilitador de recursos. En CAFCLA el profesor define la meta, el material de aprendizaje y cómo los estudiantes pueden colaborar (relaciones permitidas entre individuos o grupos). Esta práctica fomenta la comunicación y la interacción social entre los estudiantes, así como la resolución de problemas y las habilidades de colaboración.

- *WebQuest colaborativos:* esta práctica de aprendizaje construye un ambiente atractivo en el que se desencadena un razonamiento en función de los pasos que se lleven a cabo, dando sentido a la búsqueda de información. La tarea principal es desarrollar una solución al problema expuesto, razonando a partir de las respuestas a las preguntas específicas que se han planteado. En CAFCLA, el profesor es capaz de diseñar una batería de preguntas para responder en las áreas u objetos de interés. Las preguntas pueden ser formuladas genéricamente, esperando una respuesta redactada o como una prueba en la cual se ofrecen diferentes opciones de respuesta. Estos cuestionarios pueden ser adaptados a cada nivel de usuario y varios de ellos pueden ser definidos para la misma área u objeto de interés. Además, el profesor puede crear un cuestionario final que se lleva a cabo en un lugar determinado (por ejemplo, el aula) en el que se recogen las preguntas relacionadas con todos los cuestionarios que se han realizado en la actividad. Por otra parte, el profesor debe asociar cada cuestionario con su correspondiente estudiante o grupo. Esta práctica fomenta el desarrollo de habilidades de gestión de la información, tales como recepción, procesamiento y producción, y fomentan las habilidades sociales.

- *Juegos Serios:* esta práctica de aprendizaje construye juegos en los que a través de la consecución de objetivos individuales y de colectivos los usuarios participantes adquieren nuevos conocimientos, habilidades y hábitos (por ejemplo, la adquisición de buenos hábitos energéticos). En CAFCLA, el profesor es capaz de diseñar un conjunto de retos a cumplirse y determinar las recompensas que se obtienen cuando se realiza alguno de ellos. Además, el profesor puede identificar las colaboraciones existentes entre los jugadores. Por otra parte, el diseñador es capaz de determinar cuáles serán los indicadores para identificar el cumplimiento de un reto. Esta práctica fomenta las habilidades sociales y la competitividad y fomenta la adquisición de buenos hábitos.
- *Sistema de recomendaciones:* esta práctica de aprendizaje se basa en lanzar recomendaciones a los alumnos para que realicen determinadas actividades con un objetivo común. En CAFCLA, el profesor es capaz de definir una serie de recomendaciones (por ejemplo, apagar la calefacción) para que los alumnos puedan realizar actividades (por ejemplo, poner la lavadora a una determinada hora) o tomar medidas en relación a una acción (por ejemplo, apagar una luz) de forma individual y grupal. El profesor determinará de qué forma se proporcionan las recomendaciones y cómo desea recibir la realimentación de su ejecución. Esta práctica fomenta el desarrollo de buenos hábitos, la adquisición de conocimientos y la concienciación sobre el contexto y fomentan las habilidades sociales y de colaboración.

Es importante notar que el CAFCLA provee un conjunto de herramientas comunes para todas las actividades presentadas anteriormente sin importar su tipo. Estas herramientas permiten, entre otras cuestiones: 1) fomentar la interacción social mediante la relación con otros estudiantes, a través de diferentes herramientas de comunicación, tanto asíncrona (por ejemplo, correo electrónico) como sincrónica (por ejemplo, mensajería instantánea); y 2) proporcionar información contextual mediante la definición de escenarios, áreas de interés u objeto de interés, tanto utilizando el RTLS (por ejemplo, n-Core Polaris) ofrecido o como diferentes sensores inalámbricos (por ejemplo, termostatos). Además, el profesor tiene recursos para gestionar grupos e interacciones sociales, definiendo diferentes grupos de trabajo formados por el número de estudiantes que considere apropiado, asignando dispositivos que cada grupo o alumno utiliza o definiendo las interacciones permitidas entre estudiantes o grupos.

La siguiente sección presenta los ejemplos prácticos que ilustran el funcionamiento de los diferentes componentes del framework CAFCLA, describe los casos de uso experimentales llevados a cabo para evaluar su viabilidad, y resume brevemente los resultados obtenidos durante su desarrollo.

3.4. CAFCLA en el aprendizaje colaborativo

El objetivo educativo principal de este despliegue es realizar una actividad de aprendizaje colaborativo entre los niños de primaria (8-10 años) que promueve el trabajo en equipo y las interacciones sociales para lograr un objetivo común. El escenario elegido para llevar a cabo el experimento fue el Museo de Escuelas Mayores de la Universidad de Salamanca. La Universidad de Salamanca, fundada hace ocho siglos, es una institución con gran historia e importantes raíces en su ciudad. Por esta razón, es culturalmente interesante que las nuevas generaciones sean conscientes de su importancia y también conozcan algunas de las personalidades más relevantes que han sido parte de su comunidad a lo largo de la historia.

El edificio de las Escuelas Mayores se compone de dos pisos denominados Claustro Inferior y Claustro Superior (ver Figura 3.3).

El Claustro Inferior está situado en la planta baja y está formado por varias aulas en las que se ejercía la docencia históricamente. Cada una de estas aulas está dedicada a una personalidad histórica de especial relevancia en la Universidad de Salamanca. Dentro de las aulas se conservan elementos decorativos y muebles que proporcionan información sobre la personalidad que da su nombre al aula.

El Claustro Superior se encuentra en el primer piso del edificio y alberga la biblioteca antigua, la nueva biblioteca, la escalera histórica y una exposición de documentos y materiales históricos utilizados para el estudio y la investigación a lo largo de los siglos. Es importante destacar que en este Claustro pueden encontrarse detalles artísticos (como los detalles de la escalera) que difícilmente pasan desapercibidos. Además, este Claustro permite albergar exposiciones temporales.

3.4.1. Sistema propuesto

En el entorno descrito anteriormente se diseñó una actividad de colaboración en la que los estudiantes tienen que descubrir e identificar diferentes partes del edificio, materiales y lugares ilustres para, posteriormente, ubicarlos cronológicamente a lo largo de la historia de

Figura 3.3 – Evaluación de CAFCLA en un escenario real dentro del Museo de Escuelas Mayores de la Universidad de Salamanca.

la Universidad. La actividad específica se trata de un WebQuest colaborativo que involucró a dos grupos de cuatro estudiantes cada uno y se dividió en tres fases.

En la primera fase, cada grupo de estudiantes tuvo que identificar y localizar cuatro objetos de interés. Para ello, el profesor aportó pistas específicas en forma de preguntas que facilitaron e ilustraron la tarea. En esta etapa, cada estudiante tenía la responsabilidad de identificar solo uno de los cuatro objetos de su grupo. Durante esta fase, a los estudiantes no se les permitió hablar entre ellos hasta que llegaron a un consenso y aprobaron el objeto identificado por cada miembro del equipo. Para lograr este consenso, los alumnos pudieron enviar mensajes al grupo de trabajo para hacer preguntas y enviar fotos de objetos que se consideraron relevantes en base a las pistas dadas. Una vez que el estudiante identificó el objeto de interés asignado, éste solicitó el voto de sus compañeros. Si la mayoría coincidía en que era el objeto buscado, la ubicación del objeto se transmitía al resto del grupo para reunirse allí y discutir la validez de la respuesta. Al final de esta fase, cada grupo debía haber identificado y localizado los cuatro objetos de interés asignados. Esta fase, gracias a la aplicación de técnicas de Computación Social, fortaleció la colaboración y los lazos sociales entre los miembros del grupo, facilitando el trabajo en equipo y promoviendo discusiones para lograr consenso en la solución del problema social propuesto.

En la segunda fase los estudiantes tuvieron que asignar una fecha a cada objeto de interés. Esta vez los objetos de interés se intercambiaron entre grupos, de modo que la actividad fomentó las relaciones sociales entre los miembros de ambos grupos. Para ello, cada estudiante recibió la responsabilidad de identificar un objeto específico dentro de los cuatro asignados a cada grupo, así como pistas para identificar todos ellos. La diferencia con la primera fase reside en las interacciones sociales que se produjeron: en este caso, el alumno solo pudo comprobar la validez del enfoque con un miembro del otro grupo, en particular con el miembro que fue responsable de identificar el mismo objeto en la etapa anterior. Una vez que cada miembro identificó el objeto de interés, se permitió al estudiante unirse a otro miembro del equipo que no había identificado el objeto aún para colaborar entre ellos. Cuando todos los objetos fueron identificados, el grupo los visitó todos para convenir la validez de sus respuestas. Esta fase promovió y mejoró las interacciones sociales entre los grupos, la solidaridad ayudando a los compañeros, así como las discusiones para llegar a una respuesta de grupo consensuada.

En la tercera fase, los miembros de ambos grupos trabajaron juntos en el aula. En esta fase, los estudiantes compartieron la información que cada grupo había obtenido para localizar en un mapa todos los objetos de interés buscados y las fechas asociadas a cada uno. A lo largo de esta fase, se mejoraron las habilidades sociales a través del trabajo en equipo cara a cara.

Una vez descrita la actividad, el docente determinó el escenario, las áreas de interés y los objetos de interés a identificar. En este caso el escenario era todo el Museo. Se identificaron dos áreas de interés, como se muestra en la Figura 3.3: el Claustro Inferior fue el área de interés #1 y el Claustro Superior fue el área de interés #2. En cuanto a los objetos de interés, había cuatro en cada área. El área de interés #1 está formada por: el Aula Miguel de Unamuno (objeto de interés #1.1), el Aula Fray Luis de León (objeto de interés #1.2), el Aula Alfonso X El Sabio (objeto de interés #1.3) y el Aula Francisco de Salinas (objeto de interés #1.4). El área de interés # 2 incluye: la Biblioteca Antigua (objeto de interés #2.1), las Escaleras (objeto de interés #2.2), los Documentos Históricos (objeto de interés #2.3) y los Mapas (objeto de interés #2.4).

El despliegue de la actividad requirió cierta infraestructura tecnológica. Por un lado, los alumnos utilizaron dispositivos tablet con sistema operativo Android 5.0. Estos dispositivos se conectaron a Internet a través de la conexión Wi-Fi de la Universidad para obtener los datos necesarios para desarrollar la actividad. En esta actividad, la información contextual recolectada, como la ubicación de los estudiantes, objetos de interés o pistas, se realizó utilizando el RTLS ofrecido por CAFCLA. La infraestructura de localización estaba formada por ocho balizas de localización ZigBee (Sirius RadIOn) desplegadas a lo largo del escenario, cuatro en el Claustro Inferior y cuatro en el Claustro Superior (como se muestra en la Figura 3.4). Cada estudiante llevaba un tag ZigBee (Sirius Quantum) que transmitió su posición a las balizas de localización en todo momento. La información contextual relacionada con las pistas fue determinada por la posición del alumno, por lo que, en este caso, no se necesitó infraestructura de localización adicional. Además, un coordinador de información de contexto, en el Claustro Superior, recopiló la información de localización de las balizas ZigBee y la envió al servidor de datos a través de Internet utilizando la infraestructura Wi-Fi de la Universidad. Por último, un servidor de datos remoto almacenó toda la información necesaria para el desempeño de la actividad, e integró toda la lógica e inteligencia ofrecida por CAFCLA.

Una vez definida la actividad a desarrollar, la distribución de las áreas y objetos de interés así como la infraestructura necesaria para llevarla a cabo, la siguiente sección reproduce el trabajo del profesor al utilizar el framework y profundiza en los resultados obtenidos por el desarrollo de la actividad.

3.4.2. Experimentación

Figura 3.4 – La flexibilidad del CAFCLA permite la inclusión de una infraestructura técnica heterogénea para la configuración de la experimentación.

Después de completar la definición del escenario y la infraestructura técnica, CAFCLA guio al profesor en el proceso de diseño de actividades. El educador siguió un conjunto de pasos concretos en los que determinó los usuarios y grupos, el tipo de actividad y sus fases, las relaciones sociales entre los participantes, los recursos disponibles y la información contextual, etc. A continuación, se presenta todo el proceso de la actividad experimental desarrollada:

- El primer paso le ofreció al profesor una lista de actividades colaborativas a implementar, eligiendo el WebQuest colaborativo. El profesor incluyó entonces una descripción general de la actividad que reciben todos los alumnos, considerado como el enunciado de la actividad a desarrollar del que disponen. La descripción debía incluir los objetivos de la actividad y los recursos disponibles para alcanzarla.

- El segundo paso estuvo relacionado con la identificación de estudiantes y la formación de grupos. En este caso de estudio participaron ocho alumnos divididos en grupos de cuatro. En este paso, el profesor asigna a cada estudiante un tag de localización de ZigBee para obtener su ubicación. La Figura 3.5 muestra el menú para introducir los datos de un estudiante.

- El tercer paso facilitó la contextualización del escenario. En primer lugar, el profesor incluyó el mapa del entorno en el que tuvo lugar la actividad (el Museo de las Escuelas Mayores). A continuación, definió las áreas y los objetos de interés dentro de este escenario, asignando a cada una de ellas un nombre y una descripción. Del mismo modo, estableció las zonas dentro de las cuales se proporcionaba información a los alumnos. Estas áreas permitieron que el profesor entregara el contenido específico a los estudiantes o a los grupos específicos cuando entraran en una zona específica. En esta parte fue de utilidad proporcionar pistas que facilitaran la identificación de objetos de interés. En este caso, el profesor definió las áreas y objetos de interés relacionados en la sección anterior (ver Figura 3.3). Además, el profesor definió diferentes áreas donde se proporcionaban las pistas. La Tabla 3.2 muestra estas zonas, la pista que se proporcionó y el objeto de interés relacionado con cada una de ellas. Estas zonas fueron gestionadas como objetos de interés. Cada área y objeto se pueden caracterizar por diferentes nombres y descripciones en función del nivel de los diferentes estudiantes. Sin embargo, este no fue el caso dentro de este despliegue ya que todos los estudiantes se encontraban dentro el mismo nivel.

- El cuarto paso tuvo lugar tras la inclusión de toda la información relevante dentro del sistema, y consistió en todo el proceso educativo que desarrolló la actividad elegida. En esta configuración experimental, se implementó una actividad WebQuest colaborativo, por lo que el profesor tuvo que establecer cuántas fases comprendían la actividad así como el tipo de cuestionarios (test o respuesta escrita) de cada fase. Como ya se ha comentado anteriormente, la actividad se dividió en tres fases. En las dos primeras fases, los estudiantes tuvieron que identificar objetos de interés y asignar fechas, definiéndose una prueba específica para cada objeto y estudiante. Del mismo modo, el profesor definió las preguntas de los tests relacionados con cada pista, y cuya respuesta ayudó a identificar un objeto de interés. El profesor tuvo que asociar cada prueba a un estudiante o grupo, una fase y un objeto de interés. Para la tercera fase, el profesor incluyó un cuestionario para responder por escrito mediante un trabajo colaborativo entre todos los estudiantes. Este último cuestionario era el objetivo final de la actividad, a pesar de que los objetivos intermedios eran muy importantes para su consecución.

- El quinto paso fue la definición de las relaciones sociales entre los estudiantes. En primer lugar, el profesor decidió qué herramientas se les permitía utilizar para las interacciones sociales entre ellos. En este caso, el profesor integró un servicio de chat a través del cual los estudiantes colaboraron entre sí. Este chat les permitió enviar contenido multimedia, para que los estudiantes pudieran intercambiar información, y enviar imágenes para iniciar la discusión sobre la correcta identificación de un objeto de interés buscado. El profesor controlaba las colaboraciones entre los alumnos, definiendo quiénes podían hablar entre sí y restringiendo la información ofrecida por el sistema a cualquiera de ellos, así como la información compartida entre los estudiantes. Para ello, el profesor tenía que completar un formulario para el servicio de chat en el que se identificaba a los estudiantes que podían chatear entre sí. Por otro lado, en cada área u objeto de interés se marcó qué alumnos y en qué etapa de la actividad podían acceder a su información.

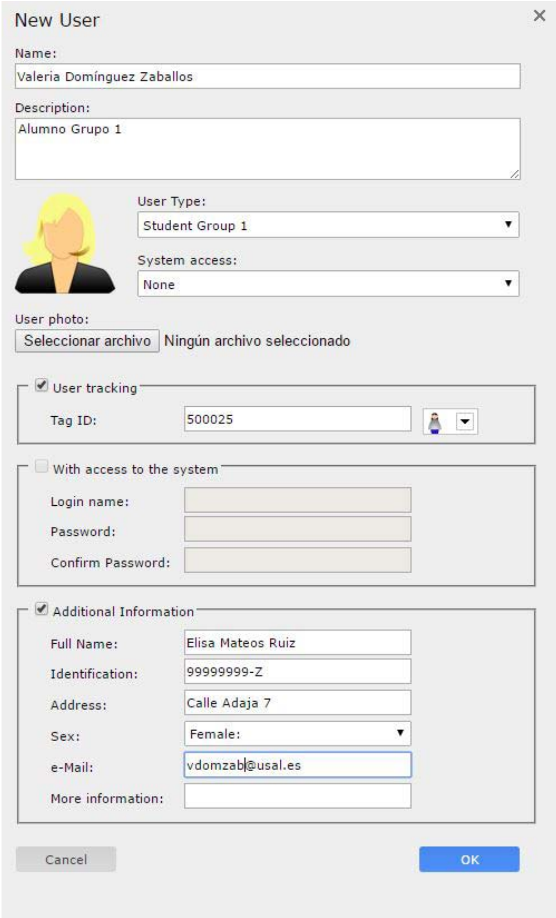

Figura 3.5 – Además de la información personal y una imagen, el menú para registrar a un estudiante en la actividad incluyó el identificador de etiqueta ZigBee asignado, el grupo al que pertenecía y su nivel de acceso al sistema (dependiendo del tipo de actividad), así como un icono que identificó al estudiante dentro del mapa de localización.

Para facilitar el seguimiento de la actividad, los profesores pudieron monitorizar y evaluarla en cualquier momento mediante el acceso al estado del proceso de aprendizaje, como se muestra en la Figura 3.6. Además, el profesor analizó cómo se realizó la actividad, consultando toda la información generada por los alumnos, desde los cuestionarios respondidos hasta el seguimiento de sus movimientos a lo largo del escenario.

Respecto al desarrollo de la actividad, las dos primeras fases se desarrollaron a lo largo de una mañana, incluyendo el despliegue de la infraestructura y su implementación. Se estimó que los estudiantes deberían haber tardado 30 minutos en completar cada fase. Sin embargo, el logro de los objetivos de la primera fase les llevó 55 minutos para el primer grupo y 40 para el segundo grupo. La segunda fase fue más rápida, finalizarla implicó 35 minutos para el primer grupo y 20 minutos para el segundo.

En base a estos resultados, podemos señalar que:

Figura 3.6 – Interfaz de supervisión de la actividad que permite mostrar la ubicación de los estudiantes.

- A partir de la reducción significativa de tiempo entre las actividades de la primera y segunda fases puede afirmarse que el proceso de adaptación de los estudiantes a la tecnología fue rápido y la curva de aprendizaje fue corta.

- El framework fue muy intuitivo a la hora de introducir información, definir información contextual o determinar las relaciones sociales. Sin embargo, este proceso fue largo y requirió preparación por adelantado.

- El balanceo de carga entre diferentes grupos no fue correcto, como se puede extraer del tiempo que emplearon para llevar a cabo las actividades. Encontrar algunos objetos de interés era mucho más difícil que encontrar a otros.

- La exactitud de la ubicación era diferente entre los claustros, siendo peor en el Claustro Alto ya que se trata de un espacio más abierto. Por esta razón se produjeron algunos errores al entregar pistas a los estudiantes.

3.5. CAFCLA en un juego de ahorro energético en edificios públicos

El objetivo de este segundo caso de uso es utilizar CAFCLA para el desarrollo de juegos serios que utilicen la información contextual y que fomenten un cambio de comportamiento hacia hábitos energéticos más eficientes en edificios públicos y/o en el lugar de trabajo. El desarrollo del juego ha demostrado que los datos proporcionados por las redes de sensores alientan a los usuarios a reducir el consumo de energía en su lugar de trabajo y que las interacciones sociales y la competitividad permiten acelerar el logro de buenos resultados, así como cambios de

Tabla 3.2 – Correspondencia de las zonas definidas para proporcionar pistas mientras realiza la actividad y el objeto de interés asociado.

Zona	Pista	Objeto de interés
Z-1.1	Asiento balaustrado	Aula Fray Luis de León
Z-1.2	Prisión	Fray Luis de León
Z-1.3	Reinas	Aula Francisco de Salinas
Z-1.4	Música	Aula Francisco de Salinas
Z-1.5	Venceréis pero no convenceréis	Aula Miguel de Unamuno
Z-1.6	Dos veces Rector	Aula Miguel de Unamuno
Z-1.7	Sabiduría	Aula Alfonso X El Sabio
Z-1.8	Rey	Aula Alfonso X El Sabio
Z-2.1	No maltrates los libros	Antigua biblioteca
Z-2.2	Frisos	Antigua biblioteca
Z-2.3	Cinco jinetes	Escaleras
Z-2.4	Adquisición de conocimiento	Escaleras
Z-2.5	Mapa mundi	Mapas históricos
Z-2.6	Animales exóticos	Mapas históricos
Z-2.7	Fernando III	Documentos históricos
Z-2.8	Alejandro IV	Documentos históricos

comportamiento que favorecen el ahorro energético.

La información contextual requerida se recoge mediante el despliegue de una WSN que facilita la adquisición de datos relacionados con el consumo de energía desde distintos puntos (temperatura, luminosidad), presencia de usuarios en determinados lugares o uso eficiente de dispositivos electrónicos y sistemas de climatización. Además, el conocimiento de la posición gracias al RTLS permite determinar qué hábitos de comportamiento tienen los usuarios y da pautas sobre cómo mejorar estos hábitos en su trabajo y tránsitos. Una Organización Virtual de agentes apoya la máquina social diseñada, lo que da inteligencia al juego y permite mejorar el proceso de aprendizaje actualizando la información contextual, monitorizando las acciones de los usuarios, proporcionando información a los jugadores, facilitando el despliegue y configuración, y mejorando la comunicación de la WSN y del RTLS desplegados. Las principales innovaciones presentadas aquí son:

- El uso de WSN y RTLS en un edificio público, para desplegar un juego individual y, al mismo tiempo, colectivo entre los usuarios.
- La gestión de este juego a través del framework CAFCLA y una VOA, para mejorar el desarrollo y despliegue de juegos y la integración de tecnologías.
- El uso de estas tecnologías dentro del paradigma de la Computación Social, con el fin de permitir mayor personalización e interacción colectiva.

3.5.1. Sistema propuesto

En este trabajo, CAFCLA se utiliza en un entorno no académico con un propósito específico: educar, sensibilizar y provocar un cambio de comportamiento en el uso eficiente de energía en edificios públicos. Con este fin, se ha diseñado y desarrollado un juego serio cuya función es sensibilizar a los usuarios, adquiriendo buenos hábitos de forma natural y fomentando un cambio en su comportamiento, de modo que se consiga el ahorro de energía mediante su uso más eficiente.

En general, el sistema monitoriza continuamente el uso de la iluminación, el uso de sistemas de climatización, el consumo de energía eléctrica en el puesto de trabajo de cada usuario, la temperatura de cada estancia, la luminosidad del entorno, y la ubicación de los usuarios. Todos los datos se obtienen en tiempo real de acuerdo con la actividad detectada en el lugar, su temperatura, su iluminación, el estado de los dispositivos y el uso del ascensor o las escaleras. Todos estos datos nos permiten comprobar si los usuarios cumplen ciertos objetivos de eficiencia energética o desafíos colectivos. Si es así, los usuarios serán recompensados con monedas virtuales o, de lo contrario, penalizados.

En este juego son de especial relevancia la recogida de datos a través de sensores, la ubicación de los participantes y las interacciones sociales entre ellos y con el entorno. CAFCLA proporciona las herramientas necesarias para manejar eficientemente el juego y las interacciones generadas. Todos estos aspectos se discuten en profundidad a continuación, donde describimos en detalle cada componente del framework y cómo se utilizan en este caso.

La capa física contiene todos los dispositivos que se utilizarán en el framework (ver Figura 3.7):

- Una infraestructura sensorial que recoge toda la información contextual: temperatura, encendido/apagado, luminosidad y consumo en cada puesto de trabajo.
- Balizas de localización y tags de identificación para obtener la posición de usuarios.
- Dispositivos móviles para implementar, modificar y acceder al juego: tablets, portátiles y smartphones.
- Puntos de acceso a Internet a través de Wi-Fi y Ethernet, así como colectores de datos y concentradores para enviar los datos recogidos por los sensores y por el sistema de localización en tiempo real.
- Un servidor para almacenar datos y ejecutar la aplicación.

La capa de comunicación establece el protocolo ZigBee mediante el que se transmitirá la información entre los sensores y balizas, así como Wi-Fi para transmitir la información al servidor y a los dispositivos de los participantes.

La capa de información contextual integra el motor de localización y toda la lógica necesaria para realizar una recogida de datos efectiva a través de la red inalámbrica de sensores.

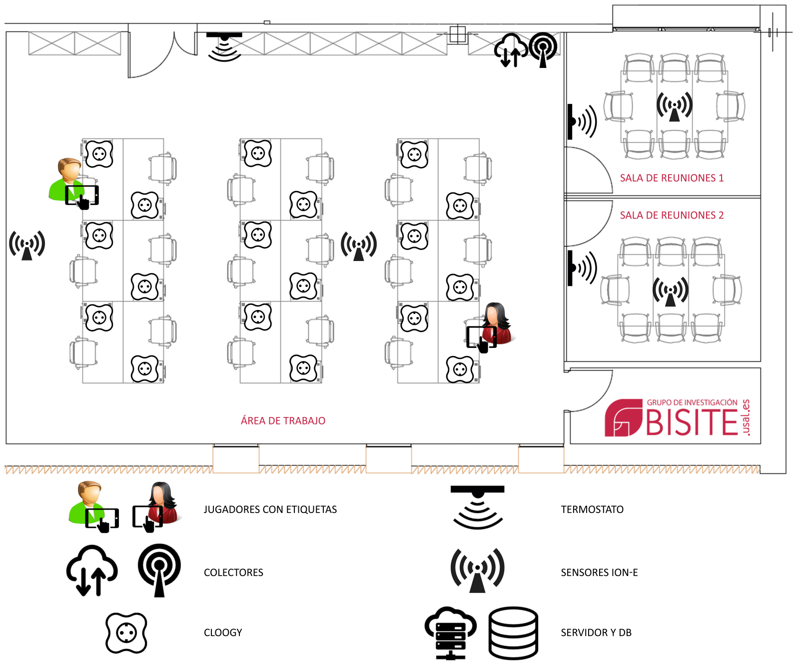

Figura 3.7 – El framework CAFCLA permite la integración de sensores heterogéneos, así como tecnologías de comunicación en la capa física.

- CAFCLA incluye n-Core (Nebusens, 2016) para implementar la red inalámbrica de sensores. n-Core utiliza el protocolo de comunicación ZigBee (IEEE 802.15.4). Los datos de los sensores se envían a través de la red ZigBee a los colectores de datos los cuales, a su vez, envían la información recopilada al servidor que aloja la base de datos mediante del protocolo Wi-Fi. Esta tecnología permite recolectar las medidas físicas que permiten al sistema determinar en tiempo real el estado contextual del entorno (sensores de temperatura y luminosidad), el consumo de energía instantáneo e histórico de cada puesto de trabajo (sensores de consumo eléctrico) y el estado de los sistemas de iluminación y climatización (sensores on/off). Esta información tiene un triple propósito: (i) permite conocer en todo momento los parámetros ambientales y de consumo que describen el contexto; (ii) proporciona información en tiempo real a los usuarios; y (iii) facilita el análisis de los datos y su uso por otras partes del sistema.

- CAFCLA integra n-Core Polaris (Nebusens, 2016) para proporcionar la ubicación., el cual permite determinar la posición de los usuarios con una precisión de hasta un metro, y que esta basado en el protocolo de comunicación inalámbrica ZigBee. Con el fin de localizar, n-Core requiere desplegar un conjunto de balizas. Estas balizas recogen la señal enviada por los tags utilizados por los jugadores. Esa señal, y sus datos asociados, se envían al servidor que implementa el motor de localización, el cual calcula la posición de cada jugador. Los jugadores usan un tag n-Core Sirius Quantum, responsable de enviar la señal de localización. Este dispositivo también está equipado con un acelerómetro que determina si el usuario se está moviendo o no. Las balizas envían estos datos al servidor de la misma manera que los datos de los sensores se envían a través de los colectores de datos Wi-Fi.

La capa de gestión incluye la máquina social, así como toda la lógica e inteligencia que permite gestionar el juego serio.

La capa de aplicación desarrolla la interfaz de interacción tanto para la configuración del juego como para su desarrollo.

Debido a que el objetivo principal del juego serio es concienciar sobre el uso eficiente de la energía, los jugadores fueron capaces de ver las acciones que tomaron y que implicaron importantes ahorros de energía (apagando las luces, no utilizando la calefacción, etc.). Gracias al uso de la Computación Social, el juego podía hacer recomendaciones a los jugadores en base a las acciones más eficientes que han sido tomadas por otros. Estas acciones se identifican a partir de los datos recogidos por los sensores, los ahorros de energía que implican y la probabilidad de que se mantengan en el tiempo.

La posición de cada usuario en el entorno, combinada con la información contextual, determinó el desarrollo del juego. Todos los trabajadores estaban involucrados en el juego cuyo objetivo principal era conseguir monedas virtuales a través de comportamientos energéticamente eficientes. Cada usuario recibió cuatro recomendaciones por día en cuatro correos electrónicos diferentes, determinados y enviados por la máquina social, que dieron una pista sobre la acción que se debía tomar. Los usuarios se agruparon en seis grupos de ahorro de energía por medio del algoritmo k-vecinos más cercanos (kNN - *k-Nearest Neighbors*) (Rodger, 2014), considerando el número de veces que usaron los sistemas de ascensores, la iluminación y la climatización durante el período basal de referencia. La máquina social personaliza todas las recomendaciones a cada grupo según los hábitos del clúster (las acciones que los usuarios no tengan en cuenta se recomiendan para fomentar la adquisición de un buen hábito) y a la reputación de la acción (aquéllas que implicaban más ahorro de energía tienen más reputación).

Si el trabajador completaba una acción, ganaba 10 monedas virtuales, de lo contrario, era penalizado con 10 monedas virtuales. Para animar a los participantes, 250 monedas virtuales los jugadores podían tomar un café o un refresco de forma gratuita. Las acciones que ayudaron a ganar o perder monedas virtuales fueron las siguientes:

- Evitar la iluminación artificial cuando la iluminación natural era superior a 200 Lux.
- No usar el sistema de climatización cuando la temperatura estaba por encima de 18°C en invierno o por debajo de 25°C en verano.
- Obtener un consumo diario de electricidad por debajo del promedio del día anterior.
- Usar las escaleras en lugar del ascensor.

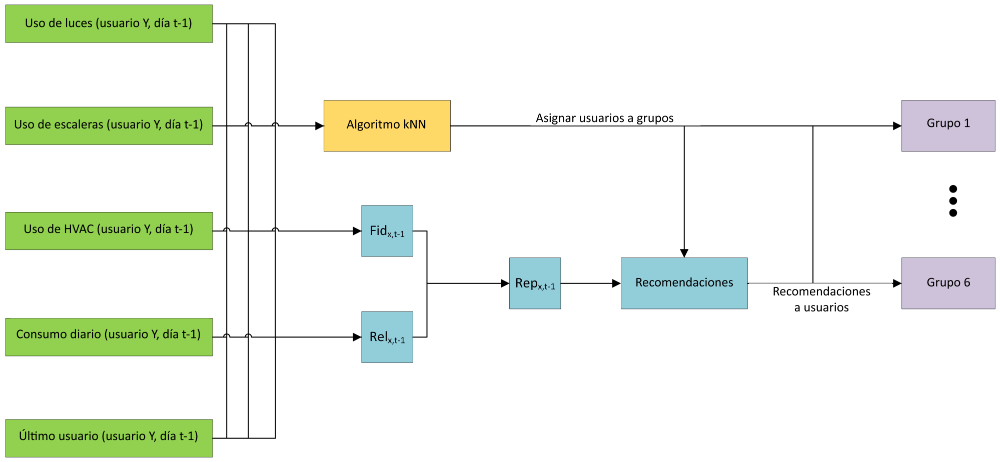

Figura 3.8 – La máquina social utiliza un algoritmo kNN para clasificar a los usuarios en diferentes grupos basados en su rendimiento energético previo. Además, asigna una reputación a cada acción para poder recomendarlas a los usuarios que menos las lleven a cabo.

- Apagar las luces y el sistema de climatización cuando el último usuario salía del laboratorio.
- Pertenecer al grupo que se comportó más eficientemente en un período de dos días.

3.5.2. Experimentación

El sistema propuesto fue evaluado en uno de los laboratorios del grupo de investigación BISITE de la Universidad de Salamanca. Las fechas seleccionadas para su desempeño intentaron homogeneizar al máximo las condiciones de trabajo, así como minimizar la influencia de factores externos. Por estas razones, se eligió el inicio del curso, después de las vacaciones de verano, ya que en este período los investigadores tienen una carga de trabajo más estable. Además, es importante mencionar que cada uno de los participantes realizó las mismas funciones y siguió el mismo horario de trabajo durante los dos meses de experimentación, de modo que los resultados fueron mínimamente influenciados por factores externos, cambios en la carga de trabajo o vacaciones. Por último, este periodo también era favorable para minimizar la influencia de las condiciones climáticas y las horas de sol: menor oscilación térmica entre los meses, horas semejantes de la luz solar durante las horas de trabajo y pluviometría similar. Según todos los factores considerados, los meses de septiembre y octubre fueron los elegidos para desarrollar el juego.

Como se puede ver en la Figura 3.7, el laboratorio tiene un espacio de trabajo común, con un área de 88 metros cuadrados, donde se ubican los puestos de trabajo de las 18 personas involucradas en el juego. Además, hay dos salas de reuniones separadas, con 12 metros cuadrados cada una, que tienen suficiente espacio para agrupar a ocho personas simultáneamente. El laboratorio está ubicado en el segundo piso del Edificio I+D+i y se puede acceder a través de un ascensor o escaleras.

La Figura 3.7 muestra cómo se definieron los puntos que miden la temperatura y la luminosidad, cómo se colocaron sensores de consumo en cada posición, cómo se ubicaron sensores on/off que determinaron el estado del sistema de iluminación y climatización, y cómo se definieron las diferentes áreas donde se desarrolló el juego: dos salas de reuniones, zona de trabajo, escaleras y ascensor entre la segunda planta y la planta baja).

Para monitorizar el consumo de energía se instaló un enchufe Cloogy[1] en cada puesto de trabajo, sumando en total 18. El enchufe incluye un sensor de consumo eléctrico, con una precisión de ±1 % ±0,5 W y capacidad de comunicación ZigBee. Todos estos sensores formaron una red ZigBee a través de la cual se transmitían datos de consumo de energía en tiempo real para cada posición. Los datos de consumo se enviaron al servidor cada 15 minutos y en tiempo real si los jugadores lo solicitaron. Estos datos son recogidos por un *crawler* integrado en la organización de gestión de datos a través de un Servicio Web desde la página web en la que se publica el consumo. Con estos datos, los usuarios podían comprobar su consumo de electricidad, su historial de consumo y su comparación con el consumo de otros jugadores, lo cual funcionó como un factor de motivación. Además, estos datos permitieron determinar qué usuarios estaban por encima y por debajo del consumo promedio de cada día. Los usuarios fueron conscientes en todo momento de que deberían apagar sus equipos y monitores si no iban a ser utilizados durante largos períodos de tiempo.

Para fomentar un uso más moderado de la climatización y los sistemas de iluminación, cuatro dispositivos IOn-E se desplegaron a lo largo de la misma red de sensores inalámbricos (ver Figura 3.7). Dos de estos dispositivos recolectaron datos en el ambiente de trabajo compartido y otros dos se ubicaron en cada una de las dos salas de reuniones. Cada dispositivo IOn-E incluye un sensor de temperatura SHT25, un sensor de luz TSL2561 y capacidad de comunicación ZigBee acoplándolo a un dispositivo Sirius RadIOn a través de un I²C digital. SHT25 es un sensor de temperatura de alta gama que funciona entre -20°C y 100°C, con una precisión de ±0,1°C cuando trabaja entre 0°C y 60°C y funciona con VDD de 3 V. El sensor de luz TSL2561 también funciona con VDD de 3 V, su rango dinámico comprende de 0,1 a 40,000 lux y rechaza automáticamente la ondulación de iluminación de 50/60 Hz. Cada variación de 0,5°C fue enviada y almacenada, mientras que la luminosidad se envió al servidor cada 60 segundos. Además, la temperatura y la luminosidad podían ser solicitadas por los usuarios bajo demanda. Los jugadores conocían en todo momento los datos recogidos por estos sensores para que pudieran evaluar si el uso de iluminación artificial o sistemas de climatización era necesario o no, basándose en las premisas prestablecidas.

Para monitorizar la posición de los usuarios, la red de sensores inalámbricos también actuó como balizas del sistema de localización, facilitando la misma con una precisión de un metro y un período de localización de un segundo. Además, se instalaron dispositivos Sirius RadIOn (ver Figura 3.7) cerca del ascensor y las escaleras en los tres pisos del edificio. Así, el sistema podía determinar dónde estaba el usuario en cualquier momento (escaleras, ascensor, sala de reuniones, etc.). Para localizar a los usuarios, cada uno llevaba un dispositivo Sirius

[1] http://www.cloogy.com

Quantum, como podemos ver en la Figura 3.7, que funciona en el sistema como una etiqueta de localización. Este dispositivo envía diferentes mediciones de señal (por ejemplo, RSSI) cada segundo a través de la red ZigBee al servidor y su posición en el sistema es calculada por el motor de localización. Al mismo tiempo, el sistema podría detectar si el jugador estaba usando iluminación o climatización. Así, el sistema fue capaz de determinar si el usuario subía al laboratorio por ascensor o usando las escaleras o qué jugador era la última persona que salía del lugar de trabajo o de una sala de reuniones, recomendando apagar luces y aire acondicionado usando para ello los sensores de encendido/apagado acoplados en cada interruptor de iluminación y termostato.

La descripción del entorno, considerando el consumo de energía, se centra en cuatro perspectivas diferentes: iluminación, climatización, consumo de energía eléctrica en todos los puestos de trabajo y uso del ascensor. Para obtener la línea de base (el consumo habitual sin implicación en el juego) el entorno fue monitorizado durante un mes. Los resultados de esta monitorización son los siguientes:

- *Iluminación de laboratorio:* la luz natural entra por las ventanas y un pequeño patio mientras que la luz artificial es proporcionada por lámparas fluorescentes. El área de trabajo común se suministra con tres líneas de tubos fluorescentes de 58 W, mientras que cada sala de reuniones se suministra con una línea de estos tubos. El laboratorio está abierto de 08:00 am a 09:00 pm, 13 horas al día durante las cuales las luces se encienden continuamente en el área de trabajo. El consumo energético del área de trabajo es de 27,14 kWh diarios. Del mismo modo, la medida del consumo de iluminación de cada sala de reuniones se tomó antes del comienzo del juego durante un mes. Los datos promedio obtenidos indican que cada sala consume 1,04 kWh por día. El consumo total de electricidad para la iluminación en todos los puestos del laboratorio es de 31,31 kWh por día.

- *Climatización:* el aire acondicionado en el laboratorio está provisto por el sistema de climatización del edificio. Sin embargo, cada uno de los espacios tiene un termostato individual que permite encender y apagar el suministro, así como regular la temperatura en el área. Este sistema está en funcionamiento continuamente durante las horas de trabajo y se desconecta automáticamente cuando el edificio está cerrado. Antes del juego ninguno de los usuarios se encargó de apagar el termostato ni en el área común ni en las salas de reuniones.

- *Puesto de trabajo:* cada puesto de trabajo cuenta con un monitor LCD y un ordenador portátil. Estos dos dispositivos se alimentan a través del mismo enchufe mediante el cual se supervisa el consumo gracias a un dispositivo Cloogy. La medición del consumo se hizo durante el mes anterior al juego, obteniendo un consumo promedio por hora de 0,1535 kWh por jugador y 1,309 kWh por jugador y día. Además, se midió una media de horas de trabajo de cada puesto fueron de 7,68 horas. Durante las horas restantes los dispositivos estaban en *stand-by*, obteniendo un consumo de 0,018 kWh por jugador a la hora y 0,2937 kWh por jugador al día. Con estos datos, el consumo eléctrico promedio medido para cada jugador durante un mes fue de 0,1715 kWh.

- *Salas de reuniones:* fueron utilizadas por 15 usuarios, que se organizaron en 5 reuniones diarias. Se utilizaron sistemas de iluminación durante todas las reuniones y 3 de ellos hicieron uso del sistema climatización.
- *Ascensor:* cada usuario sube y baja desde y hasta el segundo piso al menos cuatro veces al día: al llegar al trabajo por la mañana, durante la pausa, a la hora del almuerzo y al salir del trabajo. Los trabajadores del laboratorio fueron monitorizados en el uso del ascensor: 12 de ellos utilizaban el ascensor en casi el 90 % de los casos, ya sea subiendo o bajando, mientras que seis de ellos siempre utilizaban las escaleras.
- *Salir del laboratorio:* los últimos usuarios que salían del laboratorio no apagaban las luces ni la climatización. Las luces no se desconectaban al final del día en el 80 % de los casos, mientras que el sistema de climatización permanecía funcionando siempre una vez que todos habían salido del laboratorio.

Los 18 trabajadores del grupo de investigación BISITE participaron en el juego durante 30 días laborables:

- Los datos obtenidos del puesto de trabajo mostraron que en el consumo total promedio por día de todos los usuarios se produjo un ahorro de entre el 6,6 % y 6,9 % con respecto a las mediciones realizadas antes del juego.
- Los datos obtenidos en las salas de reuniones indicaron que el uso de la iluminación artificial se redujo en un 56 % y el uso del sistema de climatización en un 82 %. Estos ahorros se realizaron principalmente a través del juego, un argumento que se confirma con los resultados de las pruebas realizadas (t de Student), reportando una media de 2,15 veces por día en las que la iluminación se utilizó durante el juego, en comparación con la media de 5,071 antes de su desarrollo.
- Los datos obtenidos al abandonar el lugar de trabajo indicaron que todos los usuarios fueron conscientes de apagar luces y termostatos si eran los últimos en abandonarlo, lo cual se debe, en gran parte, al sistema de alerta integrado. Durante el período de 30 días, ambos sistemas se apagaron cuando el laboratorio estaba cerrado excepto los dos primeros días al comienzo del juego. Estos datos indican que el cambio de comportamiento promovido por el juego fue efectivo y significativo.
- Los datos obtenidos del ascensor mostraron que las escaleras fueron la opción elegida en más del 88 % de los casos, frente al 40 % previamente medido. Además, se disminuyó el número de veces que se utilizó el ascensor, obteniéndose una media de 4,933 en el número de veces por día durante el juego, en comparación con la media de 44,774 veces antes de su desarrollo.

De los resultados obtenidos puede concluirse que el juego es una herramienta potente para fomentar hábitos de ahorro de energía y, además, hábitos saludables, gracias al incentivo para lograr mejores resultados en el juego.

3.6. CAFCLA en el ahorro energético en el hogar

El objetivo principal de este tercer caso de uso es mejorar los hábitos de consumo de energético en las personas. El framework, diseñado desde la perspectiva de la Computación Social, facilita la implementación de funcionalidades contextuales, de localización y sociales. CAFCLA facilitó en este caso la implementación de las siguientes funcionalidades:

- Obtiene información contextual a través de la implementación de WSN que permiten recopilar datos de múltiples fuentes para caracterizar el entorno. Entre ellos, los sensores que recogen los parámetros ambientales (temperatura, humedad o iluminación) o los datos sobre la utilización de dispositivos (encendido o apagado de luces o estado de persianas y ventanas).

- Implementa un sistema de localización en tiempo real que permite identificar y rastrear a los usuarios en todo momento. Las posiciones de los usuarios permiten identificar patrones de comportamiento que ayudan a describir buenos o malos hábitos de consumo de energía.

- Integra una máquina social que facilita recomendaciones utilizando Organizaciones Virtuales de agentes que proporcionan inteligencia al sistema. La monitorización de todos los parámetros contextuales, la localización de los usuarios, la gestión de los datos, y la generación de recomendaciones, influyen en un uso más eficiente de la energía.

La implementación facilitada por CAFCLA se evaluó mediante un caso de uso experimental que valida la eficacia del uso de sistemas de localización en tiempo real y WSN. En el desarrollo se utilizó una máquina social para realizar recomendaciones que permitieron mejorar el ahorro de energía en los hogares, e influir positivamente en el comportamiento de los usuarios.

Las magnitudes físicas recogidas por los sensores son tres: temperatura (°C), luminosidad (Lux) y nivel de movimiento. El primero provee la temperatura de cada habitación dentro de las casas monitorizadas gracias a los datos recogidos por sensores específicos. El segundo da el nivel de luminosidad de cada habitación gracias a un sensor de luminosidad. El tercero provee el nivel de actividad de cada usuario gracias a un acelerómetro de 3 ejes integrado en el dispositivo portado por estos[2]. Todos los datos de sensores son accesibles a través de la API proporcionada por el fabricante. Por otro lado, el sistema de localización siempre proporciona la ubicación de los usuarios con una precisión de un metro. Además, se controla el uso de

[2] El nivel de movimiento es detectado por una regla específica integrada en la memoria del tag.

electrodomésticos (lavadora y lavavajillas) y otros dispositivos (TV y PC) mediante un enchufe inteligente que detecta el consumo instantáneo de electricidad.

Gracias a estos datos se identifican una serie de actividades que se llevan a cabo y en las que puede haber ahorros de energía potenciales, como el uso inadecuado de calefacción o la iluminación. Al fusionar esta información con el consumo eléctrico y la información en tiempo real de los sensores y sistemas de localización, la solución propuesta genera una serie de recomendaciones que promueven el ahorro de energía y, además, un cambio de comportamiento en los hábitos de consumo de electricidad.

Las recomendaciones que han sido predefinidas dentro de este desarrollo son las siguientes:

- Apagar la calefacción si la temperatura supera los 18°C.
- Apagar las luces si la iluminación es superior a 200 lux.
- Apagar la calefacción y las luces cuando la última persona salga de la casa.
- Apagar las luces si no hay movimiento en ciertas áreas, por ejemplo, cuando el usuario está sentado en el sofá viendo la televisión, jugando, etc.
- Apagar las luces de una habitación sin ocupación.
- Apagar la calefacción si no se detecta movimiento durante la noche y la temperatura es superior a 18°C.
- Optimizar el uso del calendario de calefacción mediante la identificación de los tiempos en que hay personas en casa.
- Reducir el uso de la lavadora recomendando una carga adecuada y un horario de baja energía.
- Sugerir horarios de cocinar o comidas conjuntas a los inquilinos.
- Recomendar un uso planeado y serializado del baño para aprovechar el calor y la producción de agua caliente.
- Avisar sobre los consumos en *stand-by* de los dispositivos (televisores, consolas, ordenadores, etc.).

3.6.1. Sistema propuesto

El sistema propuesto se ha desplegado en 5 casas con 3 tipologías diferentes: Tipo I, un piso de 1 dormitorio con un inquilino; Tipo II, dos pisos de 2 dormitorios con dos inquilinos; Tipo III, dos pisos de 3 dormitorios con tres inquilinos. Todas las casas tienen una cocina, una sala de

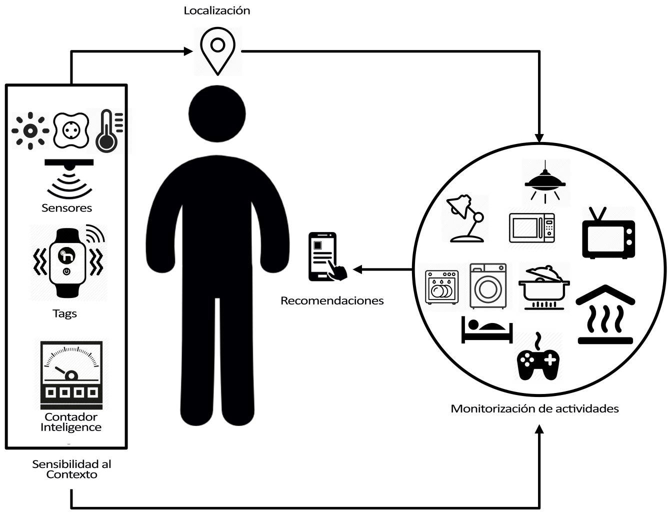

Figura 3.9 – El modelo presentado recoge la información contextual y la localización de los usuarios. Estos datos, combinados con la monitorización de actividades de los usuarios, permiten generar recomendaciones para fomentar el ahorro energético.

estar y un baño, excepto las viviendas de 3 dormitorios, que tienen dos baños. En total, 11 usuarios participan en la experimentación.

Para medir la temperatura e iluminación, la WSN desplegada disponía de un sensor en cada habitación de las casas, en la cocina, en los baños, en el salón y en el área de la puerta de entrada, lo que implica un total de 5 puntos de medición para el Tipo I, 6 puntos de medición para el Tipo II y 8 puntos de medición para el Tipo III. Estos puntos están formados por un dispositivo IOn-E (Nebusens, 2016) conectado a través de un puerto I²C digital a un dispositivo de comunicación Sirius RadIOn. El dispositivo IOn-E integra un sensor de luz modelo TSL2561 (AMS, Stiria, Austria), cuyo rango de medición está entre 0,1 y 40.000 lux. La medición de brillo se envía cada 60 segundos al servidor. El dispositivo IOn-E también integra un sensor de temperatura de alta precisión SHT25 (Sensirion, Staefa, Suiza). Este sensor es capaz de registrar mediciones entre -20°C y 100°C con una precisión de ±0,1°C. Para los fines de este trabajo, los sensores envían la temperatura al servidor cuando se produce una variación de ±0,5°C.

Para medir el consumo eléctrico, se emplearon enchufes inteligentes en los salones y dormitorios de cada casa con el fin de identificar el uso de dispositivos como TV, ordenadores o lámparas entre otros. Se utilizan dispositivos Cloogy[3] en la sala de estar y dormitorios. Incluyen un sensor de consumo eléctrico que registra el consumo cada 15 minutos, con una precisión de ±1 % ±0,5 W, e integra el protocolo de comunicación ZigBee para proporcionar los datos de consumo. Los datos son recopilados por un *crawler* que accede al Servicio Web donde se publica el consumo medido por cada sensor.

Para obtener la localización de los usuarios, un dispositivo Sirius RadIOn por habitación y un

[3] http://www.cloogy.com

dispositivo Quantum actuarán como balizas y tags, lo que enriquece el sistema gracias a su gran precisión.

La máquina social implementada dentro de esta experimentación recibe datos en tiempo real tanto del sistema de localización como de la WSN (ver Figura 3.10). Estos datos permiten identificar acciones predefinidas, malos usos energéticos o posibles mejoras al dar la situación instantánea de los usuarios y su entorno. Además, la máquina social calcula la reputación de cada una de las acciones para recomendarlas a los usuarios. Estas recomendaciones se envían a través de correos electrónicos explicando sus beneficios, su uso por el resto de los participantes, las mejoras logradas. El tema del correo sea lo suficientemente explícito para que las recomendaciones se pudieran llevar a cabo rápidamente. Además, los usuarios reciben una vibración en el tag de localización que llevan para darse cuenta de que se ha enviado una recomendación. Si lo toman en consideración, solo tienen que pulsar el botón del tag y el sistema interpreta esta señal como retroalimentación positiva.

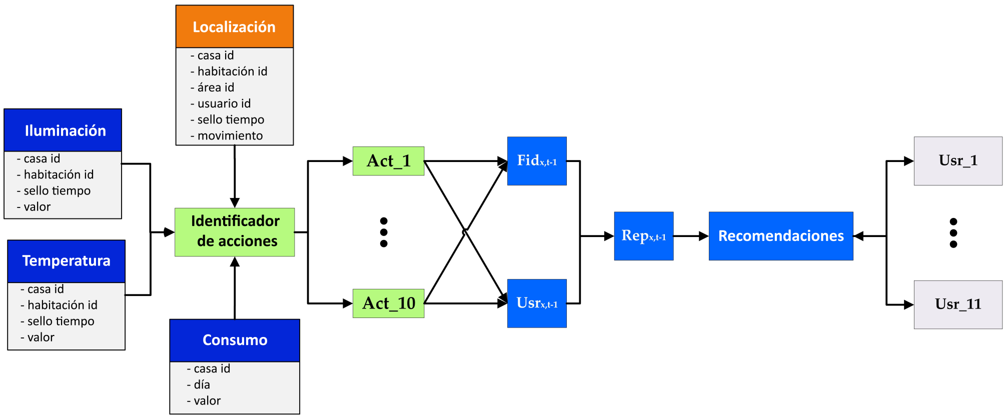

Figura 3.10 – La máquina social recibe datos del motor de localización y de la red de sensores para identificar las acciones que se están llevando a cabo. Con los datos actuales e históricos calcula la reputación de cada acción para proporcionar recomendaciones personalizadas a los usuarios.

3.6.2. Experimentación

La experimentación se realizó durante dos meses consecutivos. Durante el primer mes, se recogió el consumo diario de cada piso para crear el consumo basal de referencia para comparar con los resultados experimentales durante el segundo mes. El mes de abril fue elegido para recoger los datos de referencia y el mes de mayo para realizar la experimentación, buscando minimizar las diferencias en las condiciones climáticas, pluviometría y de luz solar que pudieran afectar los resultados.

Los datos de consumo basal de referencia indicaron que la casa 1 consumió 496,56 kWh, la casa 2 consumió 561,66 kWh, la casa 3 consumió 545,40 kWh, la casa 4 consumió 601,35 kWh y la casa 5 consumió 654,73 kWh. Puedo apreciarte en base a estos datos que el tamaño de la vivienda influenciaba en el consumo.

Durante la experimentación, los datos de consumo mostraron que la casa 1 consumió 387,41 kWh, la casa 2 consumió 470,92 kWh, la casa 3 consumió 470,24 kWh, la casa 4 consumió 493,57 kWh y la casa 5 consumió 549,04 kWh. Estos datos no evidenciaron una relación directa entre el tamaño de la casa y el ahorro.

Los resultados de los consumos indicaron que en la casa 1 el ahorro del 21,98 % fue muy significativo, mientras que el resto de casas experimentaron cambios mucho más moderados en torno al 16 %, oscilando los ahorros entre el 13,78 % para la casa 3 y el 21,98 % antes mencionado para la casa 1.

El análisis de los resultados mostró que las recomendaciones consideradas con más frecuencia fueron las relacionadas con el uso de calefacción (77 %), iluminación (84 %) y apagado de dispositivos para evitar el consumo en *stand-by* (92 %). Sin embargo, las recomendaciones sobre la optimización en el uso del cuarto de baño (4 %) o cocinar al mismo tiempo (17 %) no tuvieron un gran efecto, lo que demuestra que la máquina social ha funcionado más efectivamente en las relaciones máquina-humano que en las humano-humano.

4 Resultados

A lo largo del presente Capítulo se detallan las publicaciones que han dado como resultado de este trabajo. La Sección 4.1 enumera las publicaciones en revistas científicas internacionales, en capítulos de libros y en conferencias y workshops internacionales. La Sección 4.2 enumera los proyectos que han sustentado la investigación desarrollada.

4.1. Publicaciones

Los siguientes documentos describen el trabajo y resultados de la Tesis Doctoral aquí presentada. Todos ellos han sido publicados o aceptados para su publicación en el momento de presentar esta memoria. Además, todos los trabajos han sido publicados tras superar el proceso de revisión entre pares:

- Publicaciones en revistas científicas internacionales:

  (J1) García, Ó., Alonso, R. S., Prieto, J., & Corchado, J. M. (2017). Energy efficiency in public buildings through context-aware social computing. *Sensors*, 17(4):826.

  (J2) Alonso, R. S., Tapia, D. I., Bajo, J., García, Ó., de Paz, J. F., & Corchado, J. M. (2013). Implementing a hardware-embedded reactive agents platform based on a service-oriented architecture over heterogeneous wireless sensor networks. *Ad Hoc Networks*, 11(1):151-166.

  (J3) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2012). Using ZigBee in ambient intelligence learning scenarios. *International Journal of Ambient Computing and Intelligence (IJACI)*, 4(3), 33-45.

  (J4) García, Ó., Tapia, D. I., Alonso, R. S., Rodríguez, S., & Corchado, J. M. (2011). Ambient intelligence and collaborative e-learning: a new definition model. *Journal of*

Ambient Intelligence and Humanized Computing, 3(3), 239-247.

- Publicaciones pendientes de aceptación:

(J5) García, Ó., Prieto, J., Alonso, R. S., & Corchado, J. M. (2017). A framework to improve energy efficient behaviour at home through activity and context monitoring. *Sensors*, en segunda revisión.

- Publicaciones en capítulos de libros:

(BC1) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2015). CAFCLA: A Framework to Design, Develop, and Deploy AmI-Based Collaborative Learning Applications. *In Recent Advances in Ambient Intelligence and Context-Aware Computing (Ed. Kevin Curran)*, chapter 12, pp. 187-209, ISBN 978-1-4666-7287-1. IGI Global, Hershey, PA, USA.

- Publicaciones en actas de conferencias internacionales o workshops:

(C1) García, Ó., Alonso, R. S., *et al.*. (2016).Use of context-aware Social Computing to improve energy efficiency in public buildings. In *IEEE Symposium Series on Computational Intelligence (SSCI)*, (pp. 1-8). IEEE.

(C2) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2013). CAFCLA: An AmI-Based Framework to Design and Develop Context-Aware Collaborative Learning Activities. In *Ambient Intelligence-Software and Applications, 4th International Symposium on Ambient Intelligence (ISAmI 2013)*, volume 219 (pp. 41-48). Springer International Publishing.

(C3) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2013). Supporting Context-Aware Collaborative Learning Activities by CAFCLA. In *2nd International Workshop on Evidence-based Technology Enhanced Learning (EbTEL 2013)*, volume 218 (pp. 57-65). Springer International Publishing.

(C4) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2012, June). CAFCLA, a framework to ease design, development and deployment ami-based collaborative learning applications. In *7th Iberian Conference on Information Systems and Technologies (CISTI 2012)* (pp. 1-6). IEEE.

(C5) García, Ó., Alonso, R. S., Tapia, D. I., García, E., De la Prieta, F., & de Luis, A. (2012). CAFCLA: A conceptual framework to develop collaborative context-aware learning activities. In *Workshop on Learning Technology for Education in Cloud (LTEC 2012)*, volume 173 (pp. 11-21). Springer Berlin Heidelberg.

(C6) García, Ó., Alonso, R. S., Tapia, D. I., & Corchado, J. M. (2012). Evaluating ZigBee Protocol to Design CAFLA: A Framework to Develop Location-Based Learning Activities. In *International Workshop on Evidence-Based Technology Enhanced Learning (EbTEL 2012)*, volume 152 (pp. 125-132). Springer Berlin Heidelberg.

(C7) García, O., Alonso, R. S., Guevara, F., Sancho, D., Sánchez, M., & Bajo, J. (2011). ARTIZT: Applying ambient intelligence to a museum guide scenario. In *Ambient Intelligence-Software and Applications, 2nd International Symposium on Ambient Intelligence (ISAmI 2011)*, volume 92 (pp. 173-180). Springer Berlin Heidelberg.

(C8) García, Ó., Tapia, D. I., Rodríguez, S., & Corchado, J. M. (2010, June). Ambient intelligence application scenario for collaborative e-learning. In *23rd International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems (IEA/AIE 2010)* (pp. 407-416). Springer Berlin Heidelberg.

4.2. Proyectos

Algunos de los aspectos publicados en esta Tesis Doctoral han sido base de la investigación para cumplir con los objetivos marcados en los siguientes proyectos:

(P1) **Dream-GO. Enabling Demand Response for short and real-time Efficient And Market Based smart Grid Operation - An intelligent and real-time simulation approach**. Comisión Europea, Programa Horizon 2020. Desde febrero de 2014 hasta enero de 2019. H2020-MSCA-RISE-2014, MSCA-RISE-2014, SEP-210162060. Investigador Principal: Zita Vale.

(P2) **SOGESCLOUD - Máquina social auto-adaptativa para la gestión corporativa en la nube**. Ministerio de Industria, Energía y Turismo, Govierno de España. Desde Septiembre de 2015 hasta septiembre de 2017. TSI-100104-2015-007. Investigador principal: Juan M. Corchado.

(P3) **CLOUD-IO - Plataforma Cloud Computing para la Integración y Despliegue Rápido de Servicios sobre Redes Inalámbricas de Sensores**.Ministerio de Economía y Competitividad, Govierno de España. Desde septiembre de 2011 hasta septiembre de 2013. IDI-20111471. Investigador principal: Juan M. Corchado.

5 Publicaciones Originales

Al tratarse de una Tesis Doctoral por compendio de artículos, el presente Capítulo recoge las publicaciones originales que el desarrollo de este trabajo ha generado. El artículo incluido en la Sección 5.1 presenta la idea de unir Inteligencia Ambiental y aprendizaje colaborativo. El artículo recogido en la sección 5.2 justifica la utilización de ZigBee en entornos educativos. El artículo presentado en la Sección 5.3 describe una plataforma de agentes para gestionar redes inalámbricas de sensores. El artículo incluido en la Sección 5.4 realiza una descripción detallada del framework CAFCLA. El artículo mostrado en la Sección 5.5 aplica CAFCLA en un caso de uso para fomentar el ahorro de energía en edificios públicos a través de un juego serio. El artículo incluido en la Sección 5.6, que actualmente se encuentra en la segunda ronda de revisiones de la revista *Sensors*, ha decidido incluirse en esta memoria debido a su relevancia en la Tesis Doctoral presentada pues en él se aplica CAFCLA a un caso de uso consistente en un sistema de recomendaciones para fomentar el ahorro energético en los hogares.

5.1. Ambient intelligence and collaborative e-learning: a new definition model

La constante evolución de los dispositivos móviles y Tecnologías de la Información y las Comunicaciones (TIC) permiten a todo tipo de usuarios disfrutar de una nueva variedad de recursos que eran inimaginables hace algunos años. En este sentido, la Inteligencia Ambiental (AmI - *Ambient Intelligence*) ha surgido como una nueva disciplina centrada en las personas y orientada a facilitar sus actividades diarias. Este artículo propone la definición de un nuevo modelo que ayude a los diseñadores de aplicaciones a caracterizar la colaboración entre participantes en sistemas de aprendizaje colaborativo basado en ordenador (CSCL - *Computer Supported Collaborative Learning*) basados en AmI. El uso de dispositivos móviles y redes móviles ad-hoc (MANETs - *Mobile Ad-hoc NETworks*) es el aspecto clave en éste, ya que permiten a los usuarios acceder a los recursos bajo demanda desde cualquier lugar y en cualquier momento. Este nuevo modelo sustentará el desarrollo del framework CAFCLA, siendo la base en torno a la que se diseñará el mismo.

CSCL es un interesante enfoque en donde los participantes del proceso educativo (estudiantes y profesores) llevan a cabo actividades de aprendizaje de forma colaborativa que requieren la interacción entre ellos a través de ordenadores y otros dispositivos. El desarrollo de Las aplicaciones basadas en CSCL tiene en cuenta tanto aspectos de diseño de sistemas basados en ordenador, tales como la movilidad de los participantes, problemas de visualización de contenidos, interfaces o la gestión de áreas de trabajo comunes (por ejemplo, la coordinación de contextos de visualización y edición de texto en un documento que se está modificado por dos participantes al mismo tiempo).

La definición del modelo propuesto en este documento se basa en dos de los pilares del paradigma de la Inteligencia Ambiental: por un lado la comunicación ubicua y por otro la información contextual. Ambos pueden ser cubiertos a través del uso de dispositivos móviles y su utilización para formar redes MANET. Estas redes están formadas por nodos móviles inalámbricas que se organizan de forma dinámica utilizando topologías temporales de red arbitrarias. Por medio de estas redes, la comunicación entre personas y objetos dentro del entorno de trabajo no requiere la existencia de una infraestructura previa o cuando ésta es requerida bajo demanda. Las MANET ofrecen la posibilidad de integrar de forma fácil y transparente a los dispositivos móviles en entornos educativos, permitiendo a los estudiantes moverse libremente en el entorno de la actividad de aprendizaje, así como a los profesores dirigir la actividad en tiempo real. La inclusión de dispositivos móviles en el campo del CSCL ha hecho emerger el término MCSCL (*Mobile CSCL*).

Objetivos

Los objetivos perseguidos en esta publicación son los siguientes:

- Justificar el uso de redes móviles ad-hoc para facilitar los procesos de aprendizaje colaborativos de forma ubicua: cualquier momento - cualquier lugar.
- Diseñar conceptualmente un nuevo modelo de aprendizaje colaborativo que permita la utilización de redes inalámbricas y dispositivos móviles para facilitar el despliegue de actividades en cualquier lugar y momento.
- Describir los requisitos que el modelo debe cubrir, tanto a nivel técnico como funcional, para que el proceso de aprendizaje sea colaborativo y ubicuo.
- Describir un escenario de aplicación del modelo propuesto.

Resultados

El estado del arte planteado en este artículo demuestra que existe aún un largo camino por recorrer en el diseño de modelos que permitan el desarrollo de aplicaciones de aprendizaje colaborativo ubicuas. El desarrollo del modelo propuesto en este artículo facilita la respuesta a una serie de preguntas que ayudan a definir tanto las tecnologías a utilizar como el funcionamiento de la actividad a desarrollar: ¿Dónde se desarrolla la actividad? ¿Dónde se encuentran los participantes? ¿Qué tipo de interacciones se producen entre los participantes? ¿Qué tipo de arquitectura de comunicación se adoptará? ¿Existe infraestructura de comunicación previa? ¿Qué tecnologías de comunicación se utilizarán?

Tras la investigación y estudio teórico, este artículo define los requisitos más importantes para construir un modelo de aprendizaje colaborativo basado en AmI y CSCL utilizando MANET. En el modelo descrito los estudiantes pueden colaborar en cualquier momento y lugar, crear de redes ad-hoc móviles para llevar a cabo las tareas de aprendizaje y permite a los profesores supervisar estas tareas para orientar y gestionar el proceso de aprendizaje. Las conclusiones del trabajo propuesto han demostrado que el modelo cumple con las expectativas de un escenario educativo de AmI que sirve como base para múltiples y diferentes tareas. A diferencia de otros enfoques, este modelo permite a los estudiantes tener total libertad para comunicarse entre ellos. Además, el trabajo define un modelo general que puede ser utilizado en diferentes escenarios educativos y no sólo para una tarea o actividad en particular. Con el fin de complementar y aclarar el modelo propuesto, se describe un escenario de ejemplo real en el que el aprendizaje colaborativo y la supervisión de los docentes se produce de forma natural, en cualquier lugar donde los participantes desarrollan su trabajo.

El contenido de este capítulo fue publicado en el siguiente artículo de revista (García et al., 2012c):

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ORIGINAL RESEARCH

Ambient intelligence and collaborative e-learning: a new definition model

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Abstract The constant evolution of mobile devices and Information Technologies allows users to enjoy a new variety of features that were unimaginable some years ago. In this sense, Ambient Intelligence (AmI) has emerged as a new discipline focused on people and aimed at facilitating their daily activities. This paper proposes a new definition model that helps designers to characterize collaborative e-learning systems based on AmI and Computer Supported Collaborative Learning. The use of mobile devices and Mobile Adhoc Networks is a key aspect in this model as they allow users to access resources from anywhere on demand. The proposed model is applied to a concrete case of study as an example of its application on real scenarios.

Keywords Ambient intelligence · e-learning · Computed supported collaborative learning · Mobile adhoc networks

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1 Introduction

Currently, there is a wide range of mobile devices capable of communicating among them. These devices include mobile phones, laptops, PDAs and, more recently, smartphones and tablet PCs, among many others. During the last years the use of these mobile devices in learning environments is becoming increasingly widespread (Roschelle 2003; Anderson and Blackwood 2004). So much so that there is a new generation of people known as *digital natives* (Bennett et al. 2008). Digital natives are accustomed to using a wide range of information technologies and electronic devices, most of them fully connected to the Internet. Indeed, they are usually advanced users of the Internet and web applications, being these technologies an important pillar for their daily lives. Therefore, new research paradigms such as *Ambient Intelligence* (AmI) are being encouraged by these factors, thus rising quickly (Shadbolt 2003).

Ambient Intelligence proposes a new way to apply the technology in order to facilitate the execution of everyday tasks with variable complexity. In this sense, AmI proposes a new way of relationship between people and technology, where the use of this becomes ubiquitous, transparent for users and adaptive to the context surrounding them. This way, AmI is based on concepts such as ubiquitous computing, ubiquitous communication, context awareness, as well as the establishment of natural and non-intrusive human-system interactions (Cook et al. 2009). There is a wide range of scopes where such concepts can be applied: medicine, daily life, healthcare, security, industry or, which concerns us, education (Ducatel et al. 2001; Bohn et al. 2005; Tapia et al. 2010). Education is one of the areas that can be most improved by means of the application of AmI. Ambient Intelligence can increase and make better the

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learning methods and the way people learn and teach. New technologies, communication networks and intelligent devices open a new era of scenarios where students can learn through different, innovative and more efficient ways (Kinshuk et al. 2003).

Computer Supported Collaborative Learning (CSCL) (Economides 2008) is an interesting approach where participants (i.e., students and teachers) perform collaborative learning activities that require the interaction among them through computers and other devices. The development of CSCL-based applications takes into account aspects of the design of systems based on Computer Supported Collaborative Work (CSCW), such as mobility of participants, as well as both content display and interfaces problems in common working areas (e.g., coordination of both context visualization and text edition in a document that is being modified by two participants at the same time) (Trifonova and Ronchetti 2006). However, the design and development stages of systems based on AmI and CSCL are not easy, mainly because it is necessary to adapt them to their specific educational and social needs (Dimitriadis et al. 2004).

The definition model proposed in this paper is based on two of the cornerstones of the AmI paradigm: *ubiquitous computing and communication* and *context information*. Both of them can be covered through the use of Mobile Adhoc Networks (MANETs). A MANET is a network of wireless mobile nodes that organize themselves dynamically using temporary arbitrary topologies (Ylias and Dorf 2003). By means of MANETs, people and mobile objects can thus communicate among them without the existence of a previous infrastructure or when the utilization of such an infrastructure requires a wireless extension to be used on demand (Ylias and Dorf 2003). MANETs offer the capability to apply the use of mobile devices in the field of education so that students can freely move along with their devices. This new topic is called *MCSCL* (Mobile CSCL), which focuses on the use of mobile devices and wireless communication protocols to encourage collaborative learning situations that improve the whole learning process (Zurita and Nussbaum 2004).

This paper is aimed at presenting a model for defining some of the most important requirements needed to implement AmI-based scenarios where collaborative learning is possible. The main goal is ensuring that there will be connectivity between users anywhere and anytime. This must also include the capability to detect the proximity of potential partners to create working groups, registering any kind of interaction that has been carried out. This paper also presents an example scenario based on this model where users have full mobility and complete freedom of connection between them to exchange information transparently. All these features are performed under the supervision of teachers, in order to encourage collaboration and control the participation of all the students in the activities.

This paper is structured as follows. Next section justifies the creation of a new definition model that helps designers to characterize collaborative e-learning systems based on AmI and CSCL. After that, Sect. 3 describes the proposed model taking a set of conceptual and technical requirements as a starting point. Section 4 introduces a scenario where this model has been deployed. Finally, Sect. 5 presents the conclusions obtained and depicts the future lines of work to be followed.

2 Ambient intelligence and CSCL

The creation of e-learning systems and applications not only requires the participation of technical staff working together to design, implement and test them, but also needs the collaboration of educational experts. The educational component must be present especially in the design process, because teachers and students will be the final users and these systems and applications must be adapted to their specific social and educational needs (Echeverría et al. 2006).

Ambient Intelligence environments allow users to communicate in a ubiquitous way. Education, and more specifically CSCL, can benefit from the features provided by ubiquitous communication. Such features allow participants in CSCL activities to avoid the need to explicitly connect to a platform to share information among them. In order to facilitate CSCL, the approach presented in this paper proposes the use of mobile devices that provide enhanced ways of communication. Thus, students can learn together anywhere and anytime. To do this, they just have to utilize some mobile devices that allow them to connect to other users' devices in order to share information. Latest trends in mobile technology include devices that provide users with a wide range of communication capabilities, such as GSM/GPRS/EDGE, UMTS, HSPA, Wi-Fi, Bluetooth, Infrared, GPS or even ZigBee in a single device. These communication capabilities are especially useful in the field of education as they allow the creation of communication networks with ubiquitous features. Furthermore, the identification and localization of each user is made possible by means of the collection of context information through the sensors provided by mobile devices. In addition, there are different operating systems and platforms (e.g., Android, Windows Phone, Symbian or iOS) that allow developing and running user-friendly applications with a very interesting potential. As a result, there is an opportunity to develop intuitive interfaces and systems to facilitate the activities of individuals and the whole learning process in a transparent way (Trifonova and Ronchetti 2006). In this sense, Ambient Intelligence can help to enhance the learning process (Trifonova and Ronchetti 2006) by providing ubiquitous communication and context-awareness features that encourage learning and collaboration among users (i.e., students and teachers).

One of the most important aspects that must be covered by systems and platforms based on AmI and CSCL is that they should allow the creation of *working groups* (Koschmann 1996). These working groups can be either public or private. Therefore, each user can acquire different roles in order to interact with the rest of participants to perform distinct tasks. In addition, it is allowed the communication among participants anywhere and anytime by means of heterogeneous devices (Hummel et al. 2002). Therefore, participants can create collaborative tasks and exchange information. This way, students and teachers can generate guided discussions and share information of their interest. Furthermore, teachers can supervise the work in progress as well as the degree of satisfaction of the students when using a traditional e-learning platform through mobile devices (Andronico et al. 2004).

However, learning models that require a previous network infrastructure are difficult to use outside academic buildings and present important adaptation problems regarding the type of device (e.g., display or connectivity). More importantly, such models depend on a central element that provides the content to be accessed by students (Vasiliou and Economides 2008; Kinshuk et al. 2003), which hinders the distribution of computing and communication. Even worse, it is very difficult to collect context information with them (Andronico et al. 2004) and therefore it reduces the adaptability of the systems to the users. Thus, the lack of these features makes these kinds of solutions not be labeled as AmI-based approaches (Weiser 1999).

New ways to embed learning applications into mobile devices arise when trying to solve these shortcomings. One solution is to adapt the content of traditional e-learning to the especial characteristics of mobile devices (Kurbel and Hilker 2002). How to provide the information to students, how to determine which devices will be used and how the connection between them will be performed become the most important challenges to be addressed in the design stage.

3 Mobile adhoc networks and CSCL

The creation of collaborative networks in any place without a previous infrastructure, commonly known as *adhoc networking*, makes it easier the informal learning processes supported by mobile devices (Sharples et al. 2007). Even though all these features offer new possibilities, they present new problems that must be solved. Some of these problems are related to the heterogeneity of the devices. That is, most of the mobile devices have different displaying, networking and operating system capabilities (Kurbel and Hilker 2002). MCSCL proposes solutions to most of these challenges. There are many related works in this research area. Some research approaches are focused on the study of the educational characteristics of the new scenarios (Roschelle 2003). Other works approach the problem studying the technological requirements and proposing new architectures (Trifonova and Ronchetti 2006). It is easy to assume that the capability to interconnect different heterogeneous devices will be very useful to encourage the collaboration between students during the learning process and make it easier to develop tools that support MCSCL (Ellis et al. 1991). It can be made a rough classification of these developments by distributing them into three main groups: *m-learning collaborative solutions*, *MCSCL specific applications* and those that use *adhoc networking environments in MCSCL*. At this point it can be found two different trends. The first one seeks the integration of e-learning tools as traditional Web Services (Trifonova and Ronchetti 2004). Systems belonging to this trend have three basic functionalities for enhancing the operational and visual capacities of the devices: *Context Discovery*, Mobile Content Management and Adaptation (MCMA) and *Packaging and Synchronization* (Trifonova and Ronchetti 2006). The second trend tries to completely redesign digital courses so that they can be executed on mobile devices. In this tendency, it is usually prioritized the information that students should watch. Moreover, it is focused on developing tools intended for solving open problems, generating knowledge and encouraging the discussion of ideas (Kinshuk et al. 2003). This way, it is allowed the dynamic configuration of individual working groups, encouraging the collaboration between participants and providing the teacher with visual supervision capabilities. In addition to the adaptation of traditional e-learning platforms, there are applications specifically developed to support the CSCL using mobile devices. Such applications are considered as *real* MCSCL applications (Cortez et al. 2004) and provides an easier way to improve ubiquitous collaboration. There are approaches in which mobile devices are used to explicitly obtain a CSCL environment (Dvorak and Burchanan 2002; Kinshuk et al. 2003; Milrad et al. 2002; Zurita and Nussbaum 2004). However, these solutions do not meet the specifications of AmI since they are generally designed so that all participants use the same type of mobile device. Moreover, their architectures require a central element that provides the content and all devices must share the same communication protocol. Furthermore, these proposals are not able to create networks spontaneously, thus hindering ubiquitous communications, an indispensable aspect in Ambient Intelligence.

MANETs present a great advantage because they can cover groups of different sizes, to form different network topologies, as well as to use different communication protocols. Some requirements necessary to create a mobile adhoc learning application are socio-cultural, economic, technological (e.g., user interface, functionality, awareness, adaptation, reliability and maintainability, efficiency, connectivity) and others related to security (Economides 2008). These requirements must be taken into account when designing learning applications, even more when networks requirements are so specific. Several developments that enable the creation of adhoc networks in collaborative learning environments support the use of different communication protocols and the share of resources (Fuller et al. 2004). However, the need of both a previous network infrastructure and the configuration of the applications, as well as the limited number of participating nodes, limit the capacities of these kinds of developments. Moreover, there is also the challenge of working outside the classroom to enhance collaborative learning in museums, parks or other places with didactic interest (Vasiliou and Economides 2007). Besides the challenge of achieving peer communication without a previous infrastructure, as these kinds of activities require, it is difficult to avoid the client–server model that implements centralized network schemes (Zurita and Nussbaum 2006).

The creation of a MANET is very different in each development. In fact, the easiest way to create a network is to have a previous infrastructure, by means of either a wireless LAN deployed for this purpose, mobile nodes intended for providing the resources (Vasiliou and Economides 2007), or using nodes that create the network and register other nodes that are part of it (Zurita and Nussbaum 2006). The communication among devices is a key aspect in these kinds of networks (Vasiliou and Economides 2007). In order to solve network formation issues, it is usual to use *master* nodes, that is, network devices responsible for making up the MANET and allowing other nodes to access to it (Zurita and Nussbaum 2006). In such cases it is followed a client–server model in which the server is also used for providing with contents and services to the rest of the nodes. It is important to mention that the nodes not always have total freedom to move throughout the network. So, the mobility of the nodes and the way the teacher supervises the work must be specially taken into account. If a previous network infrastructure is needed, the nodes must be under the coverage of the network, whether formed by mobile (Vasiliou and Economides 2007) or fixed nodes (Fuller et al. 2004).

The most interesting cases for the scenario presented in this paper are those in which there is a mobile node acting as master. This way, teachers have at their disposal a terminal acting in this way and allowing them to supervise the established connections, who have registered in the network and even each of the interactions and the utilization of resources or applications made by each node (Vasiliou and Economides 2007; Zurita and Nussbaum 2006).

4 Conceptual and technical description

As depicted in the previous section, there are multiple factors that characterize the use of Ambient Intelligence, CSCL and MANETs in e-learning environments. Figure 1 shows the research areas used in our work to achieve a model based on AmI and CSCL using MANETs. In this figure, it can be appreciated how the two most important concepts covered in this paper (AmI and CSCL) converge in the use of a specific kind of wireless network as supporting infrastructure. This network consists of a set of mobile devices that can communicate among them without the need of a preplanned infrastructure.

5 Conceptual design

The conceptual design of the model is defined by answering the following six questions in order to delimit the problem:

1. *Where is the learning?* It is usual to find two kinds of learning: *formal* (inside the classroom) or *informal* (outdoors). The most common situation is the first one, while situations relative to informal learning usually represent sporadic lessons organized out of the

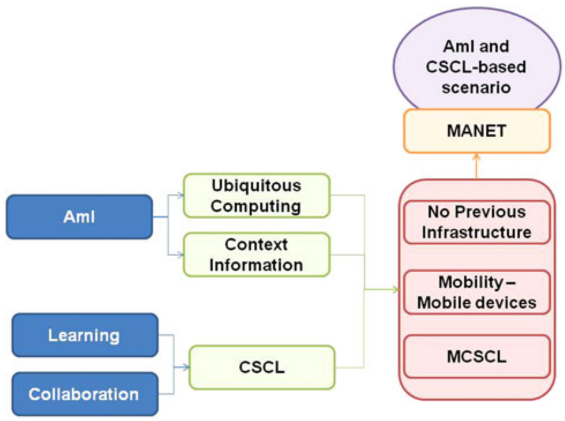

Fig. 1 Research areas addressed to use MANETs as the supporting infrastructure of an AmI and CSCL-based model

classroom (Vasiliou and Economides 2007). The latter one includes a remote access to the application, as in the adaptation of e-learning platforms, or learning examples in museums and through tourist travels (Simarro et al. 2005).

2. *Where are the actors?* Many applications that use MANETs are designed to be intended for face-to-face situations. However, there are very few approaches that handle remote learning. These support the classroom and usually the home of the participants. Thus, combined learning is not easy to find in the literature. This kind of learning is the most appropriate for the proposed scenario because it is very interesting to encourage spontaneous collaboration anywhere (e.g., classroom, home, park, etc.) (Fuller et al. 2004).
3. *Which are the most usual interactions between participants?* In the proposed model, both *student–student* and *student–teacher* interactions are considered. The most interesting scenario is that where both of these kinds of interactions are considered. Therefore, collaboration between students is encouraged, and teachers can provide support in real-time and know the status of interactions and communications in a specific workgroup.
4. *What kind of architecture is adopted?* This question is of vital importance in MANETs. On the one hand, a pure MANET should not depend on a central node that provides the connection. On the other hand, a peer-to-peer infrastructure cannot create an adequate interaction among all the participants (Zurita and Nussbaum 2006). For these reasons, those cases that describe hybrid architectures are the most useful for our purpose (Echeverría et al. 2006). These architectures include control nodes that manage communication and information exchange among the rest of the nodes. These control nodes are usually called *superpeers* (Schmidt 2005).
5. *Is some previous infrastructure used?* In order to deploy a pure MANET, there must not be a previous infrastructure (Zurita and Nussbaum 2006).
6. *What communication technologies are used?* The communication technologies utilized are often associated with the used devices. For example, mobile phones are associated with GSM, GPRS, SMS, or Bluetooth communications, while PDAs and laptops are usually related to Bluetooth and Wi-Fi protocols.

6 Model description

The purpose of this work focuses on exposing a model based on AmI and CSCL where collaboration among students is conducted through unplanned adhoc networks. The use of these new media, devices, technologies and the combination of all of them allow us to build learning communities anywhere and anytime, modifying the classic educational paradigm to accommodate into it the ubiquitous learning (Cope and Kalantzis 2009).

The model is used as a basis to describe a learning scenario where collaboration between students is improved through collaborative activities that take place both inside and outside the classroom. Therefore, each participant (i.e., student or teacher) will be able to create a network which provides resources, activities or a communication channel. These features encourage collaboration among participants and allow them to collect information, everywhere and every time. In addition, it is achieved a ubiquitous communication scenario in a natural way where none of these enumerated features has to be planned.

The main objectives set for this model are:

- There must be a deep collaboration between actors. Such collaboration is set both in formal and informal environments. Learning will not be restricted to the classroom or the activities proposed by the teacher, but informal learning must be also present. In this way, learning can occur in other places inside or out of the faculty when two students with the same subject meet.
- Teachers must know the status of the activities. Support will be given to teachers to control the activities they offer. In this way, they will be able to know and manage the formation of the groups, as well as the activity raised to each of them.
- Teachers must know the existing interactions. It is useful from the teachers' point of view to know the interactions between different students, either in the classroom or in the rest of the coverage area. This should take into account how the networks formed without the supervision of the teacher store information about their status.
- Moreover, any student should be free to collaborate with any other. However, teachers will be able to not allow a specific interaction if they do not consider it appropriate.
- Information must be able to be shared, both text (document files) and multimedia (audio, video), collected from anywhere where the activity could be carried on.

The achievement of these characteristics implies the need of an actor that offers the resources shared throughout the created network. It is proposed a peer-to-peer communication model where users are free to communicate and share data between them. Nevertheless, the communication, the access to resources or the exchange of data must be organized, controlled and registered. This way, there will be a master role that will allow a node to act as the master device, *superpeer* or *supernode* if it is able to collect information from the other nodes. Adhoc communication protocols will be adapted to the applications in order to improve neighbor discovering, connection establishment and heterogeneous devices interconnection. In this field, *superpeers* functioning will be designed and developed to reach a pure MANET infrastructure in the applications.

7 Technical requirements

After the conceptual definition of the model, it is important to describe the range of technologies that could help to achieve its design goals. In fact, the model allows using any protocol that provides communication among different devices (e.g., Bluetooth and Wi-Fi). A general description of the functioning of this is the following. No matter where users (i.e., students) are, each one of them will be able to detect others who are near to him/her (for example, in the coverage area of a Wi-Fi network) in order to exchange information. Students interested in establishing a partnership creates a network that peers can freely join.

The student who performs the formation of the network is who acts as *supernode*, recording all the time what happens in the collaborative network that he or she has created. That is, which users was involved, what information was exchanged, when the partnership was dissolved, etc. In addition, the other students keep replicas of this information for security and consistency reasons.

From these ideas, it is possible to define the technological requirements of this model as follows:

- In order to make learning performed in both a formal and an informal way, mobile devices must be used. In this case users carry tablet PCs or laptops to communicate through Wi-Fi and Bluetooth wireless interfaces.
- Collaboration and informal learning will be supported through the formation of MANETs. These networks are created through Bluetooth interfaces. Furthermore, the communication among the distinct MANETs as well as the access from them to the Internet are performed by means of Wi-Fi networks.
- In order to achieve an unrestricted informal learning it must be used a non-centralized architecture. This way, there can be a full independence from a previous network infrastructure because of the communication is peer-to-peer. Each node is capable of offering itself to create a new collaboration network through Bluetooth.
- It will be used master nodes or *superpeers* in order to provide the teachers with detailed information about the activities or interactions that have occurred in the created networks. *Supernodes* must be capable of collecting what has been happening in all networks into which they have been involved. The node that offers a new network will act as a *superpeer*. Voluntary students and teachers will act as *supernodes*.
- Software components will be installed in each device in order to be able to work in *disconnected mode* (i.e., without Internet connection). There will be two software versions. On the one hand, there will be a *light* version to be used by all the students. This version will offer all the functionalities that students will need to collaborate with each other. On the other hand, a specific software version will be developed for *Supernodes*. This will include specific functionalities to collect collaborative information and register any event.

In order to illustrate the previous statements, an example scenario is presented in the next section.

8 Example scenario

After describing the definition model, this section presents an application scenario, as an example of how this model can be applied. This scenario is focused on a university scope. Nowadays, much of the students of a faculty have mobile devices, especially laptops, PDAs or mobile phones. This fact presents an opportunity to utilize these devices in the e-learning process (Zurita and Nussbaum 2006).

To better understand the proposed model it is presented an explicit application scenario. Let's imagine a collaborative activity in the Urbanism subject at the Faculty of Architecture. The development of a partial urban plan involves an action on a specific city area without forgetting the status and the contents on the rest of the city areas, both neighboring and distant ones. There are items such as green areas, public spaces or buildings, rail or public transport infrastructures, etc. that affect equally all areas.

From the student side, the description and goals of the activities are as follows. The class is divided into several groups of students, the same number as the zoning of the city. Each group analyzes its area in depth collecting all the necessary town-planning information (topology, constructions, infrastructures, railways, public areas, private areas, etc.), storing it into data files, photos or videos. Each participant can create MANETs with peers to share information; exchange messages to organize the tasks; raise questions; complete, in a collaborative way, a concept map to reflect the organization of the area and its needs; or any other collaborative activity that may be raised. Furthermore, since the raised intervention will be the same for the whole city, it should be taken into account the information from the others. Therefore, it is necessary the collaboration with colleagues from other areas. Students can also gather information in public places (city council, land registry) which can then be spread by all participants. Furthermore, teachers can launch activities (i.e., create a new MANET) or interfere in other MANETs to observe the work status and guide students in their interactions. Similarly, the teacher can solve the questions raised by the students. It is interesting to set some partial milestones as well as a final one. This way, the teacher can collect results, assess the learning process and pick up the interactions to act accordingly (reconfiguring groups, modifying the activity, making a general explanation, etc.).

Figure 2 shows the first phase of the activity schema: there is an imaginary city divided into zones where different groups are working and whose participants will form *intra-group* (clouds) and *extra-group* (connections) MANETs. The figure shows intra-group into different clouds; while the arrows mean that each member can move from a zone to other one and form a new adhoc network with any of the participants from other groups. The teacher can move freely through all of them observing and collecting data. In this way, the scenario presents informal learning and students are capable of making collaboration achieve the goals in an easier and more effective manner. This case presents certain similarities with solutions for activities in museums (Simarro et al. 2005) or with activities raised for outdoor learning (Vasiliou and Economides 2007). However, this scenario raises an unplanned network type, in which students' collaboration is totally free, with possibility of intra and extra-groups communication. Moreover, it is not only considered the student–student interaction and the data collection by teachers (Zurita and Nussbaum 2006) or the teacher-student interaction to solve doubts or launch the activity and configure groups (Cortez et al. 2004). In addition, the teacher is involved in the whole process, being able to be part of any of the networks, solving doubts and, what we consider the most important, collecting information about occurred interactions and partial results to help him to reconfigure the activity if necessary.

Figure 3 represents the second phase of the activity. Students can share their information in class with other group members and reach through collaboration the objective planned by the teachers. Likewise, teachers can gather the information from each network freely formed and change the activity in order to better organize it to encourage the expected results.

The communication between devices is another aspect of this scenario. These are unplanned MANETs with communication between peer-to-peer participants, in which there are control nodes or *superpeers* to help them to train, organize and collect data. Previous works take into account existing infrastructures to form these networks (Zurita and Nussbaum 2004), while others utilize networks without infrastructure (Zurita and Nussbaum 2006). Nevertheless, they do not take into account either the interactions between participants or the role played by the teacher. In the presented scenario the collection of information is considered as one of the most important parts, so the teachers can know what is happening and take decisions dynamically, improving the learning process.

Nevertheless, the scenario that has been described is not the only one that can be covered by the model developed. There are many educational activities, related to collaborative learning that can take place and be enhanced by such a model. In this sense, the model can be applied to scenarios that include unplanned brainstorming activities or jigsaw activities (i.e., teaching technique where students are divided into groups with different competencies to share and explain new knowledge between them).

9 Conclusions and future work

Ambient Intelligence intends to build intelligent environments by combining the use of ubiquitous computing with technologies such as embedded and context-aware devices that adapt to the users' needs and preferences. In this sense, e-learning is an interesting area where AmI can be applied to improve the relationships between teachers and students and enrich the ways people teach and learn. Mobile Adhoc Networks can be used to add mobility to Computer Supported Collaborative Learning environments to include ubiquitous computing and context-aware capabilities, fitting the requirements that AmI demands. Existing approaches try to address these requirements, but the heterogeneity of devices is usually a problem to meet real models based on AmI and CSCL. Besides, the solutions described in the reviewed literature are aimed at solving specific problems. This implies that the generalization of these solutions is a difficult task so they cannot be applied to other educational activities or scenarios. In addition, these approaches are not able to create networks spontaneously, thus they do not provide real ubiquitous communication. Thus, they do not cover the key aspects of Ambient Intelligence. Furthermore, students, teachers and other education personnel should participate with developers when designing e-learning software, such as MCSCL applications and platforms. That is, developers should take into account all users' requirements in the design process. That is, users must be the most important part of such process.

In this regard, this paper defines some of the most important requirements to build a model based on AmI and CSCL using MANETs to meet the problems described above. Therefore, this paper proposes a model where students can collaborate anywhere and anytime, creating

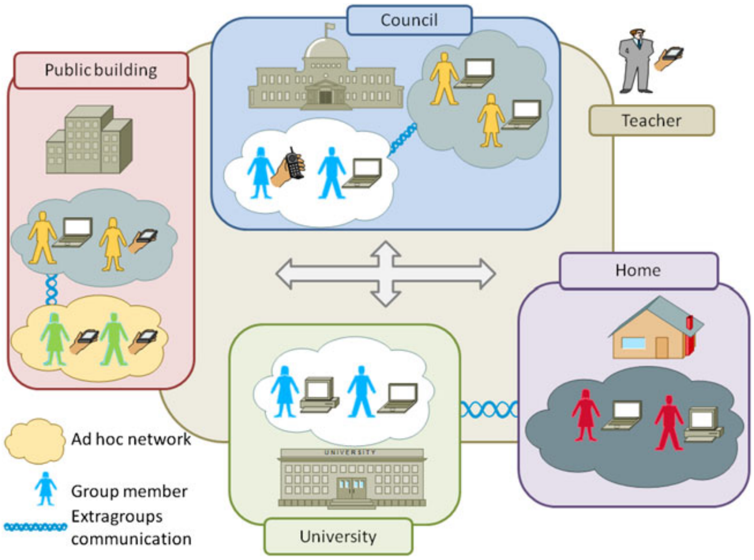

Fig. 2 Example of collaborative learning activity using MANETs outdoors. First phase of full activity

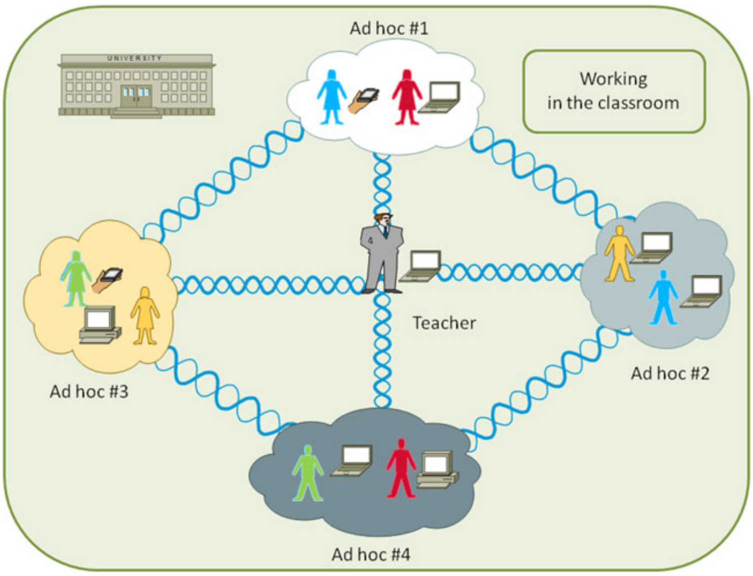

Fig. 3 Example of collaborative learning activity using MANETs in a classroom. Second phase of full activity

mobile adhoc networks to perform learning tasks and allowing teachers to monitor these tasks to guide and supervise the learning process. For this reason, this paper focuses on the conceptual description of the model without delving into technical aspects related thereto. The ultimate goal is that the model meets the expectations of an AmI educational scenario that serves as the basis for multiple and different tasks. Unlike other approaches, this model allows students to have total freedom to communicate between them anywhere and anytime. In this way, this work defines a general model that can be used in different educational scenarios and not only for a particular task or activity. In order to supplement and clarify the proposed model, a real example scenario is described. In this scenario, collaborative learning occurs naturally, in the same way than teachers' supervision, at any place where participants develop their work. The place where users perform learning tasks, the existence of a previous infrastructure and which wireless technologies are used for the learning activities are taken into account to propose the example scenario.

The first step in future work will be to improve the model and adapt and formalize it through the use of formal software engineering tools. Future work also includes the design and implementation in a real scenario of an architecture that gives support to the development of CSCL applications that meets the AmI requirements defined in this work. The real necessities of teachers and students will be taken into account during the design and development stages in order to implement fully functional e-learning applications. Furthermore, both the requirements of Ambient Intelligence and the necessities and most common learning situations where teachers and students are usually involved will be considered in order to choose the most adequate wireless technologies to address their necessities.

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5.2. Using ZigBee in Ambient Intelligence Learning Scenarios

La inclusión de las Tecnologías de la Información y las Comunicaciones, especialmente de los dispositivos móviles, en el ámbito educativo ha permitido tanto la aparición de nuevas formas de aprendizaje como la adaptación de los métodos de enseñanza tradicionales. En este sentido, el paradigma de la Inteligencia Ambiental representa un enfoque prometedor que se puede aplicar con éxito a la educación. El conocimiento generalizado, el contexto y la localización son características AmI que pueden permitir a los estudiantes recibir información personalizada de manera transparente. Afortunadamente, hay varias tecnologías que pueden ayudar a recopilar esa información. En este sentido, los Sistemas de Localización en Tiempo Real (RTLS - *Real Time Localization Systems*) son una tecnología clave que puede mejorar la contextualización en los sistemas basados en la AmI.

Este capítulo presenta el uso de un sistema RTLS novedoso basado en la tecnología ZigBee que proporciona las posiciones de los usuarios con el fin de mejorar la información de contexto en las aplicaciones de aprendizaje. De esta manera, este sistema permite personalizar el contenido ofrecido a los usuarios sin su interacción explícita, así como aumentar el nivel de granularidad de contenidos de aprendizaje proporcionado por el sistema. Esta primera aproximación del uso de información contextual en un proceso de aprendizaje permite identificar las necesidades que debe cubrir un framework de carácter lo más general posible como es CAFCLA.

Objetivos
Los objetivos perseguidos en esta publicación son los siguientes:

- Justificar el uso del protocolo de comunicación ZigBee para el desarrollo de sistemas de localización en tiempo real y la implantación de redes inalámbricas de sensores.
- Definir cómo utilizar información contextual y de localización en el aprendizaje colaborativo.
- Describir las características a nivel técnico y funcional del sistema de localización implementado.
- Describir un caso de uso a implementar en un museo.

Resultados
Este trabajo analiza el uso del protocolo de comunicación ZigBee para actuar base tecnológica para actividades de aprendizaje colaborativo, que puedan incluir información contextual, y utilizar la ubicación de los estudiantes. Además, en este trabajo se presenta un ejemplo representativo, ARTIZT: un sistema de guía de museos que incluye técnicas AmI. Este sistema hace uso de un potente sistema RTLS para determinar dónde están los estudiantes. Este RTLS, basado en una innovadora plataforma basada en ZigBee que facilita una alta precisión en

el proceso de localización, así como múltiples facilidades a la hora de diseñar, desarrollar y desplegar cualquier actividad. Por lo tanto, la información que rodea a cada estudiante en cualquier momento puede ser determinada con precisión y proporcionada a ellos en tiempo real. El uso de la red ZigBee para transportar información de localización minimiza la pérdida de datos (los dispositivos de los estudiantes contienen toda la información necesaria) y reduce el riesgo de desconexión, ya que siempre hay formas alternativas para llegar al servidor a través de la red desplegada.

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Using ZigBee in Ambient Intelligence Learning Scenarios

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ABSTRACT

The inclusion of Information and Communication Technologies, especially mobile devices, in learning environments has allowed both the emergence of new ways of learning and the adaptation of traditional teaching methods. In this sense, Ambient Intelligence (AmI) paradigm represents a promising approach that can be successfully applied to education. Pervasive computing, context and location awareness are AmI features that can allow students to receive customized information in a transparent way. Fortunately, there are several technologies that can help to gather such information. In this regard, Real-Time Locating Systems (RTLS) is a key technology that can improve context-awareness in AmI-based systems. This paper presents the use of a novel RTLS based on ZigBee technology that provides users' positions in order to enhance context information in learning applications. This way, this system allows customizing the content offered to the users without their explicit interaction, as well as the granularity level provided by the system.

Keywords: *Ambient Intelligence, Context-Aware Learning, Learning Scenarios, Location-Based Learning, Real-Time Location System*

1. INTRODUCTION

Our society is undergoing a technological evolution difficult to measure, moreover when new technologies, devices or services evolve even faster than the users' needs. Over the past years, the advances on personal computers, communication protocols, Internet or mobile devices have changed our world in a political, economic and social way. In this sense, mobile devices are becoming more ubiquitous and usable, allowing new ways of interaction and adding context-awareness and location-based capabilities for a wide diversity of application scenarios (Aarts & de Ruyter, 2009).

Ambient Intelligence (AmI) is a multidisciplinary area focused on new interaction ways between people and technology (Remagnino & Foresti, 2005). The main objective of Ambient Intelligence is enhancing the relation between users and their environment. In this sense, AmI-based systems have to take into consideration the context in which they are used (Traynor, Xie, & Curran, 2010). That is, they must have

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context-awareness properties and adapt their behavior without the need of users to make an explicit decision or interact with them, allowing applications to be more usable and efficient (Baldauf, Dustdar, & Rosenberg, 2007). People, places and objects are recognized as the three main entities when dealing with Ambient Intelligence. The place where the user is and the objects that surround him determine the behavior of the system, thus obtaining in a natural way personalized, adaptive and immersive applications (Weber, Rabaey, & Aarts, 2005).

On the other hand, mobile devices, such as laptops, tablets or smart phones, offer a wide range of possibilities to create new AmI-based systems. One important feature of these devices is the ability to know their position, which includes the location of users themselves and any other object that is part of the environment (Weber, Rabaey, & Aarts, 2005). However, the use of these devices in context-aware applications requires locating them more precisely. In this sense, Real-Time Locating Systems (RTLS) acquire a great importance in order to improve the applications based on the knowledge of the relative position of each user or object at any time.

Education has not stood aside from these advances, allowing the emergence of new ways of learning by improving classic methods through the use of technology or simply by sharing information in a different way. Mobile Learning has become the umbrella under which new ways of learning have emerged, including areas such as Mobile Computer Supported Collaborative Learning (MCSCL), based on traditional CSCL, Context-Aware Pervasive Learning or, more recently, Location-Based Learning. There are several approaches proposed by the scientific community in these research areas which share a common element: the use of mobile devices and wireless communications (Roschelle, 2003). In this sense, museums are one of the places where AmI offers all its potential for education (Ramos, Augusto, & Shapiro, 2008).

Context-aware and Location-based learning benefit any activity that takes place in a museum as these scenarios are environments where users receive a wealth of information from many sources. New information and communication technologies facilitate that the characteristics and other related information about art-works can be offered in a more understandable, attractive and easy way to students. In this sense, the context information becomes relevant in order to personalize any activity for each student at every moment (Raptis, Tselios, & Avouris, 2005). Thus, RTLS are presented as a resource that greatly improves context-awareness in AmI applications as these systems provide the position of every static or dynamic object that interacts throughout the scenario. There are different technologies that can be used when designing and deploying an RTLS, such as Global Positioning System (GPS) (Abowd, Atkenson, Hong, Long, Kooper, & Pinkerton, 2006), Infrared (IR) Pointing Systems (Oppermann & Specht, 2000), Passive and Active Radio-Frequency Identification (RFID) (Curran & Norrby, 2009), Wireless Local Area Networks (WLANs) (Cheverst, Davies, Mitchell, & Smith, 2000), or Near Field Communication (NFC) (Blöckner, Danti, Forrai, Broll, & De Luca, 2009).

This paper aims to identify and characterize the most relevant trends in Mobile Learning through the analysis of relevant work carried out in the research areas mentioned before. This analysis focuses on the study of technologies used to communicate mobile devices, as well as the type of learning activity undertaken. The results allows us to introduce the ZigBee communication protocol as a candidate to provide a base technology that enables the development of new ways of learning, focused in Context-aware and Location-based learning methods and fostering collaboration between participants by following Ambient Intelligence guidelines. Moreover, to justify the choice of this communication protocol with a well-known case study, a learning activity in a museum has been developed. Before introducing this example scenario, we have conducted an analysis of some of the most relevant trends in the contextualization of content in a museum scenario.

The following section describes the background and problem description related to the approach presented, including different ways for Collaborative Learning and Context-aware and Location-based learning. Then, technologies used to provide context and location information in museums are deeply analyzed in order to justify the example scenario presented. Section 3 presents ZigBee benefits over other technologies to improve new AmI-based collaborative learning methods and Section 4 introduces ARTIZT (Ambient Intelligence Real-Time Locating museum guide over ZigBee Technology), a systems that allows performing AmI-based learning activities in museum environments. Finally, the conclusions and future work are presented.

2. BACKGROUND AND PROBLEM DESCRIPTION

In recent years, ongoing advances in technology and communications have allowed people to be surrounded by mobile devices. These devices are increasingly powerful, easy-to-use and capable of communicating with each other in more innovative ways. These capabilities allow the creation of Ambient Intelligence systems: users' mobility is guaranteed and they are, day by day, more accustomed to the use of technology for a wide range of tasks. The use of mobile devices in educational processes has led to new opportunities for learning (Roschelle, 2003). Currently, we are able to interconnect different devices through multiple wireless communication protocols (e.g., Wi-Fi or Bluetooth), to locate them (via GPS) or to collect data from the environment (e.g., using Wireless Sensor Networks). These abilities seem to point to their suitability for different learning ways.

A. Mobile Learning

We intend to focus our study on three specific types of learning that are carried out with mobile devices: Mobile Computer Supported Collaborative Learning, Context-aware Pervasive Learning and Location-based Learning. The combination of these types of learning allows our proposal to fit into Ambient Intelligence requirements. It is important to clarify that the main reason for choosing these three variants is that they exploit the most important benefits that mobile devices provide: mobility, communication skills including collection and provision of contextual information and precise location anytime.

Mobile Learning is defined as "the processes of coming to know through conversations across multiple contexts among people and personal interactive technologies" (Sharples, Taylor, & Vavoula, 2010). This definition implies two important ideas: first of them is that technology can be involved into the learning process; the second idea suggests that mobile learning emphasizes the communication between people involved and their interaction with the context (Glah & Börner, 2010).

Based on the ability to interconnect devices we can assert that they can be useful to foster collaboration among students, that is, they can act as a tool that supports CSCL (Computer Supported Collaborative Learning) (Koschmann, 1996). The use of mobile devices into a CSCL system is known as Mobile CSCL (MCSCL) (Cortez, Nussbaum, Santaelices, Rodríguez, Zurita, Correa, & Cautivo, 2004). The analysis of the literature allows us to identify a large number of contributions that describe MCSCL systems. Among them we can find modifications of traditional learning management systems that are able to adapt usual utilities from e-learning platforms taking into account the mobile devices' requirements and specifications through its integration into Web Services (Trifonova & Ronchetti, 2006). Beyond adaptation of traditional e-learning platforms, multiple applications specifically developed to support CSCL using mobile devices have been described. Such applications provide an easier way to improve ubiquitous collaboration or foster face-to-face activities (Zurita, Baloain, & Baytelman, 2008).

MCSCL systems are usually designed with a client-server architecture in which all participants join the same network. The introduction of MANETs (Mobile Ad-hoc NETworks) into collaborative learning environments with mobile devices is intended to relax this operational model (García, Tapia, Alonso, Rodríguez, & Corchado, 2011). Moreover, MANETs allow learners to work outside the classroom to enhance collaborative learning both indoor (e.g., museums) and outdoor (e.g., parks) spaces that present any didactic interest (Vasiliou & Economides, 2007). An example of pure ad-hoc network for collaborative learning is the PASIR platform (Neyem, Ochoa, Guerrero, & Pino, 2005), designed to share resources among mobile devices in ad-hoc networks. Its design does not have to consider central elements, as information is fully replicated.

B. Context-Aware and Location-Based Learning

Ad-hoc networking is usually related to sensor networks (Meguerdichian, Koushanfar, Qu, & Potkonjak, 2001). Together with interconnected and embedded computing devices, auxiliary input/output devices and servers; ad-hoc networking provide a technological base that, when used within the educational environment, allow us to define Context-Aware Learning Environments as "setting in which students can become totally immersed in the learning process" (Laine & Joy, 2009). These environments connect, integrate and share learning collaborators, learning contents and learning services (Yang, 2006). The most important aspect in this type of system is the data acquisition from the environment in order to customize the learning activities that students must follow (Ogata & Yano, 2004).

At this time, there are several technologies integrated into mobile devices that can support learning applications, between them these that are related to identification and location. It is easy to realize that the contextual information is determined by two fundamental factors. Firstly, the identification of the element that provides the information. It is important to know anytime who or which offers information and to whom is given so we can customize content basing on the needs of students. RFID identification systems provide a technological base for this proposal (Curran & Norrby, 2009). Secondly, the location of the students is a factor to consider when customizing the contextual information: knowing with precision where each person is, we are able to develop activities in which the information received will depend on person's location. Using them, it is possible to seamlessly personalize content to students while they are freely moving throughout the workspace.

In outdoor environments, GPS technology is undoubtedly the most taken by its maturity and good performance. Takacs describes an example of learning application that uses GPS and augmented reality to provide personalized learning content through mobile phones (Takacs, Chandrasekhar, Gelfand, Xiong, Chen, Bismpigiannis et al., 2008). However, due to its nature, the GPS system does not work properly indoors. There are alternatives that allow us to have indoor location by means of other technologies, such as RFID (Curran & Norrby, 2009). However, the accuracy achieved by this kind of technology does not reach the values obtained with outdoor GPS and the proximity needed between devices becomes an important restriction. In addition, these systems require a tedious, delicate and obtrusive calibration process that affects negatively the learning applications developed over them.

As shown in the next section, museum guides especially benefit from this type of system as they can provide information from any area of interest or artwork and customize the content they offer (Abowd, Atkenson, Hong, Long, Kooper, & Pinkerton, 2006). Those scenarios are environments where users receive a wealth of information from many sources so mobile devices allow receiving real-time contextual information while giving students total freedom of movement to carry out their activities.

C. Museums: A Real Scenario

A museum scenario is an ideal environment where AmI can improve the learning activities developed. The information provided to students can be customized depending on their location or profile. AmI features encourage the creation of new museums activities approaches where information is presented in a natural, personalized and attractive way to learners with a better human-machine interaction. This way, as art-works are usually placed statically in the environment, the main goal is how to detect where students are. If we can determine, as accurately as possible, the position of the student inside the museum, we will be able to know the entire context that surrounds him every time.

Multiple technologies can be used in order to determine the position of the students. The ultimate goal of knowing the positioning of the students is to provide information, as precise as possible, about the art-works they are watching. In this sense, there are two widely used approaches: tagging the context and the use of an RTLS (Ghiani, Paternò, Santoro, & Spano, 2009). Next, it is analyzed the most used technologies in both trends.

When talking about RTLS, the first technology that comes into our mind is GPS. It has been used in context-aware tourist guides where users receive personalized information according to their position (Park, Hwang, Kim, & Chang, 2007). However, it only works outdoors and it is not an appropriate technology to develop an indoor learning activity. Some approaches try to solve indoor locating problem using combined technologies along with GPS. Cyberguide (Abowd, Atkenson, Hong, Long, Kooper, & Pinkerton, 2006), determines the users' position by means of infrared sensors. However, it is needed a direct line of sight between user and sensors, so it does not work properly in crowded environments where students move freely throughout the space.

Exploring the use of infrared sensors, the HIPPIE system delivers information about the location of user in relation to an object (Oppermann & Specht, 2000). Students point the art-work (which is provided with an infrared detector), and the system estimates where they are and provides the content. Nevertheless, this solution requires a proactive user and, as mentioned before, direct line of sight and proximity between user and object.

The action performed by the user when pointing the object (e.g., an art-work) is physically the same as is done in solutions that use RFID (Belloti, Berta, De Gloria, & Margarone, 2006) or NFC technologies (Blöckner, Danti, Forrai, Broll, & De Luca, 2009). Both technologies follow the same pattern of performance: each object all over the museum is tagged. RFID or NFC tags, containing a unique identification number, are placed near the object. If students want to receive information about an art-work, they have to place their device nearby the tag. Then, the system identifies the object and loads the relevant information. The necessity of proximity between devices and tags makes these solutions non-transparent to the user as it requires a direct collaboration. Moreover, if multiple users want to see the information about the same art-work, they must do it one by one at each time.

Bluetooth solves the peer-to-peer relation between RFID tags and users (Bay, Fasel, & Van Gool, 2005). The Eghemon system uses mobile phones that receive information via Bluetooth as users get closer to a piece of information (e.g., an art-work). These pieces can offer information to multiple devices simultaneously, but they must be close enough to them. If two pieces are close enough, the mobile device can only receive information from just one of them. Bluetooth can also be used to improve the devices locating. Bruns et al. have designed a solution where a grid of Bluetooth emitters is deployed throughout the museum, so the students' mobile phones transmit their position to the nearest emitter (Bruns, Brombach, Zeidler, & Bimber, 2007). However, location is not as accurate as desirable, because the system only knows which mobile phones are associated to an emitter. Furthermore, Bluetooth can only support the association of up to seven mobile phones simultaneously to an emitter.

The UbiCicero system (Ghiani, Paternò, Santoro, & Spano, 2009) uses Active RFID to get the position of the users. In this case, users carry an RFID reader that continuously reads signals from active tags that are close to artworks. Active RFID technology allows a better locating approach because users do not have to be as close as with passive RFID technology to detect the object. However, location information is not accurate enough because the system only detects which art-work is closer the users, so two objects that are close enough can cause interference and "confuse" the system.

It is also possible to locate mobile devices that provide information on the museum via Wireless LANs. In this case, multiple Wireless LANs are created, usually one network for each different zone. When students change from a zone to another, devices automatically connect to an available network through which contents are provided (Cheverst, Davies, Mitchell, & Smith, 2000). This solution presents several problems: different coverage areas must not be overlapped; locating provides a poor precision (never gets precision under 2 meters); and infrastructure deployment is a hard process since it is needed a thorough calibration of all devices (Zimmermann & Lorenz, 2008).

D. Summary

Throughout this section we have identified different solutions for each of the kinds of learning. Each of the technologies involved in those proposals cover a specific kind of learning. However, it is difficult to use some of them to cover all three kinds of learning at the same time. Joining these learning spaces we would be able to provide a fully adaptable environment to the needs raised by teachers in their design activities, for example in museums, as it is introduced. Thus, we can include locating and tracking of objects of interest and students in the learning environment. Then, identifying uniquely them, and recording all the interactions with each other and with the objects, we will be able to generate a ubiquitous learning environment in which fit many activities and subsequent analysis tools that will improve the whole process.

The following section discusses the use of ZigBee as an enabling technology to provide innovative learning scenarios. Its ability to create ad-hoc networks and integrate with wireless sensor networks, as well as the facilities it provides to develop real-time locating systems, allow us to consider this communication protocol as the optimal to cover simultaneously collaborative, context-aware and location-based learning scenarios.

3. ZIGBEE TECHNOLOGY TO ENHANCE AMI-BASED LEARNING

The use of mobile devices in learning activities implies the use of wireless communication protocols. The best known are Bluetooth, Wi-Fi, and GSM/GPRS. However, if we desire to be able to cover the three learning environments presented simultaneously, Collaborative, Context-aware and Location-based Learning, with a more precise and intuitive system, we propose to use Zigbee protocol.

ZigBee is a wireless communication protocol that helps to easily deploy AmI learning activities where location or context-aware information will be used. ZigBee is based on the IEEE 802.15.4 standard and operates in the 868/915MHz and 2.4GHz unlicensed bands (ZigBee Alliance, 2007). Unlike Wi-Fi or Bluetooth, ZigBee is designed to work with low-power nodes and allows up to 65,534 nodes to be connected in a star, tree or mesh topology network. Using its potential, forming ad-hoc networks or locating students, we can cover three kinds of learning that are the most used in mobile learning and Ambient Intelligence: Context-Aware Leaning, Collaborative Learning and Location-based Learning.

Due to its nature, ZigBee communication protocol enables to easily deploy communication networks. Forming ad-hoc networks becomes simple and ZigBee devices can change from a network to another in an easy way. Locating ZigBee devices is also possible, as with Wi-Fi technology, but the calibration and infrastructure deploy takes more time with Wi-Fi and its accuracy is lower (Tapia, García, Alonso, Guevara, Catalina, Bravo, & Corchado, 2012). Moreover, energy consumption is lower because ZigBee protocol has been designed for this proposal (ZigBee Alliance, 2007).

Any ZigBee device can be configured to create a network that will be accessible by others to join it quickly and easily anytime and anywhere. This feature allows the creation of ad-hoc networks in a simple way (Baronti, Pillai, Hook, Chessa, Gotta, & Hu, 2007), to facilitate, for example, carrying out a collaborative face-to-face activity between two students, collecting data from sensors that provide contextual information or receiving data through devices depending on the placement of students in an environment designed and set in advance. Moreover, we are able to receive the relative position of each node in the network regarding to the other nodes, forming, for example, a map of proximity to each other without requiring a prior infrastructure.

Furthermore, ZigBee networks allow choosing different network topologies: a star topology has an only node that centralizes all the transmissions in the network (Ran, Sun, & Zou, 2006). In a tree topology there is an element that starts the network and other devices that join it and, at the same time, give other devices access to the network. Finally, a mesh topology allows establishing communication links amongst all nodes through different routes, being able to get a full connection throughout the network. A mesh topology, together with the large number of devices that can join a network, allows achieving a high scalability, so that peer-to-peer links or networks with large numbers of devices can be formed, covering multiple ways of collaboration among the participants of the activity.

The reliability of ZigBee networks is another feature that benefits learning. The protocol offers fluctuating link capacity that allows sending information between two parties through different paths (Huang & Pang, 2007). Thus, an eventual drop of a link does not block the activity because the data is automatically sent by one of the alternative paths that the network provides. Similarly, any device that falls from a network failure will recover and join the network automatically (Huang & Pang, 2007). This feature allows more dynamic activities as they will be less affected by communication failures. The ease of developing wireless sensor networking using ZigBee is another characteristic that is useful for Context-aware Learning activities. ZigBee-based wireless sensor networks allow gathering contextual information easily through a basic infrastructure that requires a quick and easy deployment (Alonso, Tapia, García, Sancho, & Sánchez, 2011). Just connect sensors to a ZigBee device can integrate them into the learning network. This way, designers can think about multiple scenarios in which information is provided to be used by students, as might be collecting data of pollution (air pollution, light and sound) (Baronti, Pillai, Hook, Chessa, Gotta, & Hu, 2007), to share and discuss it in groups. Moreover, this infrastructure can be easily moved from a place to another without having to be configured again. This simple example allows illustrating a basic idea: the same network allows collecting data and sending data between devices in any place they are used.

Moreover, ZigBee enables to deploy an infrastructure of devices that transmit data through it and allow locating any ZigBee device moving throughout it. In other words, this technology allows deploying real-time locating systems where individual students or student groups that are developing an activity can be identified and located. These tracking systems can identify who is in a certain area and the proximity of other students who are working face-to-face, mark routes that students should follow, register all the interactions that have emerged into the network, determine the most active students or customize the content that the activity must provide depending on the student's location.

From the point of view of energy consumption, the ZigBee communication protocol has been designed to maximize energy saving (ZigBee Alliance, 2007). This aspect allows developing long-term activities with mobile devices or work in environments where it is not possible to load their batteries (e.g., a park or a museum).

Finally, we cannot ignore the potential that these kinds of networks provide for interaction analysis. The network infrastructure deployed with this technology can record the movement of participants, what devices have formed a collaborative network to identify the distance between them, or who has been in an area of interest in a museum, for example. All this information helps to improve the learning process and identify students' different roles within their group, as well as detect and correct deficiencies in the learning design carried out by educators.

4. AMI-BASED MUSEUM LEARNING SCENARIO

The AmI paradigm proposes the development of applications that provide new ways of interaction between people and technology, adapting them to the needs of individuals and their environment (Abowd, Atkenson, Hong, Long, Kooper, & Pinkerton, 2006). ARTIZT (Ambient Intelligence Real-Time Locating museum guide over ZigBee Technology) follows these premises and offers personalized contents to the students in a transparent way according to the context information.

As can be seen in the second section, there are many approaches that have been considered to create museum guides. Analyzing all of them, two ways of tackling the problem can be identified. The first one is the direct physical interaction between the student and the art-work. The second one consists of obtaining information without having a voluntary interaction by the student, where the system automatically provides information depending on students' location. ARTIZT follows the second approach. The main objective is to make interaction as much transparent as possible to students. For doing that, it is very important that context information is precise enough. This way, an accurate location of students is the most important aspect of this approach. Therefore, it is easy to know which elements (i.e., art-work) surround each student, no matter several of these elements are separated by a short distance between them. Thus, it is possible to get a whole description of the context that surrounds each student in a more precise way. Based on the context information, the content provided to the students changes dynamically. Next section describes the basic features of ARTIZT and the way it works.

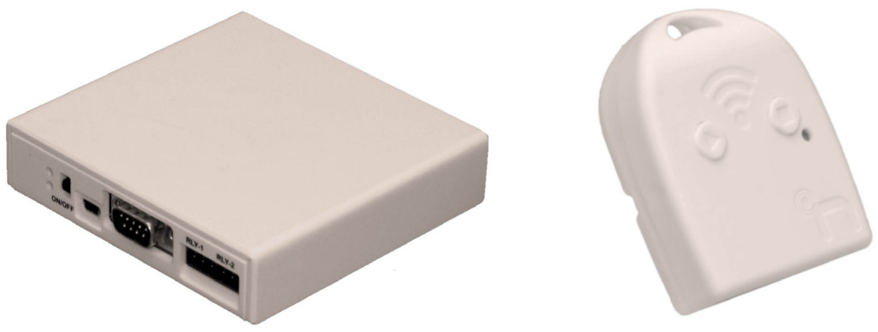
The potential of ARTIZT lies in the precision with which contextual information can be collected. In this sense, an innovative RTLS provides the system with users' positions with an error less than one meter, so it can be determined at any time which art-works are on the students' radio of interest, thus adapting precisely the information that it is provided to each user.

A. The Real-Time Locating System

The RTLS used is by ARTIZT is based on the novel n-Core platform (Nebusens, 2012), which is intended to develop ZigBee applications and provides both wireless physical devices and an Application Programming Interface (API) to access their functionalities. Each n-Core Sirius device includes an 8-bit RISC (Atmel ATmega 1281) microcontroller with 8KB of RAM, 4KB of EEPROM and 128KB of Flash memory and an ZigBee transceiver. n-Core Sirius devices have both 2.4GHz and 868/915MHz versions and have several internal and external communication ports (GPIO, ADC, I2C, PWM, and USB/RS-232 UART) to connect to distinct devices, including a wide range of sensors and actuators.

A network of ZigBee devices must be deployed all over the museum. This network is composed of a set of Sirius A (Figure 1 left) and Sirius B devices (Figure 1 right). The Sirius A devices are placed across the ceiling of the museum (Figure 2), forming a network in which it is known the specific location of each one, as well as the relative positions with each of its neighbors (i.e., closest devices). The Sirius B devices are inserted in tablet PCs that are

Figure 1. Sirius A (left) and Sirius B (right) devices

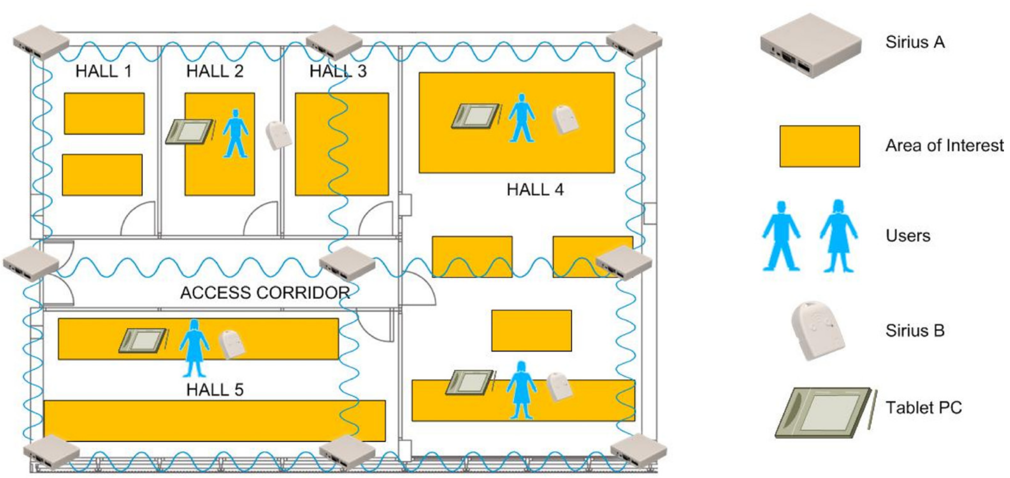


carried by the students. This way, the students can move freely through the museum.

All devices communicate via the ZigBee standard. ZigBee is a low cost, low power consumption wireless communication standard, developed by the ZigBee Alliance. It is based on the IEEE 802.15.4 protocol and operates at the 868/915MHz and 2.4GHz unlicensed bands. ZigBee is designed to be embedded in consumer electronics, home and building automation or toys and games. ZigBee allows star, tree or mesh topologies. Devices can be configured to act as network coordinator (creates and controls the network) router (sends/receives/forwards data to/from other devices) and end device (sends/receives data to/from other devices in the network).

Over this network infrastructure it is implemented a locating engine that provides users positioning whose accuracy reaches less than one meter (Tapia, García, Alonso, Guevara, Catalina, Bravo, & Corchado, 2012). The infrastructure is completely dynamic and scalable so new devices can be added at any time without affecting the rest of the network. The operation of the RTLS is very simple. Students

Figure 2. Sirius A wireless network, Areas of Interest and mobile device provided with Sirius B



carrying mobile devices (i.e., tablets) move freely around the museum. The mobile devices send periodically a broadcast signal by means of the Sirius B connected to them. The signal is received by the Sirius A devices placed all over the museum. The location engine, allocated in a central server, calculates the positions of all Sirius B devices and therefore the position of every student. Once the system knows the location of each student, an application installed on the devices of the students customizes the information which is provided dynamically.

B. Context Information Management

Once ARTIZT gets the position of the students, the information must be personalized according to every student status. Each user carries a tablet on which it is installed a light and user-friendly application developed specifically for the museum. Contextual information of the museum is included in this application so that, from the position of the students, ARTIZT decides which information is shown in the device. In order to do this it is created a map of the museum and, with the location information received by the server, it is determined the location of students continuously. In addition, each level of the museum is divided into "Areas of Interest" (Figure 2). This way, when a user enters into one of these, the application customizes all the information that is wanted to be shown to students. Reader can realize that with a so accurate RTLS, these areas can be as small as desired, so that the system can provide enhanced context information and personalize it always in a transparent way without any user interaction.

Tablets' application contains all the information that may be provided to users. Thus, ZigBee network only carries data from the devices to the server, necessary to calculate their position, and the location of the students from the server to the tablets. These communications reduce traffic data and there are always alternative paths in the network so fault tolerance increases and data loss is minimized.

ARTIZT is configured to provide the customized content. When the position of the student is known, and using a series of data that is collected before the student starts his route, the system is able to tailor the information that is being shown in the form of content or language.

5. CONCLUSION AND FUTURE WORK

Ambient Intelligence is a research area that uses ubiquitous computing a communications to improve interaction between people and technology. Currently, new mobile devices allow users to get contextual information in different ways through different technologies as GPS or RFID. The field of education can benefit from using AmI techniques in order to improve new ways of learning in a more transparent and customized way.

Nowadays, three trends that use mobile devices in learning are the most representative: Mobile Computer Supported Collaborative Learning, Context-aware Learning and Location-based Learning. The technologies that are involved in those kind of learning are usually focused to cover only one of these trends, supporting communication, location or data collection.

However, when educators want to combine different trends or use the characteristics of all of them, two or more wireless technologies should be adopted, in order to support each of the features, getting complicated and non intuitive environments. None of them provides all the requirements a scenario that tries to cover all those kind of learning needs. An environment where those kind of leaning can be mixed are museums. Museum is a scenario where applying AmI techniques becomes more meaningful: multiple contextual information that contains the museum and the great mobility of the students make their location and the data filtering process become challenges to solve in an efficient way.

Therefore, this paper analyzes the use of ZigBee communication protocol to act as a technological base for collaborative learning activities, which may include contextual information and use the location of students. Moreover a representative example is presented in this work, ARTIZT: a museum guide system that includes AmI techniques. This system makes use of a powerful RTLS to determine where students are. This RTLS, based on an innovative ZigBee-based platform, provides high precision in the locating process. Therefore, the information that surrounds each student at any moment can be precisely determined and provided to them on real-time. The use of the ZigBee network to transport locate information minimize data loss (students' devices contains all the necessary information) and reduce the risk of disconnection, as there are always alternative ways to reach the server over the ZigBee grid.

Future work includes the description of a framework that allows the use of this communication protocol to develop learning applications in an easy way. This framework will include the design and implementation of a Multiagent System that will be able to create and manage the communication all over the ZigBee network and between users.

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5.3. Implementing a hardware-embedded reactive agents platform based on a service-oriented architecture over heterogeneous wireless sensor networks

Las redes inalámbricas de sensores (WSN - *Wireless Sensor Networks*) representan una tecnología clave para recopilar información contextual proveniente de diferentes fuentes. Desafortunadamente, integrar dispositivos con diferentes arquitecturas o tecnologías inalámbricas en una única red de sensores no es una tarea fácil para diseñadores y desarrolladores. En este sentido, las arquitecturas distribuidas, tales como arquitecturas orientadas a servicios y los sistemas multiagente, pueden facilitar la integración de redes de sensores heterogéneos. Además, las capacidades de los sensores pueden ampliarse mediante agentes inteligentes que cambian su comportamiento dinámicamente. En este artículo se presenta la plataforma HERA (*Hardware-Embedded Reactive Agents*), la cual se basa en SYLPH (*Services laYers over Light PHysical devices*), una plataforma distribuida que integra aproximación orientada a servicios en redes inalámbricas de sensores heterogéneas. Como SYLPH, HERA se puede ejecutar sobre múltiples dispositivos independientemente del protocolo de comunicación inalámbrico que implementen, su arquitectura o el lenguaje de programación que utilicen. Sin embargo, HERA va un paso más allá que SYLPH y agrega agentes reactivos a la plataforma, así como un mecanismo de razonamiento que proporciona a los agentes de HERA características de planificación basadas en casos que permiten resolver problemas considerando experiencias pasadas. A diferencia de otros enfoques, HERA permite desarrollar aplicaciones en las que los agentes reactivos se incrustan directamente en nodos de sensorización inalámbricos y heterogéneos que, habitualmente, tienen una capacidad computacional limitada. HERA definirá la forma en que se llevará a cabo la gestión tanto de la red inalámbrica de sensores como del sistema de localización en tiempo real en CAFCLA.

Objetivos
Los objetivos perseguidos en esta publicación son los siguientes:

- Diseñar y construir una nueva plataforma que permita a los desarrolladores aprovechar el uso de agentes inteligentes directamente incrustados en nodos que forman redes inalámbricas de sensores heterogéneos.
- Permitir la interconexión de redes inalámbricas de sensores basadas en diferentes protocolos de comunicación inalámbricos.
- Mejorar la capacidad de recogida de información contextual de los nodos, mediante la inclusión de agentes reactivos y un mecanismo de razonamiento a la plataforma.
- Diseñar un sistema de razonamiento que permita a los agentes aprender de experiencias pasadas y así adaptar su comportamiento a la información contextual que perciben.
- Implementar HERA en un escenario real desplegando una red inalámbrica de sensores

y un sistema de localización en tiempo real.

Resultados

La plataforma HERA permite que dispositivos inalámbricos que integran diferentes tecnologías de comunicación puedan trabajar juntos de forma distribuida, independientemente de la tecnología o del lenguaje de programación que utilicen. Además, los agentes HERA son lo suficientemente ligeros como para ejecutarse en nodos de sensorización inalámbricos con recursos limitados. Por otro lado, los agentes que implementa HERA son reactivos, actuando sobre dispositivos con tiempos críticos de respuesta. La plataforma ha sido especialmente diseñada para implementar agentes y, a diferencia de otros enfoques, estos están directamente embebidos en los nodos de sensorización. HERA facilita y acelera la integración entre agentes y sensores para reutilizar recursos dentro del contexto. Este enfoque permite el desarrollo de sistemas multiagente con mayor escalabilidad y amplía las capacidades de los agentes para obtener información sobre el contexto y reaccionar automáticamente sobre él. El enfoque totalmente distribuido y el uso de redes inalámbricas de sensores heterogéneos facilita la creación de una plataforma con mayor facilidad para recuperarse de errores y más flexible para ajustar su comportamiento en tiempo de ejecución. Más aún, HERA añade inteligencia a los sensores por medio de agentes reactivos ligeros, mejorando la experiencia de los desarrolladores y usuarios de tecnologías sensibles al contexto. El mecanismo de razonamiento implementado facilita la inclusión dinámica de nuevos sensores, sin necesidad de realizar entrenamientos previos para cada uno de los dispositivos. Finalmente, el mecanismo de razonamiento puede determinar automáticamente la influencia de los sensores para establecer el estado final de cada uno de los actuadores, por lo que no es necesario indicar la relación entre sensores y actuadores.

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Implementing a hardware-embedded reactive agents platform based on a service-oriented architecture over heterogeneous wireless sensor networks

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ABSTRACT

Wireless Sensor Networks (WSNs) represent a key technology for collecting important information from different sources in context-aware environments. Unfortunately, integrating devices from different architectures or wireless technologies into a single sensor network is not an easy task for designers and developers. In this sense, distributed architectures, such as service-oriented architectures and multi-agent systems, can facilitate the integration of heterogeneous sensor networks. In addition, the sensors' capabilities can be expanded by means of intelligent agents that change their behavior dynamically. This paper presents the *Hardware-Embedded Reactive Agents* (HERA) platform. HERA is based on *Services laYers over Light PHysical devices* (SYLPH), a distributed platform which integrates a service-oriented approach into heterogeneous WSNs. As SYLPH, HERA can be executed over multiple devices independently of their wireless technology, their architecture or the programming language they use. However, HERA goes one step ahead of SYLPH and adds reactive agents to the platform and also a reasoning mechanism that provides HERA Agents with Case-Based Planning features that allow solving problems considering past experiences. Unlike other approaches, HERA allows developing applications where reactive agents are directly embedded into heterogeneous wireless sensor nodes with reduced computational resources.

1. Introduction

Nowadays, there is a wide range of devices for gathering context information about both the environment and the users [1]. In this sense, Wireless Sensor Networks (WSNs) are used for collecting the information needed by intelligent environments, whether in home automation, industrial applications or even farming, among many others [2]. There are plenty of technologies for implementing WSNs, such as ZigBee, Wi-Fi or Bluetooth. Nonetheless, it is not easy to integrate devices from different technologies into a single network [1]. The lack of a common architecture may lead to additional costs due to the necessity of deploying non-transparent interconnection elements among the different networks [3]. Moreover, the developed elements can be dependent on the application to which they belong, thus complicating their reutilization.

Therefore, it is necessary to develop innovative solutions that integrate different approaches to create flexible and adaptable systems. In this sense, the deployment of distributed architectures is presented as a solution to such problems [4]. One of the most prevalent alternatives in distributed architectures is Multi-Agent Systems (MASs) [5]. A distributed agent-based architecture provides more flexible ways to move functions to where actions are needed, thus obtaining better responses at execution time,

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autonomy, services continuity and superior levels of flexibility and scalability than centralized architectures [6]. Furthermore, the sensors' capabilities can be enhanced by means of intelligent agents, changing dynamically their behavior and personalizing their reactions [7].

The main objective of the work presented in this paper is to design and build a new platform that allows developers to take advantage of the use of intelligent agents directly embedded into nodes belonging to heterogeneous wireless sensor networks. In this sense, this paper describes the *Hardware-Embedded Reactive Agents* (HERA) platform. HERA is an evolution of the *Services laYers over Light PHysical devices* (SYLPH) platform [8–10], which allows developers to use dynamic and self-adaptable heterogeneous wireless sensor networks following a Service-Oriented Architecture (SOA) approach [4]. Unlike other approaches, SYLPH allows the interconnection of wireless sensor networks based on different radio and link technologies [10]. As SYLPH, HERA focuses specially on heterogeneous devices with reduced resources to save CPU time, memory size and power consumption. However, HERA goes one step ahead of SYLPH and adds reactive agents [11] and a reasoning mechanism to the platform, extending its context-aware features. In HERA, unlike other approaches, agents are directly embedded into the WSN nodes and their services can be invoked from other nodes in the same WSN or other WSN connected to the former one, no matter the radio technology they use. Furthermore, HERA incorporates a reasoning mechanism based on the Case-Bases Planning model [29] that allow solving problems by using solutions to similar past problems. Solutions are stored into a case memory, which the mechanism can consult to find better solutions for new problems. HERA Agents use this mechanism to learn from past experiences and to adapt their behavior according to the context information.

The remainder of the paper is organized as follows. In Section 2 we present the problem description that essentially motivated the development of SYLPH and HERA. In Section 3 the main characteristics and components of SYLPH are briefly depicted, while Section 4 presents the principal features that HERA adds over the SYLPH platform, including the HERA Agents and the Case-Based Planning mechanism. After that, some experiments aimed at testing the HERA performance are described in Section 5, including the implementation of HERA in a real scenario. Finally, the conclusions and the future lines of work are presented in Section 6.

2. Problem description and related work

Smart environments must take into account the information about the context, which can be collected by sensor networks [12]. This context information may consist of many different parameters about the people and their environment, such as the users' location, their heart rhythm, or the ambient temperature, among many others. In a real scenario, all these sensors can belong to wireless sensor nodes from different architectures or wireless technologies, forming together which is usually known as a heterogeneous wireless sensor network. In a centralized heterogeneous WSN architecture, most of the intelligence is located in a central node. That is, the central node is responsible for managing most of the features and knowing the existence of all nodes in each WSN in the system. That means that a node belonging to a certain WSN does not know about the existence of another node forming part of a different WSN, even though this WSN is also part of the system.

Nonetheless, this model can be improved using a common distributed architecture where all nodes in the system can know about the existence of any other node in the same system regardless of the technology or interface they use or the sub-network to which they belong. Distributed architectures such as Service-Oriented Architectures (SOAs) [13] or Multi-Agent Systems (MASs) [5] improve the distribution of the available resources, facilitate the reutilization of functionalities and optimize the compatibility among different platforms. In this sense, the SYLPH platform [9,10,14] was designed to address these challenges as an innovative platform for integrating heterogeneous WSNs in Ambient Intelligence (AmI) systems [15], implementing an approach based on service-oriented architectures [4,13,16,17].

Once SYLPH solves the problem of distributing resources over heterogeneous wireless sensor networks, the next challenge is to embed intelligent agents into the same heterogeneous wireless sensor nodes. At this point, it is worth mentioning again that SYLPH does not include by itself the support of agents or reasoning mechanisms. An agent can be defined as a computational system situated in an environment and able to act autonomously in this environment to achieve its design goals [5]. Expanding this definition, an agent is anything with the ability to perceive its environment through sensors, and to respond in the same environment through actuators, assuming that each agent may perceive its own actions and learn from the experience [18]. There are several agent frameworks and platforms [19–21] that provide a wide range of tools for developing distributed multi-agent systems. The development of agents is an essential component in the analysis of data from distributed sensors, and gives those sensors the ability to work together and analyze complex situations, thus achieving high levels of interaction with humans [22–27]. Furthermore, agents can use reasoning mechanisms and methods in order to learn from past experiences and to adapt their behavior according to the context, such as Case-Based Reasoning (CBR) and Case-Based Planning (CBP) [28,29]. CBR and CBP mechanisms solve new problems by adapting solutions that have been used to solve similar problems in the past, and learn from each new experience [28, 29]. In CBP, the proposed solution for solving a given problem is a plan, which is generated by taking into account the plans applied for solving similar past problems [29].

Unfortunately, the fusion of the multi-agent technology and wireless sensor networks is not easy due to the difficulty in developing, debugging and testing distributed applications for devices with limited resources [30]. The interfaces developed for these distributed applications are either too simple or, in some cases, do not even exist, which even further complicates their maintenance. Even so, there are other works that try to integrate multi-agent systems and wireless sensor networks [31–33].

ActorNet [31] is a study that describes a mobile agent platform for WSNs. ActorNet provides an abstract environment for mobile code oriented to light objects over WSNs. ActorNet platform defines as its top layer an actor language interpreter. Likewise, the platform provides services such as virtual memory management and blocking input–output operations. Thus, ActorNet allows a wide range of dynamic applications, including customized queries and aggregation functions, in the sensor network platform.

Baker et al. [32] present the integration of an agent-based WSN within an existing MAS focused on condition monitoring. In this research, it is used SubSense, a multi-agent middleware platform developed to allow condition monitoring agents to be deployed onto a WSN. The architecture of the SubSense platform is based on the model defined by FIPA (Foundation for Intelligent Physical Agents), but customized so that agents are embedded into sensor nodes. SubSense platform is implemented over 512 KB RAM SunSPOT sensor nodes using the Java Mobile Edition (J2ME).

Other works that relate multi-agent systems and WSNs talk about *Mobile Agents based on WSN* (MAWSN). Zboril et al. [33] proposes WSageNt, a platform that is implemented through mobile agents running on wireless sensor nodes. One key feature of this platform is a module for an agent control language interpretation. This language is presented as an original low-level control language known as Agent Low Level Language (ALLL). This research poses that in WSN-based agent platforms the resources limitations of sensor motes do not allow affording its development as an ordinary agent platform that should accomplish the FIPA specifications.

However, these studies [31–33] have not been designed to work with heterogeneous wireless sensor networks. These approaches do not take into account the use of such heterogeneous WSNs and they are focused on working with sensor nodes that use just an only radio technology. Because HERA is based on SYLPH, it allows devices from different radio and networks technologies to coexist in the same distributed network. In addition, HERA platform can run on lightweight sensor nodes with just 8 KB RAM, while other approaches as SubSense [32] require nodes with 512 KB RAM. Besides, in the design of HERA, it has been mainly aimed to address context-awareness and ubiquitous computing, while other existing approaches are not specially centered on dealing with these requirements. Furthermore, HERA includes a Case-Based Planning (CBP) mechanism which allows the agents to make use of past experiences to create better plans and achieve their goals, while SYLPH does not, as it is not based on agents, but only services.

In the next section, the main components and the basic operation of the SYLPH platform, on which HERA is based, is briefly described. After that, Section 4 presents the novelties that HERA offers with regard to SYLPH.

3. The SYLPH platform

HERA is an evolution of *Services laYers over Light PHysical devices* (SYLPH) [9]. In this section, the SYLPH platform is only briefly depicted, as the objective of this paper is to describe the HERA platform. For a more extended description of the SYLPH platform, please consult previous publications [9,10,14]. The SYLPH platform follows a SOA model [4] for integrating heterogeneous WSNs in AmI-based systems. SYLPH focuses specifically on devices with small resources in order to save CPU time, memory size and energy consumption. There have been other attempts to integrate WSNs and a SOA approach [34]. In SYLPH, services are directly offered by the wireless sensor nodes that are part of the platform. In the same way, any node in the platform can directly invoke a SYLPH service offered by other node in the platform, no matter if both nodes are in the same physical wireless network or not. SYLPH provides the possibility of connecting wireless sensor networks based on different radio and link technologies, whereas other approaches do not. Thus, a node designed over a specific technology can be connected to a node from a different technology. In this case, both WSNs are interconnected by a set of intermediate devices, called SYLPH Gateways and described in Section 3.4, which are simultaneously connected to several wireless interfaces.

3.1. Main components of the SYLPH platform

SYLPH implements an organization based on a stack of layers [2]. Each layer in one node communicates with its peer in another node through an established protocol. In addition, each layer offers specific functionalities to the immediately upper layer in the stack. The SYLPH layers are added over the existent application layer of each WSN stack, allowing the platform to be reutilized over different technologies. Fig. 1 shows the different layers of SYLPH and the different protocols that communicate each layer on two different ZigBee nodes (homogeneous WSN), as well as over a ZigBee node and a Bluetooth node by means of a SYLPH Gateway (heterogeneous WSN). The structure of SYLPH will now be briefly described.

- *SYLPH Message Layer (SML)*. The SML offers the upper layers the possibility of sending asynchronous messages between two nodes through the SYLPH Services Protocol (SSP). These messages specify the source and destination nodes and the service invocation in a SYLPH Services Definition Language (SSDL) format.
- *SYLPH Application Layer (SAL)*. The SAL allows different nodes to directly communicate with each other using SSDL requests and responses that will be delivered in encapsulated SML messages following the SYLPH Service Protocol. The SAL implements the service code (i.e., firmware) from within each node, allowing each one to communicate with the SYLPH platform and invoke services located in other nodes.
- *SYLPH Services Protocol (SSP)*. The SSP is the internetworking protocol of the SYLPH platform. SSP allows sending packets of data from one node to another node regardless of the WSN to which each one belongs.
- *SYLPH Services Definition Language (SSDL)*. The SSDL is the IDL (Interface Definition Language) used by SYLPH. Nodes can request the SSDS for the location of services and their specifications using SSDL.

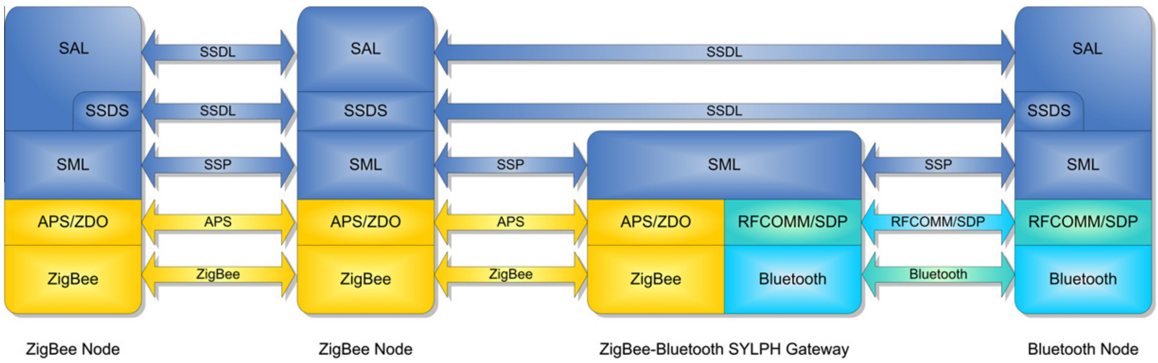

Fig. 1. Layers and protocols of the SYLPH platform.

– *SYLPH Services Directory Sub-layer (SSDS).* The SSDS creates dynamic services tables to locate and register services in the network. A node that stores and maintains services tables is called SYLPH Directory Node (SDN). A node in the network can make a request to the SDN to know the location (i.e., network address) of a certain service.

3.2. SYLPH basic operation and SYLPH Directory Nodes (SDNs)

The behavior of SYLPH is essentially similar to that of any other service oriented architecture. First, a service registers itself on the SDN and informs the network of its location, the parameters it requires, and the type of returned value after its execution. In order to do this, the service uses SSDL, described in Section 3.3. Once the service has been registered in the SDN, it can be invoked by any application using SYLPH. Any node in the network (or other subsystem connected to the WSN) cannot only offer or invoke SYLPH services, but also include SDN functionalities to provide services descriptions to other network nodes.

The UML sequence diagram depicted in Fig. 2 shows an example of the basic operation of SYLPH platform when registering and discovering services using the SYLPH Directory Nodes. For example, SYLPH node #1, belonging to WSN “A” registers itself in the SYLPH platform. For this, it sends a broadcast message searching for existing SDNs in the network. At this moment, only SDN #0 is active, so after receiving the broadcast message it sends a message to node #1 informing of its SSP address and its setup parameters. After this, node #1 is able to communicate with SDN #0 to obtain information about the possible services existing in the network. Later, node #2 registers itself on the platform. It belongs to a different WSN, called WSN “B” and perhaps uses a radio technology different than that used by WSN “A”. As node #2 has SDN functionalities, it in-

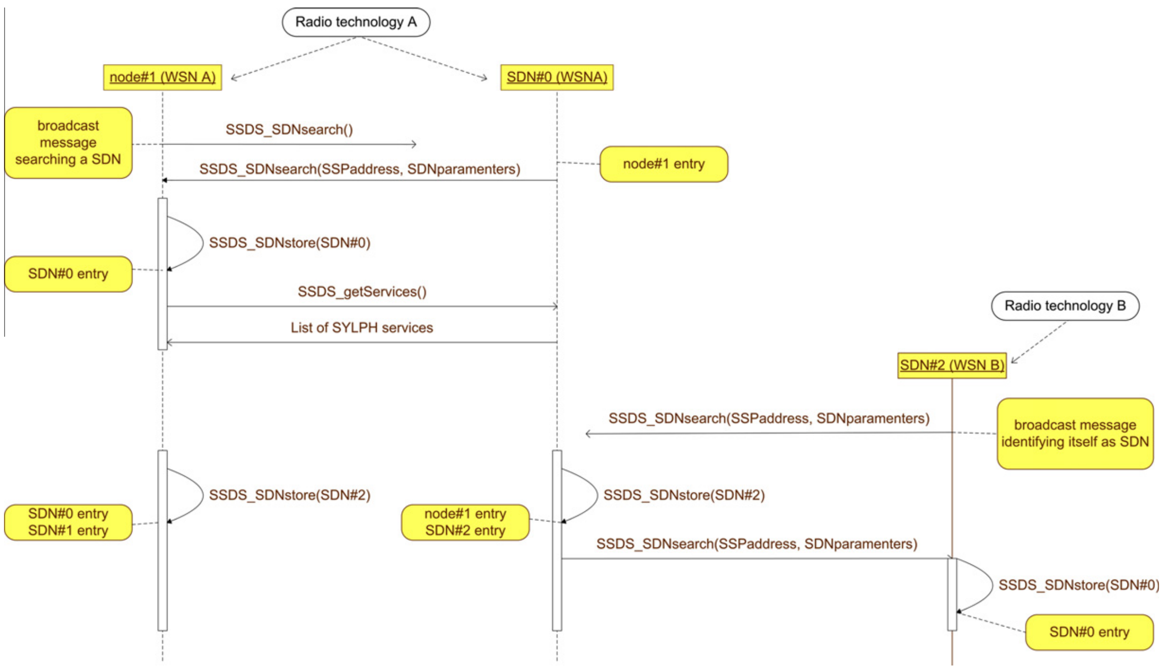

Fig. 2. Basic operation of SYLPH platform and SYLPH Directory Nodes.

forms the rest of the nodes with a broadcast message. SDN #1 stores this information on its SSDS entry list and informs node #2 about its role as SDN.

3.3. The SYLPH Services Definition Language (SSDL)

SSDL has been specifically designed to work with limited computational resource nodes [10,14]. Unlike other IDLs such as WSDL (*Web Services Definition Language*) [16], SSDL does not use as many intermediate separating tags, and the order of its elements is fixed. The reason for these constraints is to reduce processing in the devices microcontrollers. Consequently, using a simple IDL makes it possible to use nodes with fewer resources, less power consumption and at a lower cost.

The next example defines a simple service called `getLuminosity` to show the use of SSDL to define a SYLPH service. The following text represents the SSDL syntax used by developers to define this service in the node's firmware, not the version actually transmitted:

```
service getLuminosity {
  input {};
  output {
    status_t status;
    string units;
    uint16_t luminosity;};};
```

After specifying the service by means of SSDL human-readable syntax, developers translate definitions to specific code for the target language (e.g., C or nesC) and the microcontroller where the service will run. When the node registers its service in a SDN, SYLPH layers do not transmit the human-readable SSDL message, but a more compact array of bytes that describe the service and how to invoke it from other nodes. Fig. 3 shows the SSDL frames involved in the `getLuminosity` service definition (a), invocation (b) and response (c) when transmitted over SSP. When a node asks a SDN for the service definition, the SDN answers with a frame as shown in Fig. 3a. This frame describes the service identification, the address of the node that stores the service and the definition of the input and output parameters. There are *marks* to denote the input and the output parameters. Once the invoker node knows the service definition, it can make a request to the service by sending a SSP frame to the node that stores the service (Fig. 3b). Finally, response frame (Fig. 3c) does not need *marks* to separate the parameters because the output parameters must follow a specific order. However, a *string end mark* must be used to know where the string-type data ends.

3.4. Operation of SYLPH over heterogeneous WSNs using SYLPH gateways

As previously mentioned, with SYLPH, a node in a specific type of WSN (e.g., ZigBee) can directly communicate with a node in another type of WSN (e.g., Bluetooth). Therefore, several heterogeneous WSNs can be interconnected through a SYLPH Gateway. A SYLPH Gateway is a device with several hardware network interfaces (e.g., a Wi-Fi network card), each of which is connected to a distinct WSN. A SYLPH Gateway does not need to implement the layers over the SML. This fact can be seen in Fig. 1. The SYLPH Gateway stores routing tables for forwarding SSP packets among the different WSNs with which it is interconnected. When the source node invokes the service in the destination node, the SYLPH Gateway forwards the call message to the destination node through its hardware interface connected to the WSN where the destination node is located.

4. The HERA platform

HERA (*Hardware-Embedded Reactive Agents*) facilitates communication amongst agents, applications and services through the use of dynamic and self-adaptable heterogeneous WSNs. Unlike other approaches [31–33], the agents

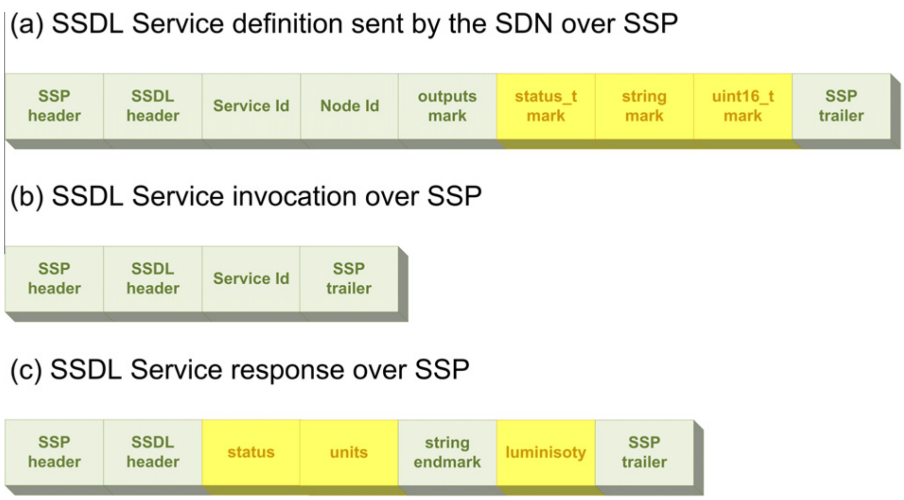

Fig. 3. Examples of SYLPH's SSDL frames over SSP.

in HERA are directly embedded on the WSN nodes and, as a result of SYLPH, HERA provides the possibility of connecting wireless sensor networks based on different radio and link technologies, whereas other approaches do not. That is, HERA allows the agents embedded into nodes to work in a distributed way and does not depend on the lower stack layers related to the WSN formation (i.e., network layer) or the radio transmission among the nodes that form part of the network (i.e., data link and physical layers). Likewise, HERA can be executed over multiple wireless devices independently of their microcontroller or the programming language they use.

Therefore, the main contributions of HERA over SYLPH are that HERA incorporates a new layer of reactive agents over the existing layers provided by SYLPH, as well as a Case-Based Planning mechanism that provides reasoning features to HERA Agents. These two main additions allow HERA to be a more powerful platform than SYLPH. One the one hand, HERA takes advantage of the main SYLPH features, that is, the distribution of functionalities over nodes with reduced computational and memory resources and using different wireless technologies. On the other hand, the HERA Agents and the HERA Case-Based Planning mechanism allow HERA to execute reactive agents that can make use of reasoning features, while SYLPH does not.

This way, developers can deploy intelligent context-aware applications by implementing HERA Agents embedded in each node. For example, a developer can design a home automation application in which is needed to collect context information from the environment using sensor nodes coming from different wireless technologies (e.g., ZigBee and Wi-Fi). In order to do this, it is necessary to have the SYLPH and HERA layers implemented for the target microcontroller and transceiver of each wireless sensor node. This way, it is easy to implement SYLPH Gateways that interconnect two or more wireless technologies through SYLPH layers for forwarding SML messages among the distinct WSNs. However, these previous developments must be done only once for each target microcontroller and transceiver, and then developers have only to implement the code of each HERA Agent they need in each node for accessing a certain set of sensors (e.g., luminosity, presence, temperature, smoke) and actuators (e.g., alarms, blinds, locks). Finally, developers can deploy a HERA Planning Agent in a central node so that HERA Agents can make use of the planning mechanisms, thus building powerful context-aware applications that learn from past experiences and adapt dynamically to new situations.

4.1. Adding the components of the HERA platform over SYLPH

The HERA agent platform adds its own agent layer over the SYLPH stack of layers, as shown in Fig. 4. This figure shows the schema of SYLPH and HERA over a ZigBee and a Bluetooth network through a SYLPH Gateway. As can be seen, HERA Agents on nodes from different radio technologies communicate each other in a transparent way thanks to SYLPH. As the HERA platform is based on the existing layers of SYLPH platform, HERA agents running on WSNs with different radio technology can communicate among themselves through one or more SYLPH Gateways, as explained in Section 4.4. Therefore, the main components added by HERA to the SYLPH's stack of layers are:

- *HERA Agents Layer (or just HERA)*. HERA agents are specifically intended to run on devices with reduced resources, precisely what SYLPH was designed for. To communicate with each other, HERA agents use HERACLES, the agent communication language designed for being used under the HERA platform. Each HERA agent is an intelligent piece of code running over the SYLPH Application Layer. As explained in Section 4.2, there must be at least one *facilitator agent* in every agent platform. This agent is the first created in the platform and acts as a directory for searching agents. In HERA, the equivalent of these agents is the HERA-SDN (*HERA Spanned Directory Node*).
- *HERA Communication Language Emphasized to Simplicity (HERACLES)*. The HERACLES language is directly based on the SSDL language. As with SSDL, HERACLES does not use intermediate tags and the order of its elements is fixed to constrain the resource necessities of the nodes. This makes its human-readable representation, used by developers for coding, very similar to SSDL. When HERACLES is translated to HERACLES frames, the actual data transmitted among nodes, they are encapsulated into simple SSDL frames using "HERA" as their *service id* field.

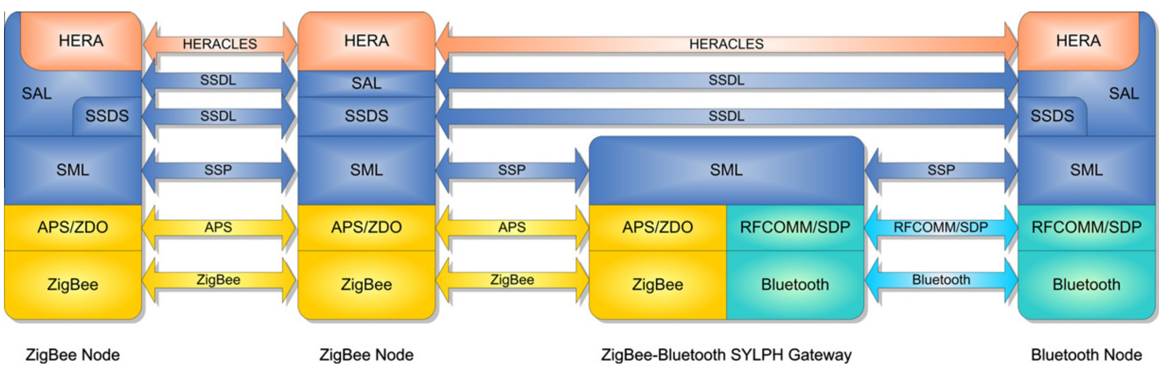

Fig. 4. Layers and protocols of the HERA platform.

4.2. HERA basic operation and HERA Spanned Directory Nodes (HERA-SDNs)

Every agent platform needs some kind of *facilitator agent* that needs to be created before other agents are instantiated in the platform [19–21]. Facilitator agents act as agent directories. This way, every time an agent is created, it is registered on one of the existing facilitator agents. This allows other agents to request one of the facilitator agents in order to know where an agent with certain functionalities is and how to invoke such functionalities. As HERA is intended to run on machines that are not more complex than sensor nodes themselves are, it was necessary to design some hardware facilitator agents that do not need more CPU complexity and memory size than what a regular sensor node has. In order to do this, HERA's facilitator agents, called *HERA Spanned Directory Nodes* (HERA-SDNs) are based on the SYLPH Directory Nodes (SDNs), described above. This way, any HERA node can perform as a HERA-SDN, just as SDNs do in the SYLPH platform. However, a HERA-SDN does not also have to be a SDN. HERA-SDN instances itself and starts the HERA platform by registering a special SYLPH service called "HERA" on a SDN stored on any node of the SYLPH network. When a new HERA Agent wants to instantiate itself through a HERA-SDN, it looks for the "HERA" service on the SYLPH network, using a primitive service of the SSDL/SSP layers. When a HERA Agent is correctly instantiated, the HERA layer also registers a "HERA" service for the agent in a SDN. In this way HERA Agents can send HERACLES messages to each other over SYLPH, referring to the service of each node with HERA Agents, including HERA-SDNs, as "HERA".

The UML sequence diagram in Fig. 5 shows an example of the basic operation of SYLPH and HERA platforms when registering services or agents on the HERA Spanned Directory Nodes. In order to start the HERA platform, an initial HERA-SDN must be created. This will be HERA-SDN #0 running on SDN #0. At that moment, other SYLPH nodes with HERA running on them can instantiate more HERA agents or even more HERA-SDNs. Because HERA is designed to run on devices with low resources that are usually connected wirelessly, it is very important that the platform does not have to depend on only one HERA-SDN (i.e., one facilitator agent). This way, if the HERA-SDN crashes (e.g., power failure or problems with radio trans-

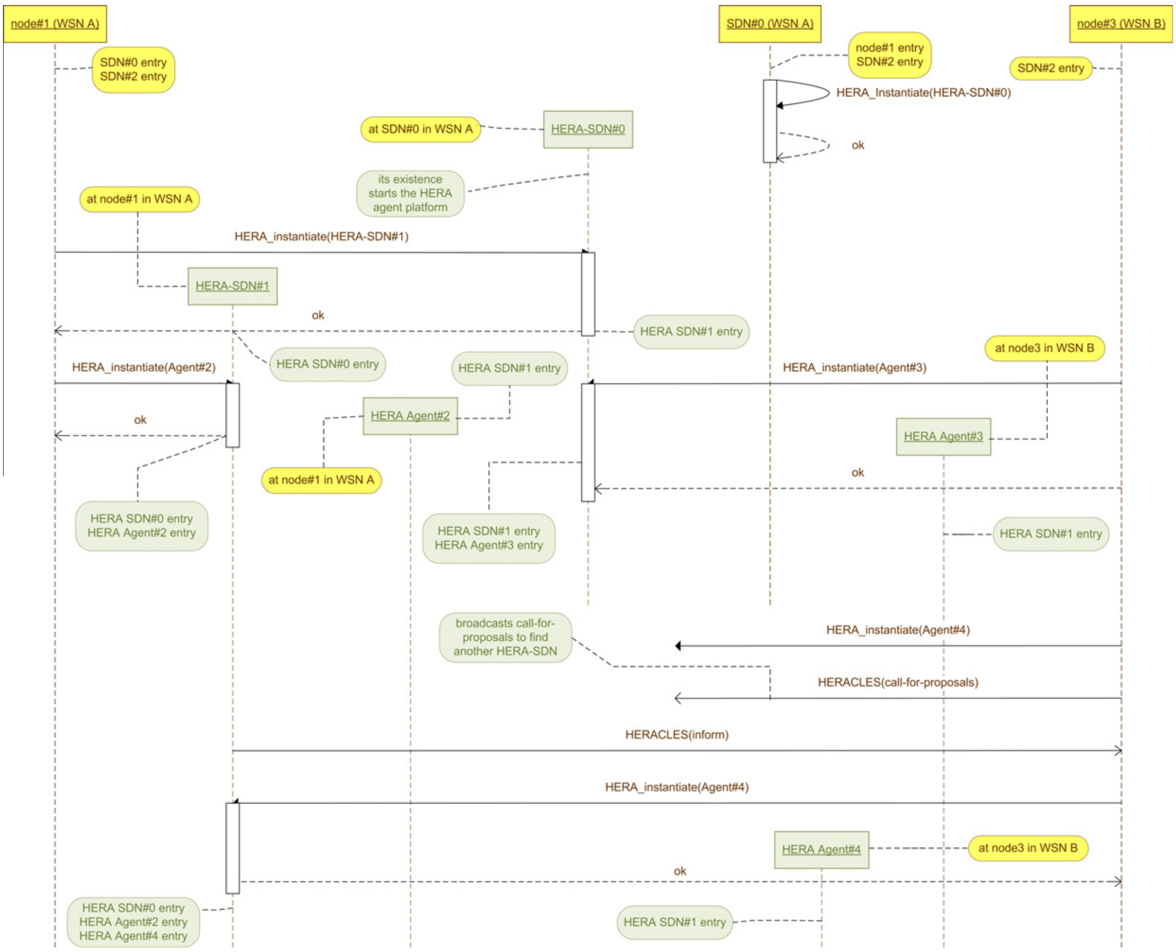

Fig. 5. Basic operation of HERA platform and HERA Spanned Directory Nodes.

mission), the HERA platform will not fail and will not need to be started again. After the creation of the HERA-SDN #0, the SYLPH node #1 uses the HERA-SDN #0 to instantiate a new HERA-SDN, the HERA-SDN #1, thus increasing the redundancy of the HERA-SDNs and the robustness of the platform. The SYLPH node #1 also instantiates the HERA Agent #2, this time through the HERA-SDN #1. SYLPH node #3, in the other WSN, instantiates HERA Agent #3 through the HERA-SDN #0, even if they are in distinct WSNs. With SYLPH, this is no longer a problem. At a specific moment, SDN #0 is powered off. After that, SYLPH node #3 looks for HERA-SDN #0. As HERA-SDN #0 does not reply, SYLPH node #3 sends a broadcast *call-for-proposal* HERACLES frame in order to find a live HERA-SDN. As HERA-SDN #1 replies, HERA Agent #4 is created through HERA-SDN #1. As shown in Fig. 5, there can be several HERA Agents in a single SYLPH node. Moreover, there can be SYLPH nodes with no HERA implementation. A SYLPH Gateway is a clear example of this, as explained below. If, at a certain moment, HERA Agent #2 wants to look for an agent, but HERA-SDN #0 is not alive again, then HERA Agent #2 also has to look for an existing HERA-SDN in the platform, thus storing entries for the two HERA-SDNs. When HERA-SDN #0 is alive again, it will be useful for HERA Agent #2 to have this redundancy on HERA-SDNs entries.

4.3. The HERA Communication Language Emphasized to Simplicity (HERACLES)

In HERA, the hardware agents communicate with each other through the *HERA Communication Language Emphasized to Simplicity* (HERACLES). This language is an extension of the SSDL used in SYLPH. As explained above, SSDL has two distinct representations [9]: one that is human-readable, similar to C language and used for services development proposals, and one embedded on frames that SYLPH nodes understand. This is done in this way because in nodes with reduced resources (memory and CPU time) it is not convenient to overload the microcontroller and the memory space with a heavy parsing method. When developing a program, programmers use the human-readable representation to define agents' functionalities, similar to that shown as follows.

```
request {
  sender agent1;
  receiver agent2;
  content {
    action(agent2) {
      inform-if {
        sender agent1;
        receiver agent2;
      content {
        message {
        state result;};};
      language HERACLES;
        ontology HERA_ONTOLOGY;};};};
      LANGUAGE HERACLES;
      ontology HERA_ONTOLOGY;};
    inform {
    sender agent2;
  receiver agent1;
    content {
      message {
        state result;};};
    language HERACLES;
    ontology HERA_ONTOLOGY;};
```

However, similar to SYLPH, HERA agents transmit the more compact representation of HERACLES as frames. The compact frames corresponding to the previous example are also represented in Fig. 6. These kinds of compact frames are what HERA agents transmit in a heterogeneous WSN based on HERA-SYLPH over the SSDL/SSP protocols. Fig. 6a shows the frame corresponding to the HERACLES *request*, whereas Fig. 6b depicts the frame corresponding to the HERACLES *inform* of the previous example.

4.4. Operation of HERA over heterogeneous WSNs using SYLPH gateways

Because of HERA is implemented over SYLPH through the addition of new layers and protocols (HERA Agents and HERACLES), it can be used over several heterogeneous WSNs in a transparent way. HERA Agents are implemented

Fig. 6. Examples of HERA's HERACLES frames over SSP/SSDL.

over the SAL layer, so HERA does not mind how many intermediate SYLPH Gateways and different WSNs there are between the location of one HERA Agent and another. This is demonstrated in Fig. 4. Both HERA Agents and HERA-SDNs communicate with each other directly through HERACLES. HERA Agents use SAL's service points to deliver HERACLES frames between agents. Since HERACLES frames are transported as other SSDL frames over SSP between SYLPH nodes, HERA Agents do not need to know which nodes other HERA Agents are stored on, or if such nodes are in remote WSNs.

4.5. HERA Case-Based Planning mechanism

As previously mentioned, some agents in HERA integrate a Case-Based Planning (CBP) mechanism. The CBP mechanism provides the agents with greater adaptation capabilities. As it is a complex and resources demanding task, the CBP mechanism has been modeled as a service provided by a special HERA Agent, known as *HERA Planning Agent*, which runs on a central node (i.e., a computer or a wireless device with moderate computational resources). The main characteristics of this mechanism are described in the remainder of this section.

CBP comes from CBR, but is specially designed to generate plans (sequence of actions) [29]. The problems and their corresponding plans are stored in a plans memory. The reasoning mechanism generates plans using past experiences and planning strategies, which is how the concept of Case-Based Planning is obtained [29]. CBP consists of four sequential stages similar to CBR stages: retrieve, reuse, revise and retain. Problem description (initial state) and solution (situation when final state is achieved) are represented as beliefs, the final state as a goal (or set of goals), and the sequences of actions as plans. The CBP cycle is implemented through goals and plans. When the goal corresponding to one of the stages is triggered, different plans (algorithms) can be executed concurrently to achieve the goal or objective. Each plan can trigger new sub-goals and, consequently, cause the execution of new plans.

The HERA CBP mechanism needs a set of HERA Agents running on a set of nodes (i.e., wireless devices). Each of the nodes is connected physically to different sensors and actuators. This way, each node in the system can transmit commands to the actuators according to the sensors measurements. Each device d_i is defined by the sensors and actuators to which it has access, as expressed in the following equation:

$$d_i = (S_i, A_i) \tag{1}$$

where S_i is the set of sensors and A_i is the set of actuators.According to the values read from the sensors, each HERA Agent running in the devices makes use of the actuators in order to achieve the required goal (e.g., stop a heater when a target temperature has been achieved). Thus, the behavior of the HERA CBP mechanism is established by a database generated from the information of the sensors and actuators. This way, when some event produces an interaction with the sensors in the devices (e.g., a user action or a variation in the environment), these devices forward the values from the sensors and actuators to a central node that runs a special HERA Agent that stores this information. This agent is known as *HERA Planning Agent*. Depending on the size of the whole system (i.e., the number of nodes in the network, as well as the number of sensors and actuators associated to them), this central node can be implemented as a computer with a database stored in a physical disk or as a wireless sensor node with a smaller database stored in an EEPROM or Flash memory. Each device d_j has its own cases memory. Each case of the device d_j follows the structure indicated in the following equation.

$$c_i^{d_j} = \left(V_i^{S_j}, V_i^{A_j}\right) \tag{2}$$

where $V_i^{S_j}$ is the set of values from the sensors associated with the device j, and $V_i^{A_j}$ the values associated to the actuators.

The reactive behavior of the HERA Agents is defined as a set of rules that determine the relation among the sensors and the actuators. The rules are generated by the HERA CBP mechanism. There are two kinds of rules: static rules and dynamic rules. Static rules are pre-defined rules that have priority over dynamic rules. Static rules determine the default behavior of each node and act also as a backup of these behaviors (i.e., they are stored directly in the nodes). Dynamic rules are automatically generated from the defined cases for each of the devices. The dynamic rules are periodically updated on every run of the HERA Agents (i.e., each time they are requested to execute a task). Fig. 7 shows the functioning of the HERA CBP mechanism when a device must execute a new task.

Both static and dynamic rules are defined using a defined grammar that facilitates the error detection and also the generation of native code that is actually running in the HERA Agents. One the one hand, static rules are stored in the database by the HERA Planning Agent following this grammar. This way, rules are formed by sensors, literals, comparison and logical operators, as well as the final action to be performed by the actuator. On the other hand, dynamic rules are defined by the CBP mechanism by means of the information of the cases shown in Eq. (2). During the recovery stage the CBP mechanism recovers the information with the sensors and actuators associated to a certain device. During the reutilization stage, automatic rules are generated from this information. For the generation of automatic rules, different algorithms based on decision rules and decision trees can be used. An example of algorithm based on decision rules is M5 [35], while J48 [36] is based on decision trees.

In HERA, the J48 algorithm is used for the generation of rules [36]. The inputs of the classifier are the value of the sensors, and the output belonging to the actuator. Using this configuration the J48 is trained, thus obtaining a decision tree that represents the behaviors of the actuators. In this sense, the different actuators are chosen as leaf nodes in the decision trees, while the sensor values are placed in the intermediate nodes. There is a decision tree according to the sensors situated in the device for each actuator. The devices can select a value of the actuators according to the value of the sensors through the decision tree, and the system only has to follow the conditions in the intermediate nodes until it arrives at a leaf node.

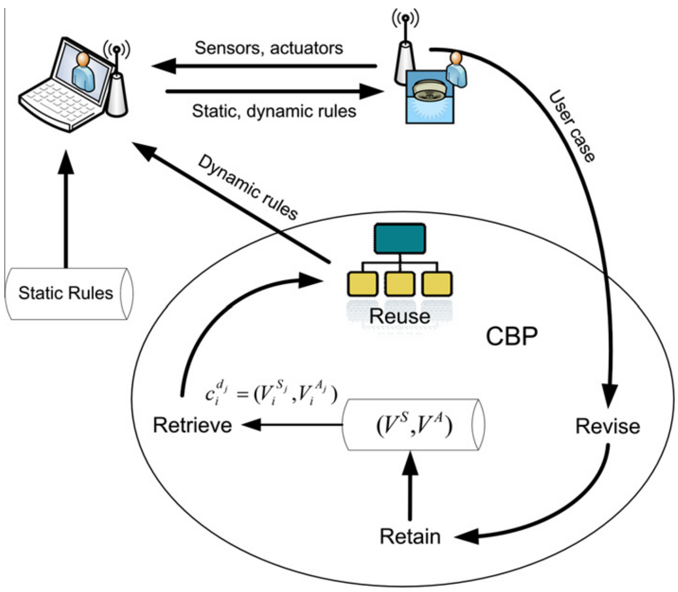

Fig. 7. Functioning of the HERA CBP mechanism.

The final schema of the decision trees would be similar to that shown in Fig. 8, and rules would be generated as indicated in the schema. The generated rules follow the grammar indicated above. The decision tree generated contains all the necessary information to generate the rules according to the grammar. The system only has to select each leaf node and move up toward the root node, introducing a new condition for each movement throughout the tree.

During the revision and learning stages, the system only stores the values of the actuators and sensors when the actuators are established manually by the users. The automatic decision of the agents are not stored in the system. The system only stores the interactions of the users as it tries to adapt to their behaviors. The system does not store generated cases as it is able to predict the behaviors, and only stores a new case when a user modifies the automatic configuration.

For the development of the rules generator system the Weka libraries are used for the implementation of J48 algorithm. JFlex and Cup are used as lexical and syntactic analyzers. By means of Cup it is generated the native code that is then transferred and executed on chips.

5. Experiments and results

This section describes distinct experiments performed to test the HERA platform. On the one hand, Section 5.1 describes a test battery performed to evaluate the instantiation of HERA Agents and transmission of HERACLES

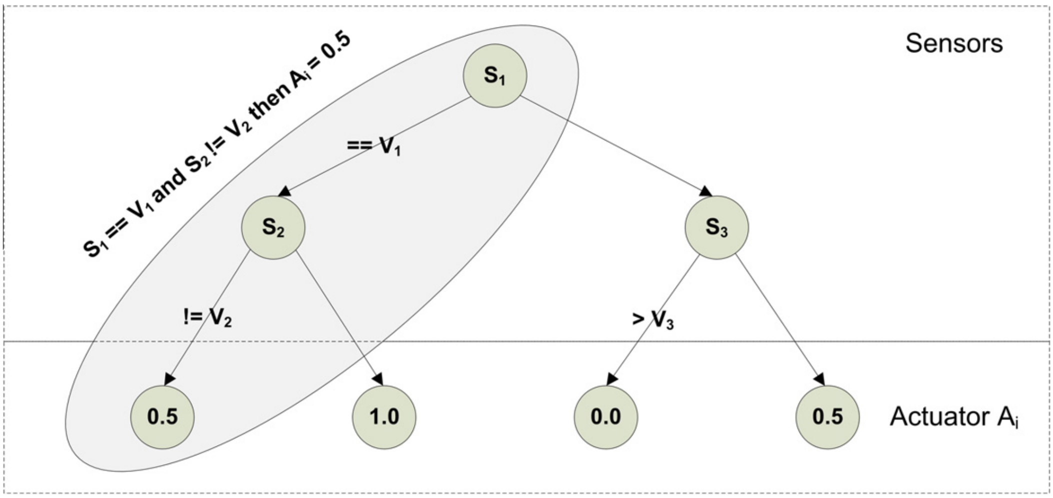

Fig. 8. Example of decision tree for the dynamic rules.

frames about them, both in homogeneous and in heterogeneous HERA WSNs. On the other hand, Section 5.2 describes an implementation of the HERA platform in order to develop some context-aware applications in a real scenario.

5.1. HERA performance tests

Several experiments were carried out to evaluate the performance of the HERA platform, mainly to test how it handled the instances of HERA-SDNs and HERA Agents and the exchange of HERACLES frames, both in homogeneous and heterogeneous HERA WSNs. In this sense, we deployed two distributed WSN infrastructures with HERA running over it, the first one formed by only ZigBee nodes and the second one by both ZigBee and Bluetooth nodes.

We have also developed an application for monitoring the state and operation of the HERA network. This application is based on a previous one we had developed for monitoring SYLPH networks [14]. As with the previous one, this application monitors all the traffic (i.e., service invocations, responses, registrations or searches) in the SYLPH network. It is necessary for the nodes to operate in debug mode, so that every time a node invokes a service it also invokes a monitoring service on a node connected to a computer (e.g., via a USB port). The node gathers all the invocations and forwards them to the monitoring application running on the computer. The same process is done for service responses, searches and registrations. The monitoring application makes it possible to observe when a node is searching for a certain service in the network, the services offered by the nodes, and the contents of the SSDS entry tables stored in the SDNs. In addition, with the newly developed application it is possible to monitor the HERA agent instances in the HERA-SDNs of the HERA platform and also the HERACLES *request*, *inform* and other frames.

The first sensor infrastructure consisted of a ZigBee network with 50 devices, one acting as coordinator and the rest as routers. The sensor infrastructure was formed by n-Core Sirius A devices belonging to the novel n-Core platform (http://www.n-core.info). Each n-Core Sirius A 2.4 GHz device includes an ATmega1281 microcontroller with 8 KB RAM, 128 KB Flash memory, an AT86RF231 transceiver and several communication ports (GPIO, ADC, I^2C and USB/RS-232 UART) to connect to a wide range of sensors and actuators [37]. ZigBee is based on the IEEE 802.15.4 standard and operates in the 868/915 MHz and 2.4 GHz unlicensed bands [38,39]. Unlike Wi-Fi or Bluetooth, ZigBee is designed to work with low-power nodes and allows up to 65,534 nodes to be connected in a star, tree or mesh topology network. The ZigBee nodes were distributed in a short-range simple mesh, with less than 10 m between any router and the coordinator. Each time the ZigBee network was formed, the nodes were powered on different random times, so that the mesh topology was different each time. However, they were some constraints: the maximum depth of the network (i.e., the maximum number of hops between the coordinator and any node in the network) was 5, the maximum number of neighbors of any node was 8 and the maximum number of children of any node in the network was also 8.

The experiments consisted of trying to start a platform with HERA over the ZigBee network. In the network, the ZigBee coordinator and a ZigBee router acted as SDNs and the other 48 ZigBee routers acted as SYLPH nodes. After the entire network was correctly created, the SDN in the coordinator tried to instance a HERA-SDN. The HERA-SDN instanced itself and started the HERA platform registering a special service called "HERA" on the SDN stored on the same ZigBee coordinator node. Then, 10 nodes tried to instance one HERA Agent in the HERA platform. Once the HERA-SDN and the 10 HERA Agents were successfully instantiated, the HERA-SDN started to "ping" every of the ten HERA Agents with a *request* HERACLES frame including an *inform-if* command and waiting for an *inform* frame as a "pong" response. Each HERA Agent was pinged by the HERA-SDN one time every 5 s during 1 h (7200 total pings tried). The experiment was run until both the platform and the agents were successfully started/instantiated 50 times. When the network could not be correctly created the run was discarded and not taken into account in the 50 runs. Furthermore, if the HERA platform could not be completely started and created (i.e., all 10 HERA Agents correctly instantiated), these runs were also discarded and not taken into account as forming part of the 50 runs. If any HERA agent crashed it was immediately restarted. HERACLES messages were registered to measure when a *ping-pong* failed and if a HERA agent had to be restarted. The results are shown in Table 1. As can be seen, it is necessary to try to create 56 times the SYLPH and HERA platforms to get 50 runs of the experiment with the 10 HERA Agents successfully instantiated in the HERA platform. This is because the SYLPH platform was not successfully created 3 times, as some of the registrations of the SYLPH nodes failed (the 0.17% of the total 2800). Likewise, the HERA platform was not successfully created (with the 10 HERA Agents correctly instantiated) 3 times, as some of the instantiations of the HERA Agents failed (the 0.56% of the total 530). This indicates that it is necessary to improve both the SYLPH network creation and the instantiation of HERA Agents. These fails are caused by the transmission fails in the ZigBee network. That is, 50 nodes in a ZigBee network trying to transmit their registrations and instantiations in the same time window provoke frame collisions and retransmissions. When the total number of retransmissions in the different layers of ZigBee and the SYLPH/HERA platforms are exhausted, nodes must finally give up. This also motivates the number of *ping-pongs* that failed (the 0.19% of the total 7200). A better Automatic Repeat Request (ARQ) mechanism could increase SSP-over-WSN transmissions. In addition, the robustness of the HERA Agents should be improved by introducing a mechanism to ping and keep running the HERA Agents and the HERA-SDNs.

The same experiments were repeated using the second infrastructure, which consisted of a heterogeneous sensor network made up of one 25-node ZigBee network and another 25-node Bluetooth *scatternet* [40], both of them interconnected through a SYLPH Gateway, in this case a computer. Bluetooth operates also in the ISM 2.4 GHz band. It allows creating star topology networks called *piconets* of up to eight devices in which one of them acts as master and

Table 1
Results of the HERA experiments comparing a homogeneous HERA WSN and a heterogeneous HERA WSN.

Only-ZigBee HERA experiments	
Total runs	56
SYLPH nodes not registered correctly (% of all tries in total runs)	5 (0.17%)
SYLPH platform not created correctly (% of total runs)	3 (5.36%)
HERA Agents not instantiated correctly (% of all tries in total runs)	3 (0.56%)
HERA platform not started correctly (% of SYLPH correctly created)	3 (5.66%)
All 10 HERA Agents correctly instantiated	50
Total pings tried	7200
Ping-pongs not completed (% of total tried)	14 (0.19%)
Total restarted HERA Agents in an hour	9
ZigBee + Bluetooth HERA experiments	
Total runs	58
SYLPH nodes not registered correctly (% of all tries in total runs)	7 (0.24%)
SYLPH platform not created correctly (% of total runs)	5 (8.62%)
HERA Agents not instantiated correctly (% of all tries in total runs)	6 (1.13%)
HERA platform not started correctly (% of SYLPH correctly created)	3 (5.66%)
All 10 HERA Agents correctly instantiated	50
Total pings tried	7200
Ping-pongs not completed (% of total tried)	27 (0.37%)
Total restarted HERA Agents in an hour	12

the rest as slaves. Several Bluetooth piconets can be interconnected by means of Bluetooth devices that belong simultaneously to two or more piconets, thus creating more extensive networks (known as *scatternets*) [40]. The Bluetooth nodes used in these experiments had a CSR BlueCore4 chip that included a RISC microcontroller with 48 KB of RAM. The 25-node ZigBee network had similar network characteristics as in the first experiment: 10 m as maximum between adjacent nodes (being all of them ZigBee routers except for the coordinator), five hops maximum depth network, eight neighbors maximum for any node and eight children maximum for any node. This way, the ZigBee network topology was different each time it was formed as in the first experiment. In the other hand, the Bluetooth network had a static topology formed by five Bluetooth *piconets*. Specifically, one of these piconets acted as the main piconet. The master of the main piconet (i.e., the main Bluetooth master) was also the node that interconnected the Bluetooth scatternet with the ZigBee network through the computer acting as SYLPH Gateway. Moreover, the four slave nodes in the main piconet were also slave nodes each of them in one of the other four Bluetooth piconets. These other piconets had each of them six nodes: a master node, a slave node being also slave in the main piconet and four more slave nodes. There were also two SDNs in this experiment, one in each WSN (i.e., a SDN in the ZigBee network and another one in the Bluetooth network). Similarly to the experiments made on the first infrastructure, the SDN in the ZigBee coordinator node tried to instance a HERA-SDN. The HERA-SDN instanced itself and started the HERA platform registering a special service called "HERA" on the SDN stored on the same ZigBee coordinator node. Then, five nodes in the ZigBee network and five nodes in the Bluetooth network tried to instance one HERA Agent in the HERA platform. Once the HERA-SDN and the 10 HERA Agents were successfully instantiated, the similar *ping-pong* process performed in the experiments with the first infrastructure was carried out. The results of these experiments are also shown in Table 1. As can be seen, it is necessary to try to create 58 times the SYLPH and HERA platforms to get 50 runs of the experiment with the 10 HERA Agents successfully instantiated in the HERA platform, a little more than in the homogeneous network. The SYLPH platform was not successfully created 5 times, as the 0.24% of the 2900 registrations of the SYLPH nodes failed. The HERA platform was not successfully created 3 times, as the 1.13% of the 530 instantiations of the HERA Agents failed. The number of *ping-pongs* that failed was the 0.37% of the total 7200. These results demonstrate that the inclusion of the SYLPH Gateway makes the formation of the whole SYLPH network a little harder. Moreover, once the network is successfully formed, there is no difference of in the service registration mechanism. However, the transmission of HERACLES frames and the robustness of HERA Agents seem to be a little more unstable in the heterogeneous HERA network. On the one hand, in a 25-node ZigBee network the number of frame retransmissions decreases with respect to a 50-node network as in the experiments made in the first infrastructure. On the other hand, the implementation of the HERA platform over the Bluetooth nodes needs to be debugged, as it is a newer development compared with the more stable HERA over ZigBee.

5.2. Implementation of HERA in a real scenario

In order to demonstrate the feasibility of the HERA platform for developing context-aware applications in a real scenario, two ZigBee networks based on the described n-Core Sirius devices [37] have been deployed in a laboratory belonging to the Bioinformatics, Intelligent Systems and Educational Technology (BISITE) Research Group (http://bisite.usal.es) of the University of Salamanca (Spain). The first ZigBee network is intended for sensing and automation purposes, while the second network is aimed at indoor locating. Both sensing and locating are key aspects when building a context-aware system in order to gather context information about the users and the environment. Both networks are formed by n-Core Sirius nodes. In addition to the n-Core Sirius A nodes, described in Section 5.1, two more kinds of nodes are used: n-Core Sirius B and n-Core Sirius D devices. These devices are smaller than n-Core Sirius A devices, even though they include almost the same internal communication ports (i.e., GPIO, I^2C, USB) to be connected to sensors or actuators. On the one hand, n-Core Sirius B devices are intended to be used with an internal battery and include two general-purpose buttons. On the other hand, n-Core Sirius D devices are aimed at being used as fixed ZigBee routers using the main power supply through a USB adaptor. These devices can be seen in Fig. 9, which also shows a plan of the laboratory where the ZigBee networks are deployed. Fig. 9a shows a Sirius

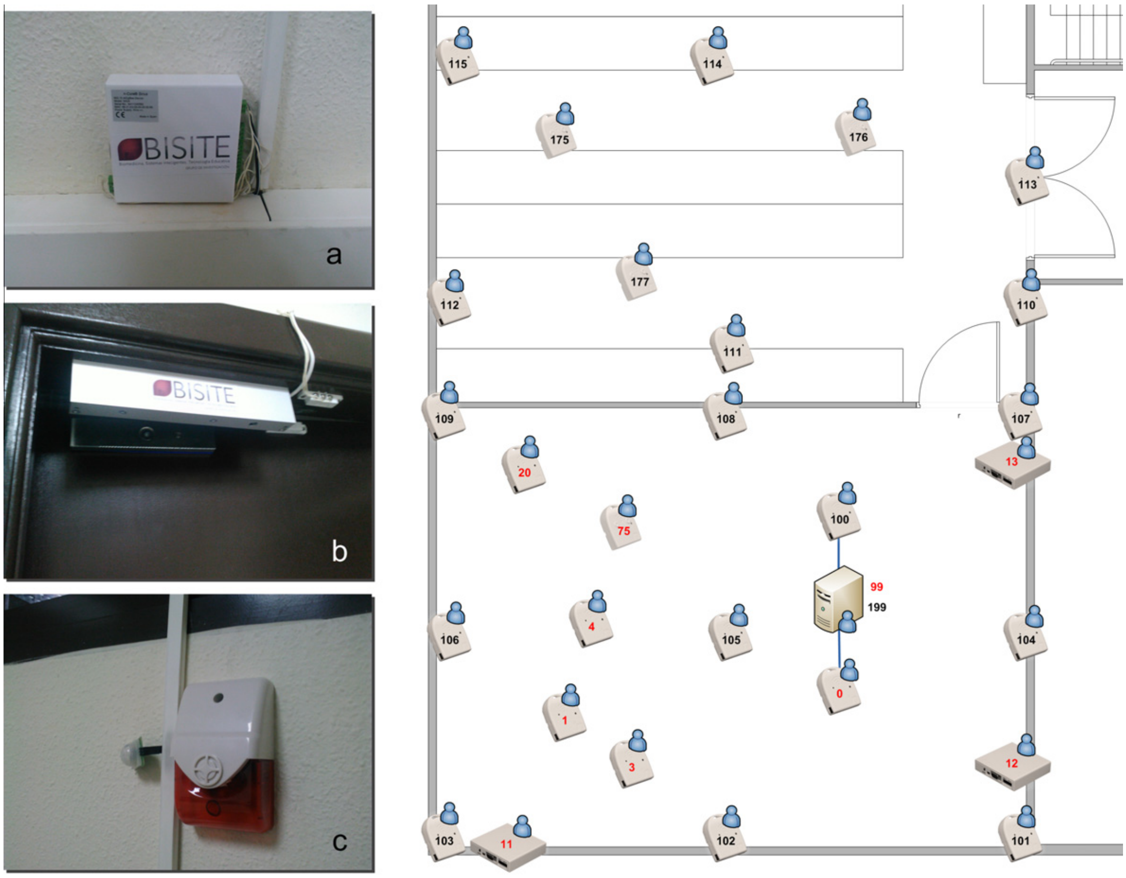

Fig. 9. Deployment of the ZigBee nodes in the implementation of HERA in a real scenario.

A deployed in the laboratory, while Fig. 9b shows an electromagnetic latch and Fig. 9c shows an opto-acoustic siren.

In a first stage of the development, the distinct layers of the SYLPH platform were implemented as C static link libraries. These SYLPH libraries can be further statically linked by code that is implemented as firmware that can be loaded into the Flash memory of the microcontrollers in the ZigBee devices. This firmware is usually loaded through a JTAG (Joint Test Action Group, common name for IEEE 1149.1 standard) programmer interface or a USB port using a bootloader application. The implementation of the SML layer and the SSP protocol are dependent of API provided by manufacturers to access microcontroller, communication ports and ZigBee features. However, the implementation of the SSDS and SAL layers, as well as the SSDL protocol, is independent of the ZigBee infrastructure and only depends on the microcontroller features. In a similar way, the implementation of the HERA layer, as well as the proper HERA Agents themselves and the HERACLES protocol, are also independent of the radio transmission protocol and are built over the SAL layer. Finally, both SYLPH and HERA layers are also implemented as dynamic link libraries over Windows operating system to be used by applications intended to access to SYLPH/HERA WSNs. These applications include monitoring applications, SDNs, HERA-SDNs, as well as HERA CBP Agents running on personal computers that are connected to one or more SYLPH/HERA WSNs through different communication ports (e.g., USB or RS-232).

Therefore, each of the nodes in the two ZigBee networks are loaded with firmware linked to SYLPH/HERA libraries. This way, all the functionalities of these devices are provided by HERA Agents. Each HERA Agent in the ZigBee nodes is intended to control one or more sensors or actuators. A monitoring application based on SYLPH/HERA runs on a PC to register and manage data gathered from distinct nodes in the networks. This PC is connected to the two ZigBee networks through two USB ports, each of them connected to the ZigBee coordinator of each network. Each of the ZigBee coordinators acts also as SDN and HERA-SDN. The HERA Agents running on the ZigBee nodes can communicate with HERA Agents running on the PC and with HERA Agents running on other ZigBee nodes to request data from sensors or send commands to actuators. Furthermore, a HERA Planning Agent runs on the PC for expanding the possibilities of the system.

Table 2 shows the description of the role for each node in the two ZigBee networks, as well as the sensors and actuators that are controlled locally or remotely through HERA Agents. The sensing and automation network allows gathering data from different sensors in the wireless nodes: temperature, humidity, magnetometer, accelerom-

Table 2
Description of the nodes of the context-aware real scenario with HERA running on it.

SYLPH node id	Description of role and sensors/actuators
Sensing and automation network	
0	ZigBee coordinator, SDN, HERA-SDN
1	– Accelerometer (I^2C), sends data to PC – Temperature (I^2C), sends data to PC – 2 buttons (I^2C), send data to PC – Joystick (I^2C), sends data to PC
3	– Magnetometer/compass (I^2C), sends data to PC
4	– Temperature (I^2C), sends data to PC – Humidity (I^2C), sends data to PC – Luminosity (I^2C), sends data to PC and controls dimmer in node #20
11	– Luminosity (ADC), sends data to PC – Presence (GPI), sends data to PC – Opto-acoustic siren (GPO/relay #2)
12	– Power socket (GPO/relay #1)
13	– Door sensor (GPI), sends data to PC and activates GPO/relay #1 in this node – Presence sensor (GPI), deactivates GPO/relay #1 in this node – Electromagnetic latch (GPO/relay #1) – Panic button (GPI), activates/deactivates GPO/relay #2 in node #11
20	– Lamp DAC dimmer (I^2C)
75	– Left button (IRQ #6), deactivates the GPO/relay #1 in node #13 – Right button (IRQ #7), deactivates the GPO/relay #2 in node #11
99	PC (node id in sensing and automation SYLPH network)
	Description of role
Indoor locating network	
100	ZigBee coordinator, SDN, HERA-SDN
101–115	Readers
175–177	Tags
199	PC (node id in indoor locating SYLPH network)

eter, joystick and buttons, luminosity, presence and door sensors. In addition, this network allows controlling different actuators (i.e., electromagnetic latch, lamp and siren) from the PC or from other ZigBee nodes. All sensors and actuators are controlled by HERA Agents running on the ZigBee nodes. For instance, a HERA Agent running on the PC can send a *request* HERACLES frame to a HERA Agent running on the node #1 (a n-Core Sirius D device) to ask for a temperature value, that will be delivered in a *inform* HERACLES frame to the first HERA Agent. Likewise, a HERA Agent running on node #4 can read itself the ambient luminosity for controlling a lamp in the node #20, which is managed by other HERA Agent. The first HERA Agent communicates with the later using *request* HERACLES frames for stating a certain value for the dimmer. Furthermore, HERA Agents running on the ZigBee nodes send periodically their sensor values to the HERA Planning Agent running on the PC using HERACLES frames. This way, the HERA CBP mechanism updates the dynamic rules from the initial static rules provided by users, as described in Section 4.5 and HERA Agents can consult the HERA Planning Agent to retrieve plans and consequently control the different actuators in the system.

Similarly, in the indoor locating network, n-Core Sirius B devices are used as tags, while n-Core Sirius D devices are used as readers. This way, n-Core Sirius B devices are carried by users and objects to be located, whereas n-Core Sirius D devices are placed at ceilings and walls to detect the tags. Each user or object to be located in the system carries an n-Core Sirius B acting as tag. Each of these tags runs a HERA Agent that broadcasts periodically an *inform* HERACLES frame including, amongst other information, its unique identifier in the SYLPH network. The rest of the time these devices are in a sleep mode, so that the power consumption is reduced. A set of n-Core Sirius D devices is used as readers throughout the environment, being placed on the ceiling and the walls. The broadcast HERACLES frames sent by each tag are received by the readers that are close to them. This way, HERA Agents running on readers store in their memory a table with an entry per each detected tag. Each entry contains the identifier of the tag, as well as the RSSI (Received Signal Strength Indication) and the LQI (Link Quality Indicator) gathered from the broadcast frame reception. Periodically, each HERA Agent running on each reader sends this table to the HERA Planning Agent running on the computer. Using these detection information tables, the HERA CBP mechanism estimates the position of each tag in the environment, which is shown by a HERA Agent running on the PC that acts as other actuator in the HERA platform, but acting over a Graphical User Interface.

6. Conclusions and future work

The HERA platform (*Hardware-Embedded Reactive Agents*) allows wireless devices from different technologies to work together in a distributed way. HERA Agents can communicate in a distributed way regardless of the technology or the programming language they use. Furthermore, HERA Agents are light enough to be run on WSN nodes with limited resources. The HERA Agents are reactive because they act on devices with critical response times. HERA is a model that successfully solves the problems it sets out to resolve. HERA is a platform specially designed to implement hardware agents. Because HERA is based on SYLPH, it allows devices from different radio and networks technologies to coexist in the same distributed network. However, HERA goes a step further than SYLPH and adds reactive agents and a Case-Based Planning mechanism to the platform, extending its context-aware features. In HERA, unlike other approaches already discussed, agents are directly embedded on the sensor nodes. HERA facilitates and speeds up the integration between agents and sensors for reusing resources in the context. This approach allows the development of multi-agent systems with increased scalability. It also expands the agents' capabilities to obtain information about the context and to automatically react over the environment. A totally distributed approach and the use of heterogeneous WSNs provides platform that is better capable of recovering from errors, and more flexible to adjust its behavior in execution time. Even though HERA is focused specially on sensor nodes with small resources, it can be implemented on almost any kind of device. HERA adds intelligence to sensors by means of light reactive agents, improving the experience of developers and users in context-aware technologies. The HERA CBP mechanism facilitates the inclusion of new sensors dynamically, without need of performing offline training for each of the devices. In addition, the CBP mechanism can determine automatically the influence of the sensors to establish the final state of each of the actuators, so it is not necessary to indicate the relation among sensors and actuators.

Future work includes the improvement of the overall performance of the HERA platform. This way, the underlying SYLPH platform will be also improved, especially in the network formation and the SYLPH Gateways. In this sense, it will be evaluated other characteristics related to HERA/SYLPH nodes such as agent execution time, sleep mode intervals and power consumption. In addition, it will be added a set of cross-layering services, so that HERA agents can modify the network parameters of each specific radio technology in a uniform way. Furthermore, we are working in the design of an efficient mechanism that allows HERA agents to move throughout different nodes, no matter the WSN technology they use. This way, we will get, for example, HERA agents to move from a ZigBee node to a Bluetooth node.

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5.4. CAFCLA: A Framework to Design, Develop, and Deploy AmI-Based Collaborative Learning Applications

El paradigma de la Inteligencia Ambiental (AmI - *Ambient Intelligence*) promueve la integración de las Tecnologías de la Información y las Comunicaciones (TIC) en la vida diaria para facilitar la ejecución de las tareas cotidianas. En este sentido, la educación se convierte en un campo donde la AmI puede mejorar el proceso de aprendizaje a través de tecnologías sensibles al contexto. Sin embargo, es necesario desarrollar nuevas herramientas que puedan adaptarse a una amplia gama de tecnologías y escenarios de aplicación. Es aquí donde la tecnología de agentes puede demostrar su potencial. Este capítulo presenta CAFCLA, un framework multiagente que permite desarrollar aplicaciones de aprendizaje basadas en el enfoque pedagógico CSCL (*Computer-Supported Collaborative Learning*) y el paradigma de Inteligencia Ambiental. CAFCLA integra diferentes tecnologías sensibles al contexto para que las aplicaciones de aprendizaje diseñadas, desarrolladas y desplegadas en él sean dinámicas, adaptables y fáciles de usar por usuarios como estudiantes y profesores.

Objetivos
Los objetivos perseguidos en esta publicación son los siguientes:

- Proveer de forma fácil y sencilla información contextual a cualquier aplicación de aprendizaje colaborativo.
- Aumentar la colaboración, gestión y usabilidad de los sistemas de aprendizaje colaborativo.
- Proponer un framework que facilite el diseño, desarrollo, implementación, despliegue, configuración y gestión de actividades de aprendizaje colaborativo que hagan uso de información contextual.
- Facilitar el objetivo anterior gracias a la integración de tecnologías que permitan utilizar redes inalámbricas de sensores y sistemas de localización en tiempo real, así como un sistema multiagente que provea de inteligencia al sistema.
- Describir un escenario de aplicación del modelo propuesto.

Resultados
En esta sección se presenta CAFCLA, un framework concebido con el objetivo de diseñar y desarrollar un conjunto de herramientas que proporcionen una base para implementar actividades de aprendizaje colaborativo basadas en el paradigma de la Inteligencia Ambiental y que hacen uso de información contextual. CAFCLA es un framework que integra diferentes tecnologías sensibles al contexto, como los sistemas de localización en tiempo real, y varios protocolos de comunicación. Tanto educadores como desarrolladores pueden desarrollar actividades de aprendizaje colaborativo basadas en el contexto abstrayéndose de la complejidad

del uso simultáneo de diferentes tecnologías. En este caso, CAFCLA se centra en proporcionar un conjunto de herramientas y métodos para los profesores, desarrolladores y personal técnico con el fin de diseñar, desarrollar y desplegar fácilmente este tipo de actividades de aprendizaje. Desde su creación, CAFCLA ha sido diseñado siguiendo las directrices establecidas por la Inteligencia Ambiental. Requisitos tales como la adaptación, la sensibilidad al contexto, la anticipación o el razonamiento han sido cubiertos por la aplicación de diferentes tecnologías de contextualización que permiten que el framework sea capaz de cubrir una amplia gama de escenarios de aprendizaje. Además, es necesario gestionar inteligentemente la comunicación y los datos para proporcionar un sistema capaz de anticipar situaciones mediante mecanismos de razonamiento. Los sistemas multiagente son la tecnología apropiada para soportar estas funciones. Por lo tanto, CAFCLA integra un sistema multiagente compuesto por diferentes agentes responsables de la coordinación y gestión de diferentes partes del sistema en función de sus funcionalidades. Además, CAFCLA presenta una forma innovadora de diseñar y desarrollar actividades de aprendizaje, teniendo en cuenta a todo el personal involucrado en el proceso y facilitando las tareas de las que cada uno es responsable.

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Chapter 12
CAFCLA:
A Framework to Design, Develop, and Deploy AmI-Based Collaborative Learning Applications

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ABSTRACT

Ambient Intelligence (AmI) promotes the integration of Information and Communication Technologies (ICT) in daily life in order to ease the execution of everyday tasks. In this sense, education becomes a field where AmI can improve the learning process by means of context-aware technologies. However, it is necessary to develop new tools that can be adapted to a wide range of technologies and application scenarios. Here is where Agent Technology can demonstrate its potential. This chapter presents CAFCLA, a multi-agent framework that allows developing learning applications based on the pedagogical CSCL (Computer-Supported Collaborative Learning) approach and the Ambient Intelligence paradigm. CAFCLA integrates different context-aware technologies so that learning applications designed, developed, and deployed upon it are dynamic, adaptive, and easy to use by users such as students and teachers.

1. INTRODUCTION

In recent years there has been a technological explosion that has flooded our society with a wide range of different devices (García, Tapia, Alonso, Rodríguez, & Corchado, 2011). Moreover, the processing and storage capacity of these devices, their user interfaces or their communication skills are improved day by day. Thanks to these advances, we are currently surrounded by technology that has changed our habits and customs (Jorrín-Abellán & Stake, 2009). All this has caused the apparition of new fields such as Ambient Intelligence, whose main objective is to simplify the use of technology to improve people's quality of life (Tapia, Abraham, Corchado, & Alonso, 2009).

Education is one of the areas in which Ambient Intelligence presents a greater potential as it pro-

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vides new ways of interaction and communication between individuals and technological systems (Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989). The usage of Information and Communication Technologies (ICT) has been present in educational innovations over recent years (Scardamalia, Bereiter, McLean, Swallow, & Woodruff, 1989), modernizing the traditional transmission of contents through electronic presentations, email or more complex learning platforms such as Moodle or LAMS and fostering collaboration between students (Collaborative Learning) (Gómez-Sánchez et al., 2009). Beside the use of those general-purpose tools in education, other tools that make more specific use of technology have appeared. This applies to those that make use of Context-awareness information and ubiquitous computing and communication, fundamental parts of Ambient Intelligence (Traynor, Xie, & Curran, 2010).

Mobile Learning has become the umbrella under which new ways of learning have emerged, including areas such as Mobile Computer Supported Collaborative Learning (MCSCL), based on traditional CSCL, Context-aware Pervasive Learning or, more recently, Location-Based Learning (Roschelle, 2003). There are several approaches proposed by the scientific community in these research areas which share a common element: the use of mobile devices and wireless communications (Roschelle, 2003).

The inclusion of context-awareness in educational scenarios and processes refers to Context-aware Learning (Laine & Joy, 2009), a particular area of application of Context-aware Computing (Dey, 2001). Moreover, the ability to characterize and customize the context that surrounds a learning situation at a certain time and place provides flexibility in the educational process. This way, learning does not only occur in classrooms, but also in a museum, park or any other place (Bruce, 2009), obtaining ubiquitous learning spaces. Thus, there is an extensive literature that addresses the problem of this kind of learning, highlighting those works that attempt to solve contextual information acquisition and providing data to users (Chen et al., 2007; Martín et al., 2010). The use and integration of different technologies and the approach to specific learning activities characterize these solutions. However, the complexity of understanding and use of the technology and solutions in the aforementioned works does not allow a wide use of them. In addition, the use of intelligent management techniques is another lack in the reviewed works. In this sense, the ability to operate in a distributed way, predict, adapt and anticipate the users' actions provides a dynamic personalization of the learning process that benefits and improves the acquisition of knowledge by students (Traynor, Xie, & Curran, 2010).

This paper presents a conceptual multi-agent framework aimed at designing, developing and deploying AmI-based educational scenarios. Teachers are able to characterize the context where the learning activity will occur through the creation of a world model in which locate data collectors (e.g., sensors), identify and characterize areas of interest (e.g., paintings in a museum), etc. Moreover, the collaboration between students and the customization of the information available is also provided and can be integrated in the activity design. The framework is supported by a multi-agent architecture that provides intelligence to the learning process by helping to manage the activity, all the communications involved, the context-awareness and the collaboration between students and teachers. In addition, developers and technicians benefit from the Application Programming Interface and the formal schemas provided by CAFCLA.

The following section describes the background and problem description related to the presented approach. Then, the main characteristics of CAFCLA are described: what kinds of activities are covered, how the context of the activity can be defined, who the users are, which activities are implemented by the framework, and how the multi-agent architecture and the context-aware technologies involved are. Later, the framework functioning is described. Finally, the conclusions and future work are depicted.

2. MOTIVATION

A growing interest in educational software, commonly known as e-learning, has appeared over recent years (Gómez-Sánchez et al., 2009). Among the wide range of existing educational software are CSCL (Computer Supported Collaborative Learning) applications (Dillenbourg, 1999). A collaborative learning system consists of a set of tools that facilitate the implementation, development and deployment of learning activities. Those activities allow different ways of interaction between the involved participants that activate learning mechanisms (Koschmann, 1996). CSCL has become an important research field within education that attracts different interests, from the purely educational to those focused on improving human-computer interaction (Gómez-Sánchez et al., 2009).

Mobile devices provide important benefits to education: mobility, communication skills including collection and provision of contextual information, as well as precise location anytime. Mobile Learning is defined as "the processes of coming to know through conversations across multiple contexts amongst people and personal interactive technologies" (Sharples, Taylor, & Vavoula, 2010). This definition implies two important ideas: first of them is that technology can be involved into the learning process; the second idea suggests that mobile learning emphasizes the communication between the involved people and their interaction with the context (Glahn & Börner, 2010). Based on the ability to interconnect devices we can assert that they can be useful to foster collaboration among students, that is, they can act as a tool that supports CSCL (Koschmann, 1996).

The use of mobile devices into a CSCL system is known as Mobile CSCL (MCSCL) (Zurita, Baloain, & Baytelman, 2008). The analysis of the literature allows us to identify several contributions that describe MCSCL-based systems. Among them we can find modifications of traditional learning management systems that are able to adapt usual utilities from e-learning platforms taking into account the mobile devices' requirements and specifications through their integration into Web Services (Trifonova & Ronchetti, 2006). Beyond adaptation of traditional e-learning platforms, multiple applications specifically developed to support CSCL using mobile devices have been described (Zurita, Baloain, & Baytelman, 2008). Such applications provide an easier way to improve ubiquitous collaboration or foster face-to-face activities (Zurita, Baloain, & Baytelman, 2008).

MCSCL systems are usually designed with a client-server architecture in which all participants join the same network. The introduction of MANETs (Mobile Ad-hoc NETworks) into collaborative learning environments with mobile devices is intended to relax this operational model (Vasiliou & Economides, 2007). Moreover, MANETs allow learners to work outside the classroom to enhance collaborative learning both indoor (e.g., museums) or outdoor (e.g., parks) spaces that present any didactic interest (Neyem, Ochoa, Pino, & Guerrero, 2005). New mobile devices are equipped with features that facilitate the acquisition of contextual information and location. Contextual information includes any data that can be used to characterize a person, place or object that is considered relevant to the interaction between users, between user and applications or systems, or even between systems and applications (Tapia, Abraham, Corchado, & Alonso, 2009). In addition to the relevant information that context provides, it is important to consider other parameters that relevantly affect this type of information, such as identification, time and location (Traynor, Xie, & Curran, 2010). The information exchange taking place between technology and users, in order to contextualize an environment in which learning takes place, and customize the content of the learning activity can be understood as collaboration. Thus, Context-aware Learning must take into account the interactions between people and the different technological components of the system in all its combinations.

2.1. Providing Context-Aware in Learning

Providing contextual information and fostering collaboration between students benefit the learning process (García, Tapia, Alonso, Rodríguez, & Corchado, 2011). Moreover the combination of Collaborative and Context-aware Learning naturally leads to thinking about ubiquitous learning spaces, characterized by "providing intuitive ways for identifying right collaborators, right contents and right services in the right place at the right time based on learners surrounding context such as where and when the learners are (time and space), what the learning resources and services available for the learners, and who are the learning collaborators that match the learners' needs" (Hwang, Yang, Tsai, & Yang, 2009).

A better understanding of environment through technology allows educators to customize the content provided to students. Similarly, technology facilitates the interaction with the environment and between students. This should be reached in a way as transparent and ubiquitous as possible. The technologies used for the collection of contextual information and for the communication between different devices are the cornerstone of the different works presented here. Literature about Context-aware Learning proposals has been deeply reviewed in this work. Some of the most representative works are classified in this paper, following technological criteria related to communications and data collection.

A first approach to provide contextual information is "tagging the context". Even though RFID (Radio Frequency IDentification) is the most spread technology (Blöckner, Danti, Forrai, Broll, & De Luca, 2009), there are other technologies such as NFC (Near Field Communication) or QR Codes (Quick Response Codes) (Tan et al., 2009) which are growing fast. As can be seen in the usage of Active RFID, both location and context-awareness are closely related: knowing precisely location of objects and people allows determining what is surrounding them and, consequently, characterizing the context in which they are involved. GPS (Global Positioning System) is the most used technology to provide location in Context-aware Learning (Driver et al., 2008; Padovitz et al., 2008). This location system provides a high accuracy level and is currently implemented in a wide range of smart phones and mobile devices. In those cases, the mobile device provides a position to the system. Those solutions are used in different scenarios such as route planning (Padovitz, Loke, & Zaslavsky, 2008) or student's scheduler management (Driver & Clarke, 2008). However, most of those works do not implement a specific case of use, but propose a general purpose model in which GPS technology is included to facilitate the provision of contextual data.

Furthermore, GPS technology does not work indoors because of the direct vision necessary between satellites and devices. However, indoor environments are very common in learning: museums, laboratories or the school are places where activities that require mobility can be developed. Trying to cover this lack, different location systems based on Active RFID (Blöckner, Danti, Forrai, Broll, & De Luca, 2009) or Wi-Fi (Martín, Peire, & Castro, 2010) are used. Both cases the performance of systems is similar: student's position is determined by the access point which is providing coverage in each moment. This type of approach has significant limitations when developing context-aware learning activities: the location accuracy is too poor. This situation presents an important problem when areas where context information is different are close (e.g., two paintings in a museum).

Changing the way of contextualizing the environment where the learning activity occurs, some tendencies propose the use of sensor networks (Martín, Peire, & Castro, 2010). A sensor is an electrical or mechanic device that measures a certain physical magnitude. In this case environmental characterizations are reduced to those data provided by the sensors (Chen, Yu, & Chen, 2007). In order to make the learning process more transparent to students, ad-hoc networks are considered to collect and transport data from sensors to remote points (Chen, Yu, & Chen, 2007). These networks facilitate the connection between devices anytime and anywhere without a previous infrastructure.

The review of the literature evidences some lacks in the Context-aware Learning systems proposed until now. Even some works try to combine different technologies to cover as much situations as possible (Martín, Peire, & Castro, 2010), most of them only cover specific learning situations, as those where tagging context with RFID/NFC (Tan et al., 2009) is necessary or those where learning occurs outdoors (Padovitz, Loke, & Zaslavsky, 2008). The combination of both situations is only addressed by M2learn (Martín, Peire, & Castro, 2010). However, this solution does not provide a precise and efficient location systems or the possibility to integrate wireless sensor networks, except for RFID systems.

2.2. AmI to Raise Collaboration, Management, and Usability

None of the solutions mentioned before takes into account Ambient Intelligence guidelines. The proposed solutions focus their work on the architectural description, framework developers or end-user applications whose designers have not taken into account how complex will be them for educators or students. Some aspects such as designing intuitive and attractive interfaces or abstracting end users from the complexity of technology, issues on which Ambient Intelligence pays special attention, are not taken into account. Thus, if these aspects are excluded from each solution's design process, the final result may be rejected by students and educators. For this reason, the design process must take into account, from the beginning, the opinion of all the interested parties (Gómez-Sánchez et al., 2009), that is, educators, designers and developers. This way is easier to accomplish with Ambient Intelligent issues related to user interfaces and usability of final applications.

Moreover, the works analyzed in this review do not include mechanisms for data or communication management. Ambient Intelligence emphasizes the transparency of technologies for users. In addition, technology is used to ease ordinary tasks or improve activities and the quality of life (Traynor, Xie, & Curran, 2010). In this sense, systems that combine different technologies do not facilitate mechanisms to change between them (e.g., different communication protocols) attending to the needs of a situation. Similarly, data have to be managed in an intelligent and efficient way. Most of the literature reviewed does not include this issue, using only standard data repositories that only consider persistency and consistency (García, Tapia, Alonso, Rodríguez, & Corchado, 2011). Functionalities like data redundancy to solve network failures help to make the system dynamic and benefit data accessibility with independence of the place and the moment.

In this sense, multi-agent systems are used in learning and collaborative learning applications for different purposes. Multi-agent architectures are commonly designed to adapt contextual information in context-aware learning systems (Yaghmaie & Bahreininejad, 2011), manage the performance of learning activities (Lu, Chang, Kinshuk, Huang, & Chen, 2011) or deploy mobile devices (Macarro, Pedrero, & Fraile, 2009). Although collaboration between agents is considered by those works, collaboration between students is not properly taken into account when these multi-agent systems are designed.

Even though it is well known that collaboration benefits the learning process (García, Tapia, Alonso, Rodríguez, & Corchado, 2011), collaboration between students is an issue not considered by many proposals (Chen, Yu, & Chen, 2007). Including mobile devices and wireless communication protocols in any learning design that requires mobility (as discussed in this paper) is nowadays necessary. Mobile devices easily connect each other so including collaboration between students is an easy task, increasing the variety of activities and improving the learning process.

Furthermore, this work is developed following Ambient Intelligence guidelines, such as personalization of the provided context or transparency and ease of use for teachers and users. Moreover, the inclusion of reasoning mechanisms facilitate the personalization of data provision or the communication management of these kinds of complex systems (García, Tapia, Alonso, Rodríguez, & Corchado, 2011).

3. FRAMEWORK OVERVIEW

CAFCLA (Context-Aware Framework for Collaborative Learning Applications) is a multi-agent framework focused on the design, development and deployment of collaborative learning applications that make use of contextual information. CAFCLA involves multiple users and characterizes each one according to their role in the design, development, deployment and implementation of a learning activity. Moreover, CAFCLA takes into consideration all aspects surrounding the whole learning process design. These aspects include the objectives or goals that students must reach, the contents of the learning activity, the teaching resources available, the physical or virtual spaces selected or the assessment and activity monitoring. All these aspects do not only involve the teacher, but there is also a technical component that must be undertaken by staff that sometimes do not present an education profile. More specifically, three different roles can be identified in the process of design and development of activities considered in this work.

First, there are the teachers (educational profile) who are responsible for the conceptual and contextual design of the activity. They guide the development of the activity and the content of it. Second, there are the software developers that design and develop the end user application and implement all the necessary infrastructure to carry out the activity (software oriented technical profile). Third, the process requires the participation of technical staff to deploy the hardware infrastructure needed for the activity (hardware oriented technical profile).

As any learning process needs students, this role is included into CAFCLA. Thus, there are four types of users defined in CAFCLA: teachers, developers, technicians and students. Each of them has different profiles and skills to access and manage the different functionalities of the framework. A brief description of each user's functions is depicted here:

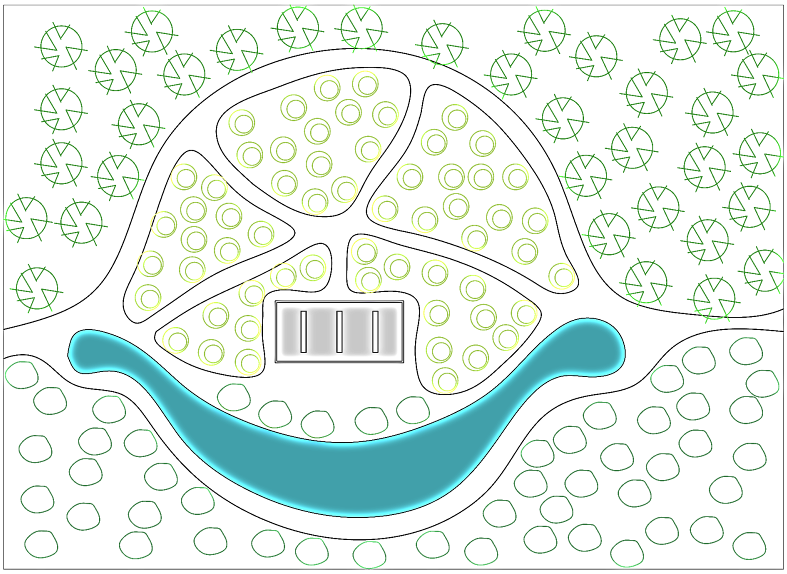
- **Teacher:** Responsible for designing the activity that will be deployed using CAFCLA. Some of the task that teachers carry out includes defining which students participate in the activity, what kind of activity is carried out, which collaborations between students are allowed, which areas and objects of interest are described in the activity, which are the objectives of the activity and which is the data that the system will store to be provided during the activity.
- **Developer:** Makes use of all the tools provided by CAFCLA (analysis and design, programming, etc.) to develop the application that students will use, according to the activity designed by teachers.

- **Technician:** Responsible for deploying the technology infrastructure needed to carry out the activity developed using CAFCLA, following the premises and recommendations set by the framework.
- **Student:** The participant who finally conducts the activity designed by the teacher. They can access the resources offered by the application through different devices selected for that purpose. In addition, they are able to collaborate between them to achieve the objectives of the activity. Their performance follows the rules set by the teacher at all times.

Once CAFCLA users have been defined, the way in which contextual information is organized is described. According to AmI premises, CAFCLA emphasizes on technological transparency and ease of use for both students and teachers. Contextual information is closely related to the environment where the activity takes place, so any place or item can provide relevant information to be used in the learning process. Thus, teachers are able to describe any place or item relevant to the activity regardless of size and location. In order to better structure contextual information, three description levels have been defined, so that the information can be provided with the granularity required by the activity.

- **Scenario:** The whole scenario where the activity takes place. It represents the physical space where the activity will be deployed. To better illustrate the explanation a botanical garden has been chosen to deploy a collaborative learning activity. This scenario consists of an outdoor enclosure where different species of trees, shrubs and flowers grow. Furthermore, in the center of the enclosure there is a greenhouse where multiple flower species grow (Figure 1). In this case the scenario is the botanical garden and it could be divided into two sub-environments: the first one that includes all the study to be performed

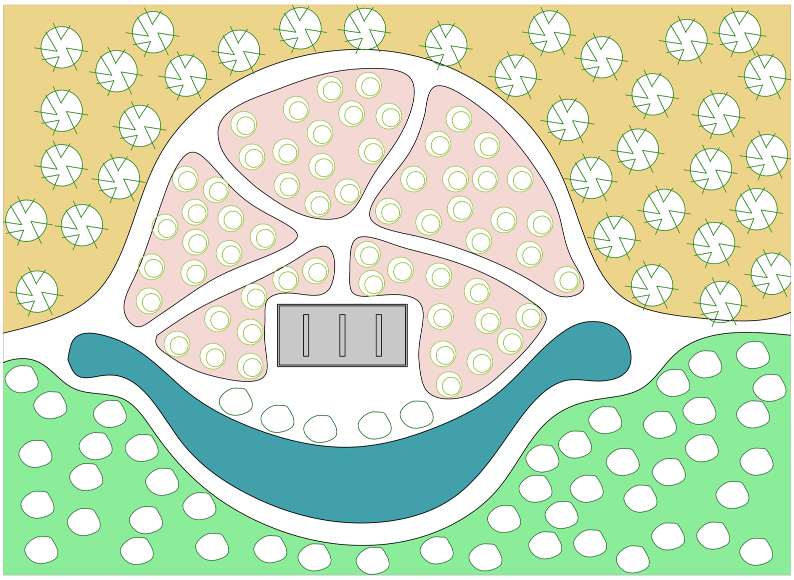
Figure 1. Botanical garden scenario and greenhouse in the middle



in the greenhouse (indoor plants), and the second, which would cover the rest of the botanical garden, including all the growth area of outdoor plants.

- **Area of Interest:** Different areas that determine spaces in which a relevant part of the activity will take place. These areas include a physical space where one or several goals of the activity should be reached. The teacher is responsible for identifying, locating and making relevant contextual characterization into them. The areas of interest provide contextual information to the students in the way that the design made by the teacher shows. Continuing the example of the botanical garden, in the external environment three different species of trees grow: pine, oak and poplar. In this case the teacher can create four areas of interest: three individual areas covering spaces where trees grow (marked in Figure 2 in brown for pines, pink for oaks, and green for poplars) and a fourth area which is the greenhouse. For each of them, the teacher defines the physical space that it delimits. It also includes a description of each area, based on the design of the activity, that is given to students.
- **Object of Interest:** in the same way that the environments in which the scenario is divided in different areas of interest, within these areas can be included several specific objects that are interesting to the learning activity. Teachers follow the same procedure as in previous cases, since they are responsible for identifying, locating and characterizing these objects. In the example of the botanical garden there may be multiple objects of interest within each of the areas of interest. For example, in the greenhouse grow a wide variety of flowers, and each kind may be an object of interest so teachers are able to identify, place and characterize each one into the greenhouse (Figure 3).

Figure 2. Areas of interest into the botanical garden scenario



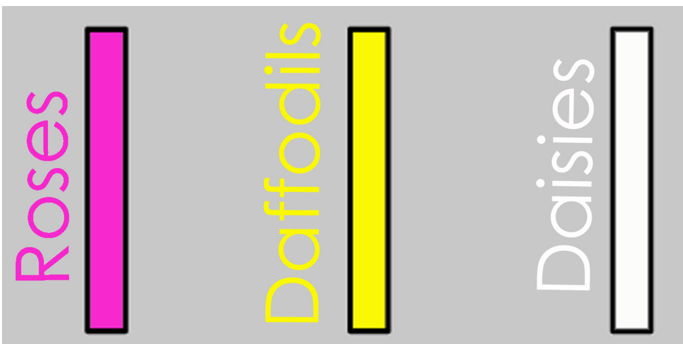
The activities that can be deployed using CAFCLA is another important part of the framework implementation. Different collaborative activities have been evaluated to be integrated by CAFCLA and three of them have been selected: “Treasure Hunting”, “Collaborative WebQuest” and “Jigsaw”. Different criteria have been taken into account to choose these activities. First of all, these activities can be deployed anywhere and anytime. Secondly, collaboration is possible to be included in all of them. Thirdly, the activities allow teachers to create a learning process that can be monitored and modified at all times. Fourthly, the participants of these activities can be divided into different groups. And finally, all of them can include different routes or physical paths to be followed by the students. However, CAFCLA is an open framework that is able to integrate any other activities that teachers may consider in the future.

Depending on the chosen collaborative activity, the teacher can add the necessary data to complete the learning process. More specifically, the requirements to be considered for each of the activities that are included are described as follows.

First activity implemented is a Treasure Hunt. In this activity the teacher can create working groups that are assigned to the corresponding students and determines which devices are used by each student’s group. Students that form a group are able to collaborate with each other at all times. Furthermore, the teacher can define different routes that students must follow to uncover clues and collect information. After setting the scenario, the areas of interest and the objects of interest, the teacher defines each route on the map, and indentifies which are the clues given to each group. Routes do not have to be composed of one only path, but may include branches that allow the division of tasks between the different students that are part of the group. The teacher can assign a path or more to a particular group and also may indicate which tracks are key, so that the students are required to complete a milestone to continue receiving information. Finally, the teacher defines a challenge or final question that must be completed or answered with the information received on each track, such as a questionnaire, a document or a presentation to be made.

Collaborative WebQuest is the second activity implemented. The process of defining and describing the scenario, the areas and the objects of interest, the users and the groups of students is common to all the activities. In this activity the teacher is able to design a battery of questions to be answered in each area of interest. Questions can be presented to be answered in a written way or as a test which offers different response options. These questionnaires can be tailored to each users’ level and several can be defined for the same area

Figure 3. Objects into the “Greenhouse” area of interest



or object of interest. In addition, the teacher can create a final questionnaire to be performed at a particular location (e.g., the classroom) which summarizes all questions regarding the questionnaires that have been made in the activity. Likewise, the teacher has the capacity to define different working groups formed by the number of students it may consider, assigning devices that each group or student uses. Likewise, the teacher indicates the questionnaires that each group must respond. The onset of the activity is performed for each group in the particular zone determined by the teacher through a first task in explanation of the activity.

The last implemented activity is a Jigsaw. As in the previous activities, the process of defining and describing the scenario, the areas and the objects of interest, the users and the groups of students is the first step to be completed. In this activity the teacher divides the activity into different subjects to study individually and then in different groups. First, the teacher assigns each student a specific topic in which will be "expert". Later, two different types of groups are formed: on the one hand by students who have been assigned with different topics (each group will consist of an expert in each of the different themes described) and on the other hand by "expert" students in the same topic. Similarly, the teacher determines which of the areas of interest that have been created belongs to each of the assigned topics. For the proper operation of the activity, the teacher indicates what documents will be generated at each of its stages: single phase, experts phase (collaboration among students working under the same topic) and group phase (collaboration among students working on different topics). The final result of the activity (e.g., a presentation) should be exposed by the group's leader, a role that is assigned by the teacher.

Moreover, CAFCLA integrates a set of technologies that enable the framework to provide all the functionalities that each level requires. Among them are wireless sensor networks, positioning systems and real-time wireless communication protocols that facilitate the transmission and reception of information between users and the environment. For managing the information, communication and collaboration in an intelligent way, CAFCLA also integrates a multi-agent system. From a technical devices standpoint, the teacher may decide to use different communication devices (e.g., smartphones, laptops, tablet PC, etc.) and associate each one to the students. The assignment can be one to one, one to many (i.e., a device assigned to several students to work in team with one machine) or many to one (i.e., a student can work with several devices based on the needs of the moment). Next section explores these technological features of the framework.

4. FRAMEWORK DESCRIPTION

CAFCLA is a framework aimed at designing, developing and deploying AmI-based educational scenarios, focusing on collaborative and context-aware activities. The framework integrates a set of wireless context-aware technologies and communication protocols (e.g., GPS, ZigBee, Wi-Fi, or GPRS/UMTS). Those technologies allow establishing collaborative activities based on Ambient Intelligence among students and teachers. In this sense, communication models vary dynamically depending on the activity; for example, following a client-server model to perform a data query or forming an ad-hoc network to gather contextual information. Thus, the contextual information is always available and may be modified every time.

As shown in Figure 4, CAFCLA has several interconnected layers that joined provide all the necessary functionalities offered by the framework. At the lowest level is the physical layer. This layer consists of all devices (such as tablet PC, smart-phones, laptops, etc.), sensors or any other physical element involved in the system. Above the physical layer the communication layer is placed. This layer includes all the communication protocols currently integrated in the framework: 3G/GPRS, Wi-Fi and ZigBee. Over the communication layer appears the context-aware layer. This layer integrates GPS, a ZigBee based real time locating system and different ZigBee based wireless sensor networks. Thus, the framework can provide contextual information at anytime and anywhere. The management layer is designed so that the context-aware layer and the communication layer can operate in an efficient, predictable and distributed way. This layer integrates a multi-agent system that provides with intelligence to the framework. As is discussed in more detail in the next section, the different actors manage available communications, the background data needed by the students or the proper schedule of learning activities. Finally, the application layer includes the API (Application Programming Interface) offered by CAFCLA to develop services or applications that make use of the remaining layers and will be used by educators to design, develop and deploy the learning activity that students will carry out.

Figure 5 shows how the communication takes place between the different components of CAFCLA. Any application developed with CAFCLA uses the API provided by the framework. Multiple choices of design, programming and implementation are offered by the framework to make the process easy and fast, as well as hide the technological complexity associated. This API provides all the functionality offered by the multi-agent system and context-aware technologies integrated into the framework. Moreover, the system also integrates a distributed database where developed data and services or applications are stored.

From now on, this paper defines the functionalities provided by the multi-agent architecture designed and the context-aware technologies involved, both integrated into CAFCLA.

Figure 4. CAFCLA layers diagram

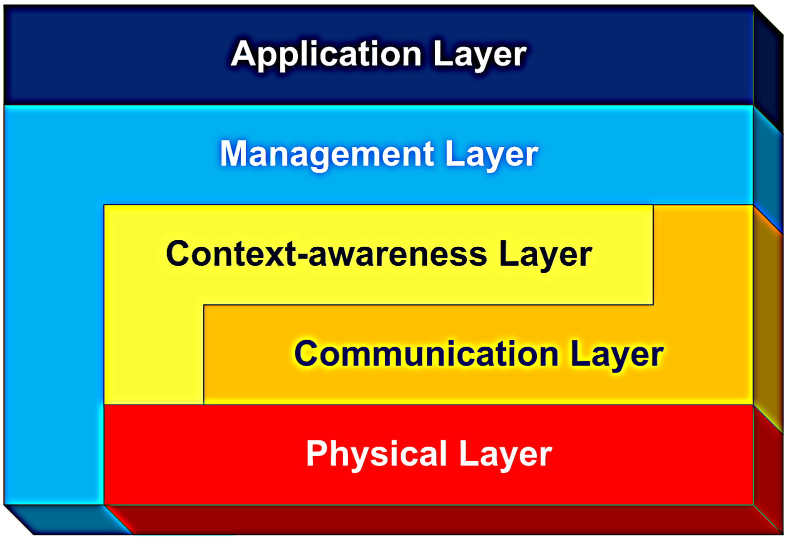
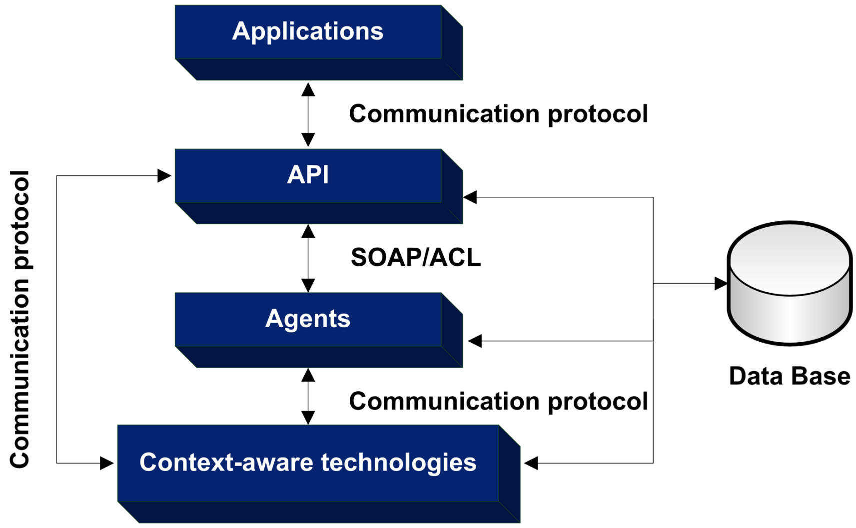


Figure 5. CAFCLA communication schema



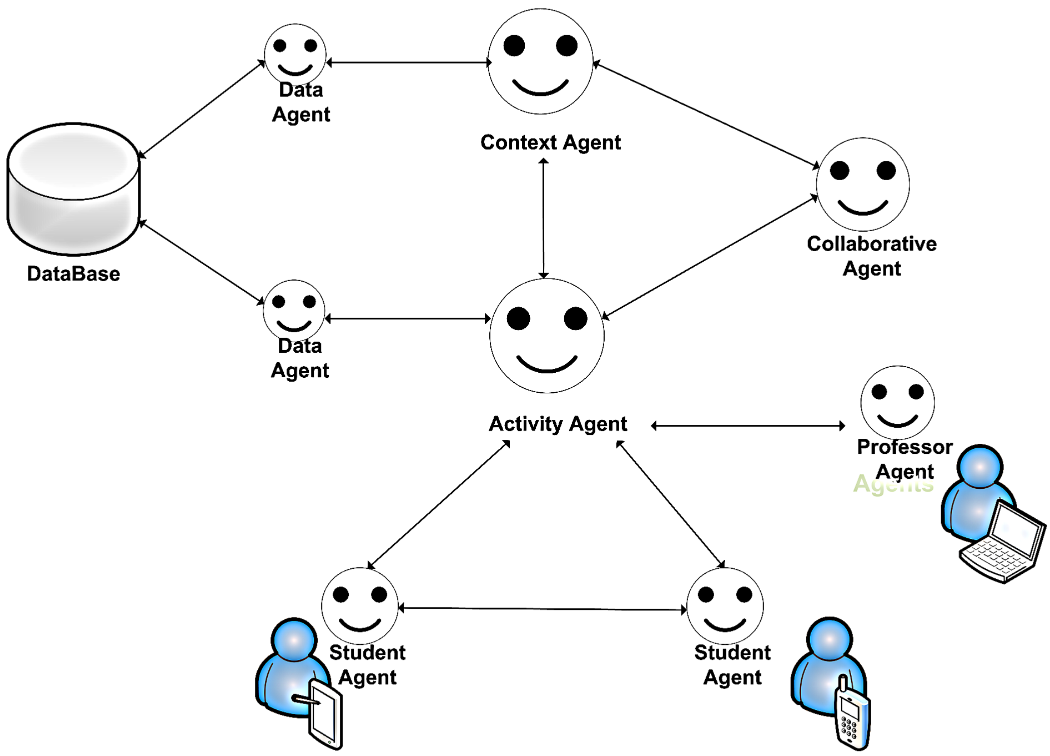
4.1. CAFCLA Multi-Agent Architecture

Ambient Intelligence guidelines require consideration into the design process of framework different features such as distributed way operation, adaptability or the ability to predict and anticipate the users' decisions (Tapia, Abraham, Corchado, & Alonso, 2009). These requirements, along with context-sensitive technologies, facilitate the dynamic customization of the learning process. Therefore, the acquisition of knowledge by students is improved by the use of richer scenarios (Li, Feng, Zhou, & Shi, 2009).

Agent Technology covers these features and provides information to the framework due to its pro-activity, mobility and ability to reason (Tapia, Abraham, Corchado, & Alonso, 2009). The multi-agent architecture is responsible for the management of the contextual information, the communications and the learning activity process. The system's functions include planning and reasoning mechanisms. These mechanisms are integrated into deliberative agents BDI (belief-desire-intention) (Tapia, Bajo, Sánchez, & Corchado, 2008). Figure 6 shows the different deliberative agents based on the BDI model included in CAFCLA. The role of each of them is as follows:

1. **StudentAgent:** This agent stores the student's profile and all the information related to the activity process concerning a particular user. Its operation depends on a learning plan designed by teachers that the student has to follow. Therefore, it is continuously connected to the ActivityAgent to further plan the learning activity. It allows the students to interact with the end-user application adapting its contents to the requirements of each student depending on the device used.
2. **ProfessorAgent:** This agent monitors the entire process of the activity: communicating with the ActivityAgent, creates, modifies and monitors the development of an activity, and creates or modifies a role of a student.

Figure 6. CAFCLA agents schema



It can be considered as an interface agent that provides the interaction between the teacher and the system to perform all the tasks mentioned before.

3. **ActivityAgent:** This agent coordinates and manages the whole activity. It receives all the information from the ProfessorAgent (profiles, contextual data, collaborations, etc.). As it communicates with the ContextAgent, it decides which information is provided to each student at a particular time and learning activity model.
4. **ContextAgent:** This agent is responsible for controlling all the information gathered by the sensor network. It also interacts with the DataAgent to update data from any physical service implemented by the sensor network and monitors the users location. The agent is responsible for coordinating and monitoring the wireless sensor network that collects environmental data and the Real Time Locating System that determines the position of each student within the scenario.
5. **DataAgent:** This agent maintains the integrity of data during the learning process. It decides what data should be stored at all times in order to have full availability during the activity process. It relates to the ActivityAgent which indicates what information should be stored or asks for a specific information. Moreover, this agent collects information from the Context-Agent, related to the position of the student or the wireless sensor network.

6. **CollaborativeAgent:** This agent monitors the entire process of the activity communicating with the ActivityAgent and with the ContextAgent. With the information received from the ContextAgent it can know where each student is at all times. The CollaborativeAgent combines this data with the available collaborations that gets from the ActivityAgent to suggest on real time new collaborations that can take place in the activity.

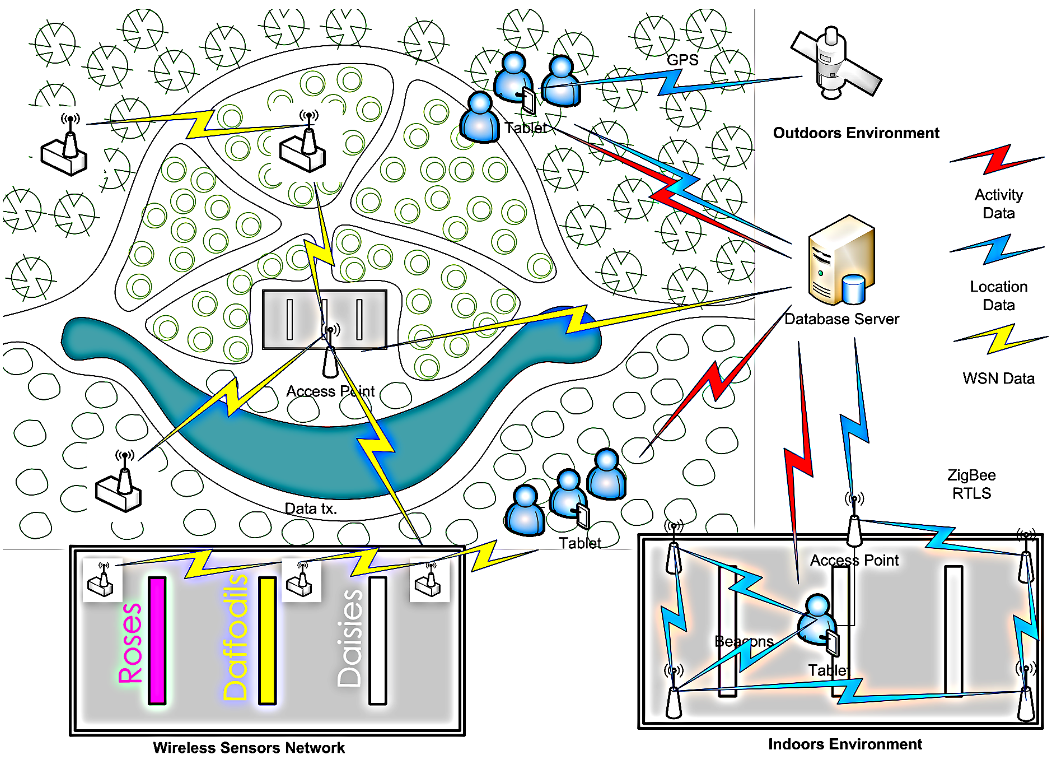
4.2. Context-Aware Technologies

Contextual information is useful in the educational process, facilitating the acquisition of new knowledge and training. The use of contextual information allows a better understanding of the environment surrounding the learning and student in a given time. With this knowledge, the information received by the students can be dynamically optimized, customized and adapted to their needs and requirements.

In order to provide contextual information for a wide range of learning scenarios, CAFCLA integrates three different context-aware technologies. More specifically, CAFCLA integrates location capabilities and a platform to deploy wireless sensor networks.

As shown in Figure 7, the main purpose of integrating these technologies is to cover the widest range of possible learning situations. Thus, the contextualization of any object or place will be facilitated by an outside location and / or a representative indoor plan of the place or places where the learning activity is taking place. Thus, the system knows when and what information should be provided to students based on knowledge of

Figure 7. CAFCLA working schema



their positions. Moreover, some contextualization can involve physical measurements, so CAFCLA offers the deployment of wireless sensor networks.

The functionalities of each of the context sensitive technologies integrated into the framework are described in the next sections.

4.2.1. Wireless Sensor Networks

The integration of a platform to deploy sensor networks in the framework is useful to cover situations in which the contextualization of an environment requires the collection of physical quantities.

CAFCLA integrates the n-Core platform (Nebusens, 2013), which allows the integration of multiple sensors (e.g., temperature, humidity or pressure). The sensors form a mesh network through which data are sent to the access point that sends information to the CAFCLA data server. There, information is stored and processed. Moreover, the sensors can be connected with other ZigBee devices (e.g., a laptop or Tablet PC) and share the data they collect through an ad-hoc connection established in that moment for that purpose. In this case, educators must decide the location of each sensor, the data type and how often data have to be collected and sent to CAFCLA data server. So CAFCLA records where each sensor is placed and implements the protocol to communicate with other sensors, users or data server.

Students will be able to receive data from sensors as they approach them by forming an ad-hoc network. Furthermore, the system is aware of which student has approached, so that the information provided can be customized or filtered.

4.2.2. Outdoor Real Time Locating System

The outdoor location system, specifically the GPS positioning system, is fully integrated into a wide range of mobile devices. For this reason, it is easy to integrate this technology into learning activities. This functionality requires a GPS device and maps platform like Google Maps or OpenStreetMap. CAFCLA integrates all the necessary logical background that may be available on the system and hides all the complexity inherent to the use of this technology to educators.

When designing an activity, teachers draw an area on the map. There, all the contextual information related to the area is placed, including different versions of information that are used in different activities or by different users. The system is capable of associating an area to one or more descriptions, so that personalization is easy to achieve. During the development of the activity, students use an integrated GPS device that transmits its position continuously. When the student enters into a characterized area or approaches an object of interest, he or she receives contextual information according to the design of the activity.

4.2.3. Indoor Real Time Locating System

CAFCLA also provides an indoor Real Time Locating System. The main reason to include this technology is the technical failure of the GPS system to determine the position of users indoors. The Real Time Locating System is based on n-Core Polaris (Nebusens, 2013), a system that uses the ZigBee wireless communication protocol and that determines the position of users with up to 1 meter accuracy.

The n-Core platform facilitates the localization process. The area where the tracking system is deployed is equipped with a set of beacons called n-Core Sirius D. These beacons are able to communicate and send information about the location of a student to the network access point. Each student has a ZigBee device called n-Core Sirius B that communicates with the beacons closest to his position. Beacons collect different types of signals sent by mobile devices and send them to the access point. The access point sends all information to the activity server where a location engine calculates the position of the student.

Teachers include any kind of information related to any area and students can receive the same way as it is done with the GPS tracking system. Thus, the complexity for educators is reduced and they only have to worry about what information is included in the system regardless of where they perform contextualization.

5. CAFCLA FUNCTIONING

To illustrate how CAFCLA works, this section describes the design process of an activity on the teacher's side. The same example scenario in which the activity takes place in previous sections, the botanical garden, has been chosen.

The implemented activity is a Collaborative WebQuest. Students must answer different questions by identifying different trees and flowers in the botanical garden. They should also collect information about temperature and humidity in different parts of the park, in order to relate each plant to certain specific physical conditions. In addition, students must work together to identify all plants. For this, different groups of students have access to different parts of the total set of information. Once the scenario is described, CAFCLA guides teachers on the design of the learning activity by following different steps.

In the first step, the teacher defines a collaborative activity to be designed and developed from a given list. Then, the teacher must complete a general description of the activity that all students will see. This description can be regarded as an available statement of the activity to be developed by the students. It indicates what the objectives of the activity are and which resources are available to carry it out.

After choosing the type of activity, the teacher has to include the students who will participate in it (see Figures 8 and 9). This activity will be performance by 18 students divided into six groups of three people each one. Each group has assigned with a Tablet PC and a ZigBee tag to be located.

After inclusion of the participants in the activity, the teacher can contextualize the scenario, the areas of interest and the objects of interest,

Figure 8. Adding users with CAFCLA

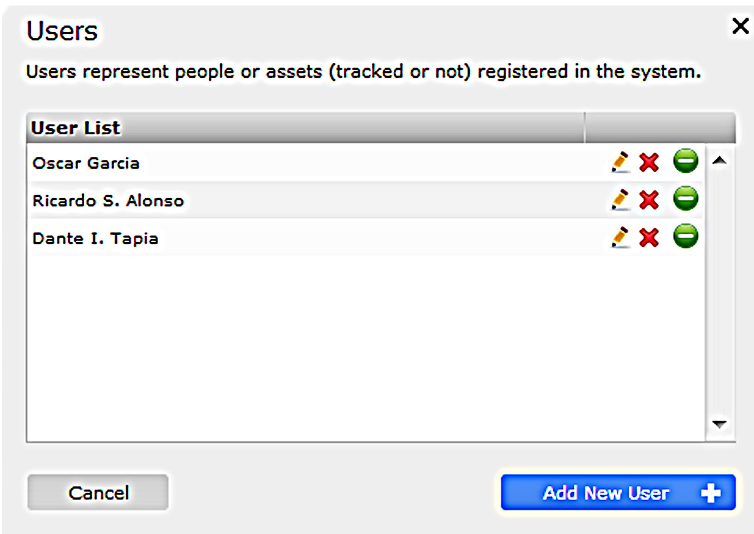
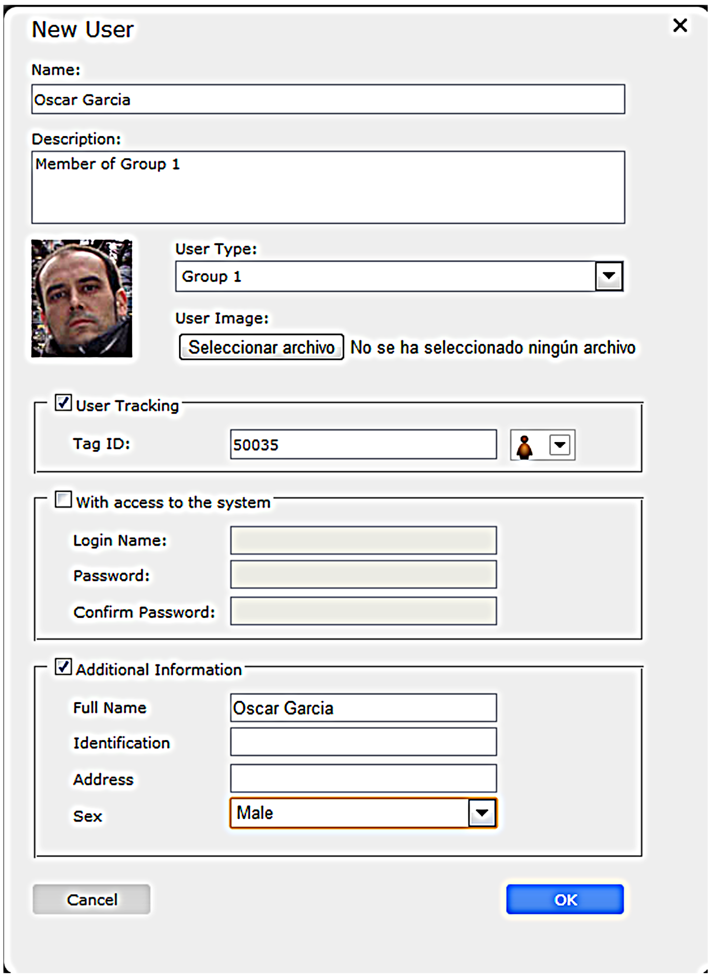


Figure 9. Registration form for a new user



so that each one offers and provides personalized information to each student. The scenario of the activity designed is the botanical garden. Then, it is divided into two areas of interest which are "Outdoor Plants" and "Indoor Plants". At the same time, each area of interest is divided into three objects of interest. "Outdoor Plants" contains the objects of interest: "Pines", "Oaks" and "Poplars". Meanwhile, the area of interest "Indoor Plants" consists of the next objects of interest: "Roses", "Daffodils" and "Daisies".

To make a success of contextualization, the teacher includes a plan of the scenario, in this case a map of the botanical garden. Then, he creates the two areas of interest to provide personalized information. In this case the teacher identifies the outdoor environment as "Outdoors Plants" area of interest and the greenhouse where flowers grow as "Indoors Plants" area of interest (see Figure 10).

To accomplish this task, the teacher determines if the working environment is indoors or outdoors. If the area of interest is indoors, CAFCLA asks to provide a more detailed plan of the environment and also asks to place it within the main map of the activity.

Each area and object is characterized by a distinctive name and different descriptions according to the different students' level. In this case the same level has been considered for all students. In the next step CAFCLA asks the teacher whether to place a sensor to collect data from the environment. In this case, six temperature sensors and six humidity sensors are placed throughout the botanical garden and the greenhouse. More specifically the teacher places one temperature sensor and one humidity sensor in the area where each object of interest is placed. The teacher simply selects the type of sensor he wants to integrate, places it on the plan of the activity and associates it to the object of interest.

At this point it becomes necessary to attach the contextual information and the user information to the learning process. Being a WebQuest activity, the teacher will have to identify, on first place, how many phases comprise the activity and what types of questionnaires will arise in each phase (test or written response). In this case the teacher designs an event of two phases: during the first phase the first three groups will work in the "Outdoors Plants" and the other three in "Plants Indoors". Each group receives information only from the objects of interest that are included into the area of interest assigned for this phase. The test will consist of questions specific to each object of interest that students receive upon entering the area occupied by each. The teacher must include this test and characterize them with the phase they will be provided and the groups that can receive the test.

Similarly, the teacher defines the second phase of the activity. In this case there will be a collaboration between groups from different areas of interest to share information. A group that in the first phase worked in "Outdoors Plants" collaborates with a group that worked in "Indoor Plants". So that, they share the answers of the tests completed in the first phase in order to complete a global writing questionnaire. The teacher must match these collaborations according to his criteria. In this phase the groups circulate freely throughout the scenario and they will receive generic information of each object of interest as help to complete the questionnaire. Moreover, they are free to send questions to the other group to solve doubts about the sharing information. From the standpoint of collaborative activity, the teacher has the ability to limit the collaborations between students, restricting the information offered to them and that students offer each other. Thus he is able to control the working groups, establishing in advance who should work with whom by the only selection of groups or by selecting potential partners for collaboration.

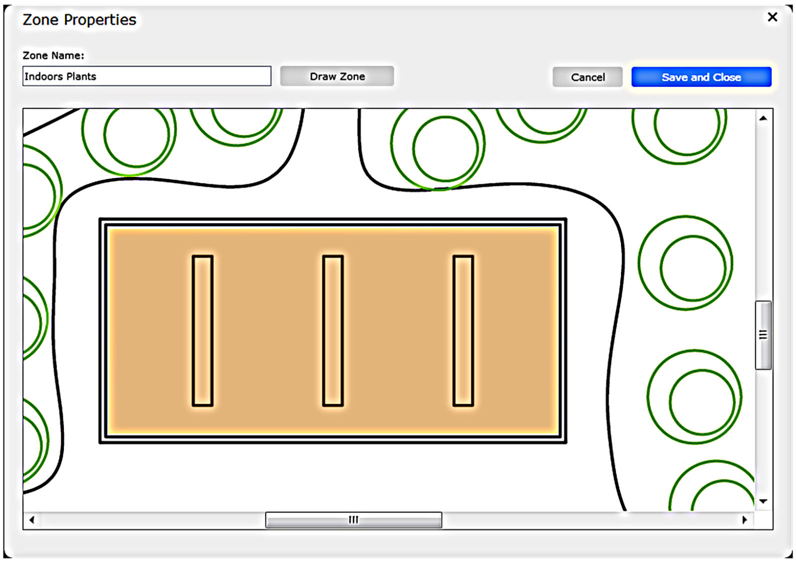
The main objective of the activity will be reached at the end of the second phase. At this moment each group must complete the writing questionnaire to be evaluated by the teacher.

Moreover, the monitoring and evaluation of the activity are also considered in CAFCLA. The teacher can access at any time to the state of the learning process. The teacher has the ability to change the groups based on the progress of the activity and even to modify the questionnaires or planning according to specific needs of the moment. In addition, the teacher can see, in retrospect, how the activity was performed, receiving information communication between students, reporting or responding to questionnaires, how they have carried out the routes or the rate of participation of each student in the full group activity.

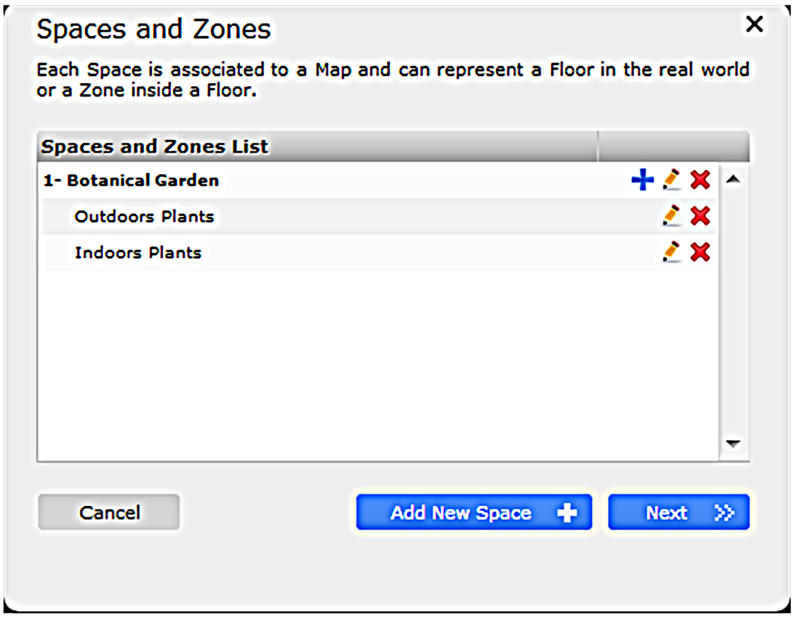
Once the teacher has included all the information of the activity, CAFCLA facilitates the development process by using the application

CAFCLA

Figure 10. (a) Defining "Indoors Plants" area of interest with CAFCLA; (b) areas of interest in the example activity



(a)



(b)

programming interface it offers. This API includes all the programming tools needed to develop applications designed through the use of CAFCLA. In addition, the development process is not only facilitated by the use of the API, but also the framework provides developers with a filtered set of programming functions and design diagrams to be used in each section. Thus, the developers can program the system according to the specification made by the teacher in a short period of time.

Finally, CAFCLA identifies the devices that are necessary to implement the activity and where they need to be placed. In addition, CAFCLA suggests the network topology and communication protocols that must be integrated in the activity. Furthermore, proposes how to implement CAFCLA storage and data management systems.

6. CONCLUSION AND FUTURE WORK

The use of Information and Communication Technology in the different areas has increased in recent years thanks to the emergence in society of mobile devices, easy access to currently existing technology and the many features they present, such as communication protocols and context-aware technologies. However, it is difficult to develop applications to squeeze all the potential offered by technology, especially when the main objective is the development of technological applications that are transparent to users, as is suggested by the paradigm of Ambient Intelligence

For this reason, and centered in the field of education, CAFCLA has been designed with the objective to design and develop a set of tools that provide a basis for designing, developing and implementing Ambient intelligence based collaborative learning activities that use contextual information. CAFCLA is a framework that integrates different context-aware technologies, such as Real Time Locating Systems, and several communication protocols that abstract educators and developers of context-aware collaborative learning activities from the complexity of the use of different technologies simultaneously. In this case, CAFCLA focuses on provide a set of tools and methods to teachers, developers and technical staff in order to easily design, develop and deploy this type of learning activities.

Since its inception, CAFCLA has been designed following the guidelines established by Ambient Intelligence. Requirements such as adaptation, context awareness, anticipation or reasoning have been covered by the implementation of different context-aware technologies that allow the framework to be able to cover a wide range of learning scenarios. Moreover, it is necessary to manage communication and data intelligently to provide a system capable of anticipating situations through reasoning mechanisms. Multi-agent systems are presented as an appropriate technology to support these functions. Therefore, CAFCLA integrates a multi-agent system composed of different agents responsible for the coordination and management of different parts of the system depending on their roles. Moreover, CAFCLA presents an innovative way to design and develop learning activities, taking into account all staff involved in the process, facilitating the tasks each one is responsible.

Future work includes the design, development and deployment of a specific use case where all the features of CAFCLA are implemented. This work will be developed by different teachers and developers in order to compare the results reached by all of them and evaluate the framework in different real scenarios. So that, all the features implemented by CAFCLA will be evaluated and improved thanks to the feedback of final users.

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KEY TERMS AND DEFINITIONS

Adaptive Learning: Educational method in which contents are adapted, using computers or other interactive devices, to students' needs.

Agent Technology: Artificial intelligence software that learns and automate processes.

Ambient Intelligence: Considered as a vision of the future in which electronic environment will be sensitive and responsible to people's needs.

Computer Supported Collaborative Learning: Pedagogical vision in which interaction between students through computers or interactive devices is the base of the learning.

Context-Aware Learning: Educational method in which contents are adapted to the environment in which the learning process is taking place.

Location-Based Learning: Educational method in which contents are adapted the location in which the learning process is taking place.

Ubiquitous Computing: Computer science branch wherein computing devices are everywhere.

5.5. Energy efficiency in public buildings through context-aware social computing

El desafío de promover cambios de comportamiento en los usuarios que conduzcan al ahorro de energía en edificios públicos se ha convertido en una tarea compleja que requiere la participación de múltiples tecnologías. Las redes inalámbricas de sensores tienen un gran potencial para el desarrollo de herramientas, como los juegos serios, que fomenten la adquisición de buenos hábitos energéticos y saludables entre los usuarios en el entorno de trabajo. Este artículo presenta el desarrollo de un juego serio utilizando CAFCLA, un framework que permite integrar múltiples tecnologías que brindan tanto información contextual como Computación Social. El desarrollo del juego ha demostrado que los datos proporcionados por las redes de sensores alientan a los usuarios a reducir el consumo de energía en su lugar de trabajo y que las interacciones sociales y la competitividad permiten acelerar el logro de buenos resultados y los cambios de hábitos que favorecen el ahorro energético.

Objetivos
Los objetivos perseguidos en esta publicación son los siguientes:

- Diseñar y desarrollar un juego serio bajo el uso del framework de aprendizaje colaborativo CAFCLA.
- Fomentar el ahorro energético y la adquisición de buenos hábitos en los usuarios (trabajadores) de un edificio público.
- Fomentar el aprendizaje colaborativo y la concienciación en el ahorro energético.
- Utilizar técnicas de Computación Social para fomentar la colaboración entre los usuarios del juego.
- Dotar de inteligencia al sistema mediante el uso de Organizaciones Virtuales de agentes.

Resultados
Este artículo presenta un juego serio basado en el paradigma de la Computación Social que integra tecnologías avanzadas a través del framework CAFCLA, incluyendo redes inalámbricas de sensores y un sistema de localización en tiempo real. Además, el juego integra Organizaciones Virtuales de agentes para crear una máquina social que personaliza recomendaciones para los usuarios. Esta integración permite resolver los problemas de interacción hombre-máquina y de sensibilidad contextual, logrando el objetivo principal del juego: que los usuarios adquieran buenos hábitos de ahorro de energético en edificios públicos y en el entorno de trabajo.

El juego ha sido desarrollado en uno de los laboratorios del grupo de investigación BISITE y, en comparación con otros juegos similares, podemos afirmar que el uso del framework proporcionado ofrece un gran potencial para el desarrollo de sistemas que pretenden promover un cambio de comportamiento en los hábitos de consumo de energía de los usuarios. El caso de estudio mostró que las interacciones sociales fomentan el crecimiento del interés en mejorar el rendimiento individual a través de la competencia entre los jugadores. Además, se fomentó la adquisición de buenos hábitos energéticos para beneficiar al grupo en lugares, como el entorno de trabajo, donde la consciencia del consumo de energía es a menudo nulo.

Por último, es importante señalar que la flexibilidad del framework CAFCLA es un valor añadido en comparación con otras soluciones. Esto se debe a que la integración de múltiples tecnologías y protocolos de comunicación puede mejorar sustancialmente la sensibilidad al contexto,

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Energy Efficiency in Public Buildings through Context-Aware Social Computing

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Abstract: The challenge of promoting behavioral changes in users that leads to energy savings in public buildings has become a complex task requiring the involvement of multiple technologies. Wireless sensor networks have a great potential for the development of tools, such as serious games, that encourage acquiring good energy and healthy habits among users in the workplace. This paper presents the development of a serious game using CAFCLA, a framework that allows for integrating multiple technologies, which provide both context-awareness and social computing. Game development has shown that the data provided by sensor networks encourage users to reduce energy consumption in their workplace and that social interactions and competitiveness allow for accelerating the achievement of good results and behavioral changes that favor energy savings.

Keywords: behavioral change; serious games; context-awareness; collaborative learning; energy efficiency; social computing; virtual organizations

1. Introduction

In the last several years, energy efficiency has become a capital policy for many countries around the world. It is widely recognized as the most cost-effective and readily available means of addressing numerous energy-related issues, including energy security, the social and economic impacts of high energy prices, and concerns about climate change [1]. As a consequence, there have been many efforts to develop and deploy hardware solutions (smart meters, smart plugs, smart sensors, etc.) and sophisticated control structures to measure and control energy consumption in grids, buildings and households, and these solutions have been proved to be technologically affordable and sustainable [2,3].

One of the most important problems to solve, both technically and socially, is energy consumption in public spaces and work environments. Within these environments, the building sector plays a crucial role as far as energy consumption is concerned, thus efforts and resources are used in making them more efficient [4]. Energy waste in these areas is quite high due to several reasons. On the one hand, the implementation of technological solutions that enable efficient energy use is not spread out among old buildings or, at least, among those above a certain age. On the other hand, users' comfort level is very difficult to model because of the disparity of requirements among each user, making it difficult to deploy automatic energy management systems in buildings [5]. However, above these and other reasons, the most important issue that affects the misuse of energy in public buildings is the users' behaviour, which generally wastes these resources carelessly (do not turn off lights, leave monitors or PC working all night, make needless use of lifts, etc.), largely because they have no direct awareness of the generated energy bill [6].

Sensor networks have been postulated, by their own nature, as an optimal technology for the fulfilment of efficient energy use in public buildings [7]: some of the proposed solutions use these networks to determine what enhancements are needed when improving the air conditioning in building climate [8]; other systems use presence sensors and timers to manage lighting; techniques based on the analysis of consumption of devices through smart meters are commonly used to give feedback and educate users [9]; finally, other works go further and develop intelligent control systems to act on resources, such as the HVAC (Heating, Ventilation and Air Conditioning) [9], or consider the integration of automation platforms [10]. However, due to numerous reasons, the results are far from expected: modelling, data analysis or automation are sometimes inefficient, intelligent systems do not usually take into account users' requirements and, the most important issue, not all of them influence a sustained change in users' behaviour.

Most of the abovementioned methods require users' wilfulness to analyse information and change their habits in order to reduce consumption [3]. To improve this aspect, it is necessary to find mechanisms that encourage and educate users on the efficient use of energy, produce greater energy savings through user loyalty [11]. In this sense, serious games have great potential because they are designed to attractively educate and promote changes in the behaviour of its participants [3,12]. Users enjoy, have fun and interact among them while gaining awareness of the problem to be solved [13]. Offering tangible incentives enables more effective learning of the habits sought. Furthermore, the development of these games over extended periods of time can reinforce the objectives achieved, so that users acquire behavioural changes gradually and transparently over time [13]. Until now, several serious games have been developed in combination with sensor networks such as IBM CityOne Game, which proposes real problems related to the environment and energy saving that users have to solve [13]; EnergyLife, which provides awareness of the consumption of electrical devices through sensor networks and awards users with points if this awareness improves with time [14]; Power Explorer, which also works with data from sensors to raise young people's awareness with regards to energy consumption [15]; or Energy Chickens, where the health of a virtual chicken is reflected by the user's energy savings when using some selected devices [3].

The development of serious games imposes an interesting challenge since they have to succeed in improving motivation, encouraging participation and enhancing the learning process. To address this challenge, Context-aware Learning is presented as an alternative with high interest because: by collecting real time data, it obtains the characteristics of the environment in which the game is taking place; it provides knowledge on the position and status of both objects and people; and, more importantly, it enables the customization of the game content depending on the needs of each user and their surrounding environment [16]. Context-aware Learning systems use the information gathered from the environment to enhance users' learning and behavioural change [17]. Context-aware systems make use of Wireless Sensor Networks (WSNs) and Real Time Locating Systems (RTLS) to collect information that enables monitoring, replicating or interacting with the environment where the game is taking place [18]. WSN and RTLS provide dynamic, efficient and flexible infrastructures that collect contextual data regardless of the chosen location [19].

Despite all the examples mentioned above, the combination of sensor networks with serious games has not obtained satisfactory results so far. Firstly, they have not reached high levels of loyalty, and, secondly, results that would prove a substantial change in the behaviour of participants have not been achieved yet. It is therefore necessary to provide custom tools that take into account the habits, preferences, ambitions and interactions of people that can be sustained over time. In this paper, the implementation of social computing by means of virtual organizations of agents is proposed as the best alternative to cover all of these needs. This approach requires the use of mechanisms that connect multiple devices and manage the information collected intelligently [20]; it allows a more efficient management of the information collected by hardware resources; it enables higher levels of personalization in the services provided to users that derive from sustained and efficient actions over time; it facilitates the administration and development of the game; and it provides the necessary background to support the design, development and deployment of systems in which the communication and management of WSNs require advanced competences [20].

The aim of the work presented in this paper is to provide a new framework for the development of context-aware serious games that spark a behavioural change towards more energy efficient habits. The development of the framework is carried out using CAFCLA (Context-Aware Framework for Collaborative Learning Applications) as a basis for its technical and social features implementation [21]. The social computing perspective has been taken into account when designing the framework, permitting the use of social and contextual information. The contextual information required is gathered through the deployment of a WSN that facilitates the acquisition of data related to the energy consumption from different aspects (temperature, luminosity), the presence of users in certain places or the efficient use of electronic devices and HVAC systems. In addition, the RTLS permits determining what behavioural habits users follow and gives guidelines on how to improve these habits in their work and transits. A virtual organization of agents supports the social machine, and this gives intelligence to the game and enables and enhances the learning process [22,23], updating contextual information, monitoring users' actions, providing information to players or facilitating the deployment, configuration and communication of the WSN and RTLS deployed. The framework has been assessed through an experimental implementation of a serious game, which intends to improve users' habits with regards to efficient energy use in a public building. The main innovations presented here are:

- the use of WSN and RTLS in a public building, to deploy an individual and at the same time, collective game between users;
- the management of this game through the CAFCLA framework and a virtual organization of agents, to improve game development and deployment, and the integration of technologies; and;
- the use of these technologies within the paradigm of social computing, in order to enable higher customization and collective interaction.

The rest of the paper is structured as follows: Section 2 describes the context surrounding the work presented, including research efforts to: motivate behavioural change of consumers, design serious games for energy efficiency, apply context-awareness for energy savings in buildings, propose context-aware learning tools, and develop social computing machines to deploy this sort of games. Section 3 depicts the deployed system that creates the serious game, including a comprehensive description of both the framework and each of the components conveying the different layers. Section 4 details the experiment and discusses the results obtained through an empirical implementation in a real scenario. Finally, Section 5 exposes the main conclusions that have emerged from the research and experimentation.

2. Previous Works

The work presented hereafter inquires into the process of obtaining a more efficient use of energy and the users' behavioural change necessary to obtain it. To accomplish this issue, the section we present addresses previous works on this topic. Furthermore, in the analysis of the state-of-the-art, different solutions that make use of serious games are analysed. Context-aware and energy saving in buildings are depicted in order to identify solutions and tendencies within this field. More specifically, our work emphasizes the benefits of context-aware learning, an effective way of changing user behaviour, paying particular attention to the sensor infrastructure that has to be deployed in order to obtain an operative framework. Finally, any system must be properly managed so, to this end, social computing and virtual organizations of agents are presented as an alternative that meets all of the requirements sought by our system.

2.1. Behavioural Change for Energy Efficiency

There are many studies that support the theory of technical implementations being more effective if accompanied by a change in the users' behaviour, and there are even trends that give more value to the change of consumption practices than to technical implementation [24]. Therefore, it is necessary to model the behaviour of users to determine what the users do, where they do it and why they do it [25]. The design of models that promote behavioural change differs, depending on whether it is for domestic or non-domestic users. While home users have a direct contact with energy costs, the policies implemented in the non-domestic sector are made at the organizational level. Consequently, they lack a direct relationship with the behaviour, habits and benefits for the users, workers, or other stakeholders. For this reason, motivating such users to acquire good energy saving habits is an arduous task that requires a firm commitment on the part of the corporations and has to promote the use of attractive tools that support and reinforce the acquisition of these habits [26].

The direct relationship between the users and the expenses related to energy consumption in their homes has made this area the focus of research [27]. Among the proposed solutions within households are those based on providing feedback to users on their consumption by using advanced metering infrastructures, such as smart meters [28], displays reporting real-time consumption [29] or even recommendations on the use of more efficient appliances [30]. However, the high penetration of Information and Communication Technologies (ICT) in the society has facilitated the development of other solutions that take into account useful social information for users to encourage behavioural change among users [31]. These solutions include disciplines such as media, entertainment or gaming [12].

Despite these efforts, research and proposed solutions to promote behavioural change in public buildings and offices have not yet been deeply addressed [32], although many studies show that it is feasible to reduce energy demand in office by changing user habits, behaviours and lifestyle [33,34]. More specifically, real-time monitoring of energy consumption, feedback to users and behavioural change can affect up to 40% of the whole energy consumption in a public building [34]. Some of the proposals that have been made so far have extrapolated the solutions used in homes to offices, such as the use of smart meters [33] or the efficient management of HVAC systems [34]. However, promoting behavioural change in users requires that they are aware of the benefits of an efficient energy use [35], as well as the efficient use of the most demanded resources, such as MELs (Miscellaneous Electric Loads, including PC, scanners, printers, etc.) [36], which consume more than 25% of energy in offices [36]. Much of the strategies that resolve this issue are based on providing awareness among users in different ways: through interventions that promote their sustainable use [37], through interactive posters and motivation of users [38] or by giving feedback via email or other communication channels [36].

The work described in this paper aims to cover existing gaps in these incentive methods through a more attractive use of the technology. Concretely, it develops games that help users to learn good habits that favour saving energy at the office. The following subsection deals with the use of serious games as a tool for behavioural change that promotes energy efficiency.

2.2. Serious Games

As it is widely recognized, games are usually related to entertainment and, although they have always been applied in the educational processes, the growth and the implantation of the ICT have allowed them to become more popular. Serious games have a specific purpose related to learning, understanding or social impact, addressing both cognitive and affective dimensions by the application of game design, dynamics and concepts that stimulate and make more attractive the interaction of the student with the learning process.

Serious games are a broad trend in which traditional mechanisms of games are used in multiple environments such as public policies [39,40], defense [41,42], business management [43,44], healthcare [45,46], education [47,48] or energy saving [49–51], among others [52]. The main objective of these games is to teach, paying special attention to the educational purpose beyond entertainment, but not neglecting it. In this way, games allow users to acquire skills through play-based activities by using their inherent playfulness and interactive characteristics. They also facilitate the motivation, training and engagement of participants, as well as their learning process by improving the performance of a specific objective through the acquisition of new knowledge and skills [53,54].

Serious games have the optimal characteristics that can influence user behaviour to be more energy efficient in public or working environments [43]. They have been used in different areas to promote this change [55,56]. One of the main reasons for their use is that games allow higher levels of engagement and stimulate innovation, and the use of short cycles feedback favours this change, as well as making well-defined rules or defining achievable short-term goals.

Various approaches to serious games in the energy sector are being piloted or commercially deployed, each adopting differing gamification techniques and having different key objectives [3,49–51]. In [3], the authors develop a serious game to save energy and change behaviour in an office environment, saving 13% in energy consumption, but the behaviour change does not persist in time. In [12], the researchers present a social game to promote energy saving behaviour by giving information to the consumers through a game, but results show a small drop in the use of energy (around 2%). A common factor is their use of granular and real-time energy data, which allows them to provide instantaneous feedback. Moreover, most of these solutions are based on the awareness given to users in the attempt of raising and enhancing this awareness. However, the implementation of serious games in office environments is hardly used and is mostly based on providing awareness of energy consumption and promoting energy saving [3].

Despite the multiple solutions and researches that have been analysed, the exploitation of ICT within this field can be performed. One of the main weaknesses found is related to the use of WSNs when designing and deploying serious games for energy efficiency. While the technology used is practically based on obtaining consumption, mostly from smart meters, the WSNs offer a great potential to collect other kinds of environmental data that could create richer activities from the parameters on user behaviour obtained during the game. The following subsections outline the importance of context-awareness and energy saving in buildings, and, after that, the contextual information in the learning process focusing on its benefits.

2.3. Context-Aware and Energy Saving in Buildings

As mentioned in previous sections, real-time monitoring of energy consumption, among other factors, can affect up to 40% of consumption in buildings [34]. In this sense, context-awareness systems become the ideal technology to obtain real-time environmental information from the locations to be characterized and where energy savings are encouraged [10].

Throughout the literature, multiple works have been presented in order to optimize energy efficiency in buildings by using context-aware technologies [32–34,57–61]. The design and deployment of context-aware systems allow for determining which factors influence the energy consumption at any time, including the use of devices (open window, light on, open blinds, etc.) [32–34,57], environmental conditions (temperature, humidity, lighting, etc.) [57–59] or the users' location (home, work, market, etc.) [60,61].

Among the works focused on providing contextual information to facilitate energy savings, Han et al. propose a semantic service that allows for integrating multiple sensors [58]. Their main objective is to favour the automation of tasks in buildings and thus improve the energy consumption. Kamienski et al. recognize the difficulty of integrating contextual technologies in real environments [59]. To solve this problem, they have designed IMPReSS, a project based on the rapid integration of IoT (Internet of the Things) technologies but that is still in the implementation phase. Kamilaris et al. considers that monitoring of electricity consumption is highly important in buildings. They combine it with the integration of environmental sensors, device profiles and occupancy information in order to develop a richer source of information and more potential data to be used [34].

Moreover, there are other works in which a more precise and concrete contextualization is done. Thomas et al. integrate sensors to measure luminosity, temperature, doors and blinds status, etc., as well as a location system through movement sensors [57]. The system presented facilitates energy saving thanks to the execution of rules based on registered behaviours and activity awareness. Other studies present occupancy identification and locations systems as the newest trends in this kind of solutions. Indoor location via RFID+IR (Radio Frequency Identification + InfraRed) systems [60] or those based in BLE (Bluetooth Low Energy) [61], improve energy efficiency by automating some tasks or by customizing services [61].

Despite of all the above, there is a lack of solutions that address the problem from a global point of view and that offer flexible and adaptable solutions to a large number of use cases, abstracting the underlying technology from problem solving, as it has been developed in this paper.

2.4. Context-Aware Learning

Context-aware Learning arises from the inclusion of context-awareness in the learning process [62,63]. Thus, the educational process takes advantage of the flexibility provided by the use of real-time environmental information within the process [64]. Moreover, the use of technologies that allow for obtaining contextual information, such as WSN or RTLS, enriches the learning process [64].

Serious games benefit from the inclusion of contextual and location data for their design and development [65,66]. From this point of view, sensor networks make it easier to obtain an accurate "energy picture" of the environment in which the game is played [8–10]. At the same time, sensors allow for acting automatically on the environment once the parameters of user behaviour are determined. In addition, the ability to locate users in real time allows for launching challenges that promote and enhance both energy saving and the acquisition of good habits. In [8], sensors are used to acquire data that permits modeling a building in terms of energy consumption and use this information to improve its use. In [9], temperature and humidity sensors collect data to improve the use of the HVAC system, achieving a more comfortable working or home environment. In [10], a system helps designers to select the best parameters to control energy consumption, getting up to 23% energy savings in a real scenario.

Many games developed for encouraging efficient energy usage do not consider the use of sensor networks and real-time location of users to enrich the learning process. Similarly, it is unusual to find solutions designed for the workplace, so the immersion of wireless sensor networks in these environments to promote good energy habits seems very productive. The solutions in the aforementioned research integrate different technologies to meet the objectives of a specific game. Moreover, there is no generalization in the proposals, so they cannot be used for any purpose other than the one defined by their authors. Finally, the use of intelligent management techniques is not taken into account in the researches; these techniques improve the game and the behavioural change through prediction, adaptation and anticipation of users' actions.

The next subsection introduces the social computing paradigm and justifies the added value that it offers to the process of behavior change sought in the research described in this paper.

2.5. Social Computing

Recent tendencies have led to the social computing paradigm for designing social systems that helps us build sociotechnical tools where humans and machines collaborate to resolve social problems [67,68]. These tools have a high level of complexity and require the use of artificial intelligence to manage artificial societies; however, they have the capacities needed to provide effective collaboration between humans and machines [68]. Virtual organizations of agents are particularly well suited as support for the development of these systems [69]. They enable the description of structural compositions and functional behaviour, and the inclusion of normative regulations for controlling agent behaviour, for the dynamic entry/exit of components and for the dynamic formation of agent groups [70].

The social computing paradigm aims to create social entities managed both by technology and social processes known as Social Machines. These entities allow systems to generate recommendations to users, such as the social machine developed by Amazon [71], to perform a task through the collaboration of a human and a machine, as it is found in the CAPTCHA (Completely Automated

Public Turing test to tell Computers and Humans Apart) system to authenticate users [72], or to predict social dynamics from behaviour data, as it is done by Twitter [73].

At the same time, social networks have become one of the most used Internet activities. Opinions on products, services, etc. posted in social networks increasingly impact the decision making process for purchases or even choosing a service. It is also known that social networks enhance engagement in activities or games. Currently, there are many initiatives to engage people in behavioural change using known social networks such as Facebook or Twitter. There is a number of proposals that address the problem of behavioural change for energy efficiency by using serious games through social networks [38,40]. However, human–machine interactions are not deeply addressed in these solutions leaving aside—for example, contextual information that may be useful in the field of our focus. Moreover, these proposals do not offer working infrastructures that allow for integrating different technologies, various communication protocols, diverse ways of promoting social relations, or the intelligence for managing the system based on the needs of the game.

In the remainder of this paper, a framework is proposed based on social computing and context-awareness that enables us to create learning scenarios, such as serious games, which encourage and enhance a change of behavior in consumers so that they use energy more efficiently in their workplace.

3. System Overview

This section addresses all the issues related to the deployment of a serious game in a way that encourages users to use resources efficiently and manages to change their habits in an office environment. The work depicted here uses the framework proposed previously CAFCLA (Context-Aware Framework for Collaborative Learning Activities) [21], focused on collaborative learning through the use of contextual information.

3.1. Background

As mentioned above, CAFCLA is a framework whose main purpose is the integration of different technological resources to make the design and development of learning activities easier, based on contextual information and social computing. Within this context, CAFCLA allows its users to have multiple resources offered so that, through them, the use of contextual information and social interactions is simplified. In addition, this integration does not only help to design learning activities, but also enables a faster start by reducing the time taken for its development.

CAFCLA has been used for collaborative learning activities that use contextual information in museums [74], gardens [21] and other educational settings [64]. In this paper, CAFCLA is used in a non-academic environment with a specific purpose: to educate, raise awareness and trigger behavioural change in the efficient use of energy in public buildings. To this end, we have designed and developed a serious game whose function is to make users aware, acquiring good habits naturally and changing their behaviour, so that they save energy by using it more efficiently.

In general, the system continuously monitors the use of lighting, the use of HVAC systems, the electrical energy consumption at the site of each user, the temperature and luminosity of the environment, and the location of users through a WSN. Thus, all data are obtained in real time according to the activity in the laboratory, its temperature, if the use of lighting is being efficient, if users turn off or suspend their devices when they leave their job, and whether users use an elevator or the stairs to reach the lab. All of these data will enable us to check if users meet certain energy efficiency targets or collective challenges. If so, users will be rewarded with virtual coins and penalized otherwise.

In this game, the collection of data through sensors, the location of participants and the social interactions among them and with the environment are of special relevance. CAFCLA provides the tools required to efficiently manage the game and the interactions generated. All of these aspects are discussed in depth in the next section where we describe in detail each component of the framework and what they are used for in this case.

3.2. Framework Description

The game designed using CAFCLA requires the integration of different physical devices and technologies. As shown in Table 1, CAFCLA has been designed following a scheme of interconnected layers. Each layer includes a set of technologies that fulfil the requirements of the game. These devices and technologies will support communication, sensor data collection and contextualization of the environment, and provide intelligence to the system and even facilitate the development of the application used by players.

Table 1. CAFCLA (Context-Aware Framework for Collaborative Learning Applications) layers diagram and technologies associated with each one.

Layer	Technologies
Physical	Tablet, smartphone, temperature, luminosity, on/off and consumption sensors, location beacons
Communication	Wi-Fi, ZigBee, 4G/3G/GPRS
Context-awareness	WSNs, Real Time Locating System
Management	Social Computing, Virtual Organization of Agents
Application	API, Web interface game

In the following sections, and with the objective of understanding the functionalities of CAFCLA better, a description of each layer is provided. A brief explanation is also included on the reason for each technology selected and its function.

3.2.1. Physical Layer

The physical layer contains all of the devices that will be used in the framework (see Figure 1):

- An infrastructure that collects all contextual information: temperature on/off, luminosity and consumption sensors, integrated into plugs that monitor the power consumption of each job site.
- Location beacons and identification tags that obtain the position of users.
- Mobile devices to deploy, modify and access the game: tablets, laptops and smartphones.
- Internet access points via Wi-Fi and Ethernet, as well as data collectors and hubs, to send the data collected by sensors as well as by the real-time locating system.
- A server to store data and run the application.

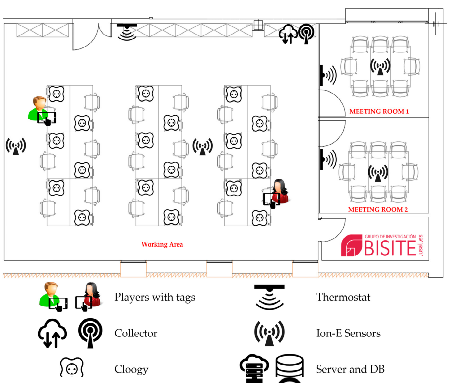


Figure 1. The CAFCLA (Context-Aware Framework for Collaborative Learning Applications) framework enables the integration of heterogeneous sensors as well as communication technologies in the physical layer.

All of these technologies are integrated by CAFCLA transparently to users, making an appropriate use of each depending on the needs raised by the game at any time of its performance.

3.2.2. Communication Layer

CAFCLA integrates different communication protocols to send and receive information between different physical devices: Wi-Fi, 4G/3G/GPRS and ZigBee to transmit data between mobile devices, from any sensor to the collectors and hubs, and to locate users. In addition, CAFCLA is an open framework that enables the integration of any other protocol that may be needed.

3.2.3. Context-Awareness Layer

To gather contextual information, CAFCLA has integrated the wireless sensor network and the real time locating system platform:

- To deploy the wireless sensor network, CAFCLA includes n-Core [75] which uses the ZigBee communication protocol (IEEE 802.15.4). The sensors data are sent through the ZigBee network to data collectors, which, in turn, send the information collected to the server hosting the database through the Wi-Fi protocol. This technology allows for collecting the physical measures that permit the system to determine in real time the contextual status of the environment (temperature and luminosity sensors), instant and historical energy consumption of each job site (electricity consumption sensors), and the status of lighting and HVAC systems (on/off sensors). This information serves a threefold purpose: (i) it allows for knowing at all times the environmental and consumption parameters that draw the context; (ii) it provides real-time information to users; and (iii) it facilitates the analysis of the data and their use by other parts of the system.
- To provide the location, CAFCLA integrates n-Core Polaris [76], which allows for determining the position of users with up to one-meter accuracy based on the ZigBee wireless communication protocol. In order to locate, n-Core requires a set of beacons to be deployed, and they collect the signal sent by tags that are worn by the players. That signal, and its associated data, is sent to the server that implements the location engine, which calculates the position of each player. Players wear an n-Core Sirius Quantum tag responsible for sending the signal, and it is also equipped with an accelerometer that determines whether the user is moving. The beacons send these data to the server in the same way that sensor data are sent through Wi-Fi data collectors.

n-Core allows for the deployment of the wireless sensor network and the location system using the same platform and physical infrastructure. Furthermore, both systems share data collectors to send data to the server.

3.2.4. Management Layer

This layer integrates the social machine, which is in charge of context-awareness and operation of the communication layers in a distributed, effective and predictable way. One of the biggest challenges that the development of Social Computing systems has to face is the communication and coordination between the participating entities, whether human or machine [23]. To address this challenge, we propose the use of virtual organizations of agents [77,78]. This technology dynamically creates agent organizations, defines functional behaviours such as schedules, tasks or services, and establishes logical structures and interactions, relationships or roles [20].

The main purpose of the management layer is to implement the social machine using virtual organizations. The proposed architecture includes different organizations (see Figure 2):

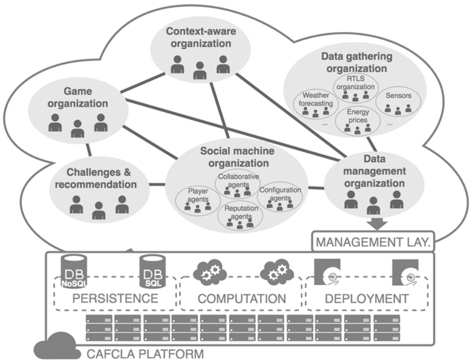


Figure 2. The virtual organization supports the social machine, which governs the recommendation of energy efficient actions and collective challenges.

- *Data gathering organization*: the data that are available to the system come from different sources that require a thorough control. This organization is responsible for managing these heterogeneous sources, such as sensor networks, the location system or even the published or consulted information, among others. Moreover, the organization is responsible of the reliability of the data collection, as well as the management of the security aspects related to this task.
- *Data management organization:* this organization is responsible for maintaining the integrity of data during the game. It makes decisions on what data should be elaborated and stored at all times. This organization classifies the information to be delivered, depending on the context and social information that surround the player at an instant. Moreover, the organization registers and stores the actions classified as energy efficient actions (actions that involved energy savings). Finally, this organization handles the security and integrity of all the data involved in the game.
- *Context-aware organization*: this organization manages the information collected by the sensor network. It needs to be coordinated with the data management organization to update the information from any physical service implemented by the sensor network.
- *Game organization*: the whole activity is under control of this organization (management and coordination). The information from the social machine (players, contextual data, information, etc.) is received and managed by this organization. It finally decides which information is provided to players according to the stage of the game.
- *Social machine organization*: this organization is responsible for performing analyses that extract socially relevant information related to the interaction of different agents:

    - *Player agents*: store the information related to the game process and are grouped in organizations, creating two types of interactions: player–player and player–machine.
    - *Configuration agent*: this agent creates, modifies and monitors the development of the game and establishes the social rules of the social machine organization.
    - *Collaborative agent*: it monitors the communication with the Context organization and the Activity organization. It is grouped in organizations.
    - *Reputation agent*: manages the reputation of actions. This reputation is based on the reliability (if they have involved energy savings) and the fidelity (if they have been continued over time). The social machine recommends the most reputed actions, where the reputation of action x during the day t is defined as:

$$Rep_{x,t} = \overline{Fid}_{x,t} * \overline{Rel}_{x,t}, \quad (1)$$

where $\overline{Fid}_{x,t}$ and $\overline{Rel}_{x,t}$ are the averaged fidelity and reliability of action x until the day t, respectively,

$$\overline{Fid}_{x,t} = \sqrt[t]{(1 + Fid_{x,1})(1 + Fid_{x,2}) \dots (1 + Fid_{x,t})} - 1,$$

$$\overline{Rel}_{x,t} = \sqrt[t]{(1 + Rel_{x,1})(1 + Rel_{x,2}) \dots (1 + Rel_{x,t})} - 1,$$

and $Fid_{x,t}$ is the fidelity (i.e., the number of times the action x was performed during day t), and $Rel_{x,t}$ is the reliability (i.e., the net energy savings of action x during the day t).

- *Challenges and recommendations organization:* this organization is responsible for producing engaging personalized actions for the players to reach the objectives set in the Game organization.

The implementation of the virtual organization has been made through the PANGEA (Platform for the Automatic coNstruction of orGanizations of intElligent Agents) platform [79], a multi-agent architecture and organizational-based platform designed to facilitate the design and implementation of autonomous reactive and deliberative agents. The platform was developed to implement open multi-agent systems by providing several tools to create, manage and control virtual organizations, including organizational aspects. Its main features are: (i) the creation of organizations and sub-organizations; (ii) the management of roles; (iii) the management of services; (iv) the management of rules; (v) the management of security and (vi) the management of reliability of the system.

PANGEA permits the integration of agents developed in different languages, such as Java or C++. Moreover, the communication language used is IRC (Internet Relay Chat) although KQML (Knowledge Query and Manipulation Language) and FIPA-ACL (Foundation for Intelligent Physical Agents) are also integrated by the platform. In this paper, Java and IRC were the chosen languages to integrate the virtual organization of agents needed [79].

3.2.5. Application Layer

The top layer in CAFCLA schema is the application layer. This layer supports the social and serious game development and provides the interface for players and game organizers, as well as other components that are a part of it, such as the configuration of different devices. As an implementation example, the next section presents the case study of a serious game where players were rewarded or penalized depending on their behaviour in energy savings within a work environment.

Furthermore, it is important to mention that CAFCLA provides several tools that establish collaboration between players (e.g., deciding on meeting times), and they can provide contextual information at any time, which is necessary so that players can make the best decisions, and it also gives recommendations on the decisions that could be taken in order to be rewarded (e.g., turn off the monitor when they finish working).

3.3. Trust and Security

Within the system developed, agents establish relationships with other agents, with other non-agent software or with humans. For this reason, the security and reliability during the game deployment is an important aspect to consider. The use of PANGEA, as the base platform for the creation of the virtual organizations of agents, permits the integration of security and reliability mechanisms in the game easily and intuitively [79].

As can be seen in Figure 3, PANGEA provides a set of agents that permits the control of the organization in all aspects, including security and reliability. When developing the system presented in this paper, the integration of security and reliability has been organized in three different levels: data, operation and communication.

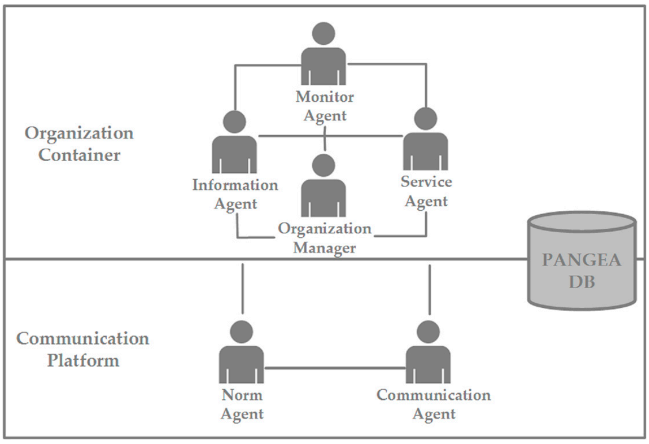


Figure 3. Overview of PANGEA (Platform for the Automatic coNstruction of orGanizations of intElligent Agents) platform architecture and the different agents that are implemented to manage virtual organizations and ensure their correct organization, security and reliability.

At the data level, the mechanisms deployed include verification of agent identity when accessing the data to ensure that it has the right permissions and that the appropriate information is delivered to it. The *Information Agent* is responsible of this task and manages the data access in the platform. Moreover, the *Organization Manager* establishes, coordinates and manages all permissions for an efficient data management.

On the other hand, at the operation level, multiple security and trust mechanisms are implemented. Among them, the registration of agents and the verification of their entrances and exits in the system. The *Organization Manager* controls both the registration and verification, and it is also in charge of the unique identification of the agents within the system and of the management of organizations and sub-organizations. Moreover, reliability is provided by the managing of the life cycle of the agents and by starting any agent in the case of failure. The *Monitor Agent* is in charge of these two important tasks in the system. Finally, to complete the security at operation level, the *Service Agent* records and controls the operation of all of the services.

Furthermore, the platform integrates security and reliability mechanisms at a communication level. In this sense, the *Norm Agent* ensures the compliance of all communications with the norms of the organization. All of the communications include encryption using TLS (*Transport Layer Security*) because of its easy integration in Java and IRC, and adopt standards defined by the use of languages such as IRC or KQML. Moreover, the *Communication Agent* controls the communication between agents and records the interactions among them to react properly in case of failure. Finally, the *Monitor Agent* is responsible for ensuring the secure communication between agents [79].

The following section presents and discusses the deployment and results obtained from the described serious game from the viewpoint of energy efficiency, noting the benefits of using CAFCLA and sensor networks for these types of games that are intended to promote a behavioural change.

4. Results and Discussion

In this section, we depict all of the issues related to the development of the game. Firstly, we briefly describe the serious game. Secondly, we give a description of the environment in terms of energy, the technical infrastructure deployed and the concrete energy efficiency measures that are taken during the game performance. After that, we present and analyse the obtained experimental results.

4.1. Serious Game Approach

The main objective of the serious game is to raise awareness in the efficient use of energy. Players were able to view the actions they have taken that have involved significant energy savings (turning off lights, not using HVAC, etc.). Since social computing was used, the game could make suggestions to the players on the most efficient actions that have been taken by others. These actions are identified due to the data collected by the sensors, the energy savings they entail and the probability that they will be maintained over time.

The position of each user in the environment, combined with contextual information, determined the development of the game. All workers were involved in the game whose main objective was to get *virtual coins* through energy efficient behaviours. Each user received four recommendations per day in four different e-mails, determined and sent by the social machine, and they gave a clue on the action that should be taken. The users were clustered in six *energy saving groups* by means of the k-nearest neighbour (kNN) algorithm [80], considering the number of times they used the elevator, lighting and HVAC systems during the baseline period (see the next section and Figure 4). The social machine customizes all of the recommendations to each cluster according to the habits of the cluster (actions that users do not take into account will be recommended to foster a good habit) and to the reputation of the action (those that implied more energy savings got a better reputation than the ones with less energy saving impact).

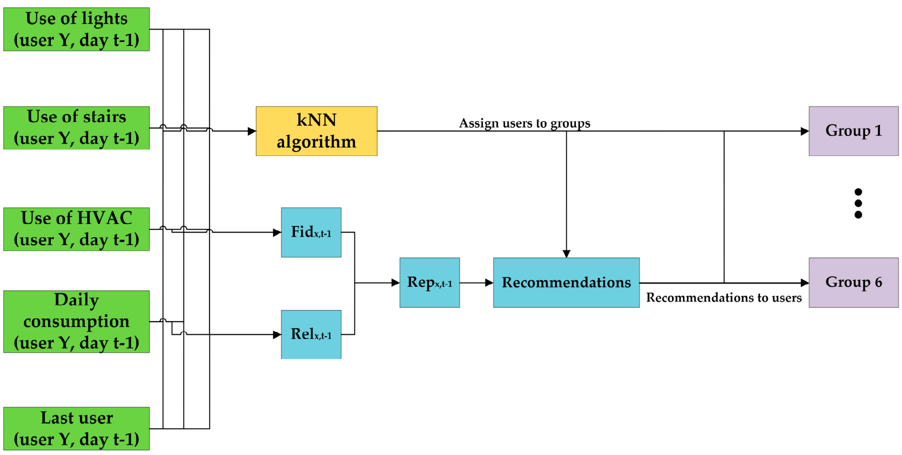


Figure 4. The social machine uses a kNN algorithm to classify the users into different groups based on their previous energy performance. In addition, it assigns a reputation to each action to be able to recommend them to the users who carry them out less.

To encourage participants, 250 virtual coins permitted players to grab a coffee or a soft drink for free. If he/she completed the action, he/she earned 10 virtual coins; otherwise, he/she was penalized with 10 virtual coins. Actions that helped win or lose virtual coins were as follows:

- Avoiding artificial lighting when natural lighting was greater than 200 Lux (200 Lux is the recommended luminosity for environments requiring moderate visibility lighting);
- Not using the HVAC system when it was above 18 °C in winter or below 25 °C in summer;
- Obtaining a daily electricity consumption below the average of the previous day;
- Using the stairs instead of the elevator;
- Turning off the lights and HVAC system when the last user left the laboratory;
- Belonging to the group that behaved more efficiently in a two-day period.

4.2. Sensoring Structure and Consumption Baseline

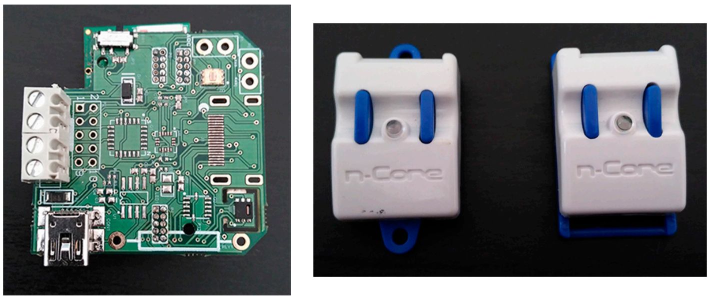
The proposed framework was assessed in one of the laboratories of the BISITE research group of the University of Salamanca. The selected dates for its performance tried to homogenize to the maximum the work conditions, as well as to minimize the influence of external factors. For these reasons, the beginning of the course, after summer holidays, was chosen, since, in this period, researchers have a more stable work load. In addition, it is important to mention that each of the participants performed the same functions and followed the same working schedule (working hours) during the two months of experimentation, so that the results were minimally influenced by external factors, changes in workload or holidays. Finally, to minimize the influence of weather conditions and sunshine hours: lower thermal oscillation among the months, similar sunlight hours during business hours and similar rainfall each month. According to all of these factors considered, the months of September and October were chosen to develop the game.

As can be seen in Figure 1, the lab has a common workspace, with an 88 square meter area, where the positions of the 18 people involved in the game are located. In addition, there are two separate meeting rooms, with 12 square meters each, which have enough space for eight people simultaneously. The laboratory is located on the second floor of the I+D+i (R&D&I) Building and can be accessed via an elevator or stairs.

Figure 1 shows how different points that measure temperature and luminosity were defined, consumption sensors were placed in each position, on/off sensors which determined the state of the lighting and HVAC system were located and the different areas where the game took place were defined (two meeting rooms, working area, 2nd and ground floor stairs and 2nd and ground floor lifts).

To monitor the power consumption a Cloogy [81] power plug was installed at each workstation, forming a total of 18. The plug includes an electrical consumption sensor, with an accuracy of $\pm$ 1% $\pm$ 0.5 W, and ZigBee communication capability. All of these sensors formed a ZigBee network through which real-time power consumption data for each position was transmitted. Consumption data was sent to the server every 15 min and in real time if the players asked for it. This data is collected by a crawler integrated within the Data Gathering Organization through a Web Service from the web page in which the consumption is published. With this data, users could check their electricity consumption at all times throughout the day, their consumption history and its comparison to the consumption of other players, which functioned as a motivational factor. Furthermore, these data allowed for determining which users were above and below the average consumption each day. It was intended that users were aware, for example, of the times that they should turn off their computers and monitors if they were not going to be used for long periods of time.

To encourage a more moderate use of HVCA and lighting systems, four IOn-E devices were deployed along the same wireless sensor network (see Figure 5). Two of these devices collected data in the shared work environment and one was located in each of the two meeting rooms. Each IOn-E device includes a SHT25 temperature sensor (Sensirion, Staefa, Switzerland), a TSL2561 light sensor (AMS, Stiria, Austria) and ZigBee communication capability by coupling it to a Sirius RadIOn device (Nebusens, Salamanca, Spain) through a digital I^2C. SHT25 is a high-end band-gap temperature sensor that operates between –20 °C and 100 °C, with an accuracy of $\pm$ 0.1 °C when it is working between 0 °C and 60 °C, and works with 3 V VDD (Voltage Drain Drain). The TSL2561 light sensor also works with 3 V VDD, its dynamic range comprises from 0.1 to 40,000 Lux and automatically rejects 50/60-Hz lighting ripple. Each variation of 0.5 °C was sent and stored. Meanwhile, luminosity was sent to the server every 60 s. Moreover, temperature and luminosity could be asked by users under demand. Players knew at all times the data collected by these sensors so that they could assess whether the use of artificial lighting or HVAC systems was necessary or not, based on the premises set out in Section 3.2.5.



(**a**) (**b**) (**c**)

Figure 5. Sirius devices deployed to form the WSN and RTLS. (**a**) IOn-E sensor board, (**b**) Sirius RadIOn and (**c**) Sirius Quantum.

The wireless sensor network monitoring power consumption, temperature and luminosity also enabled the localization of all users within the work environment with an accuracy of 1 m and with a location period of 1 s. In addition, Sirius RadIOn devices were deployed (see Figure 5) both near the elevator and the stairs on the three floors of the building. Thus, the system could determine where the user is at any moment (stairs, elevator, meeting room, etc.). To locate the users, each one carried a Sirius Quantum device. As we can see in Figure 5, it works in the system as a location tag. This device sends different signal measurements (LQI (Link Quality Indication), RSSI (Received Signal Strength Indication)) every second through the ZigBee network to the server and its position in the system is calculated by the location engine. At the same time, the system could detect if the player was using of lighting or HVAC. Thus, the system was capable of determining if the user rose to the laboratory by elevator or using the stairs or which player was the last person leaving the workplace or a meeting room, recommending to turn off lights and air conditioning by using for this purpose the on/off sensors coupled in each lighting switch and HVAC thermostat.

The description of the environment, considering energy consumption, is focused on four different perspectives: lighting, HVAC, electrical energy consumption at all workplaces and use of the elevator. To obtain the baseline, the usual consumption without involvement in the game was monitored during one month. The results of this monitoring are as follows:

- *Laboratory lighting:* lightning enters naturally through the windows and a small courtyard. Furthermore, artificial light is provided by fluorescent lamps. The common working area is supplied with three lines of 58 W fluorescent tubes, while each meeting room is supplied with one line of these tubes. The lab is open from 08:00 a.m. to 09:00 p.m., 13 h a day during which lights are lit continuously in the work area. The energy consumption of the working area is 27.14 kWh every day. Similarly, the measure of the lighting consumption of each meeting room was taken before the start of the game during one month. The average data obtained indicates that the use of each room consumes 1.04 kWh per day. Total consumption of electricity for lighting in all units of the laboratory is 31.31 kWh per day.
- *A/C:* the air conditioning in the lab is given by the *HVAC system* of the building. However, each of the spaces has an individual thermostat that allows for turning the supply on and off and regulating the temperature in the area. This system is constantly in operation during the working hours and it is automatically disconnected when the building is closed. Before the game, none of the users took care of switching off the temperature either in the common area or in the meeting rooms.
- *Workstation*: each workstation is provided with an *LCD monitor and a laptop*. These two devices are fed through the same plug through which consumption is monitored by a Cloogy device. The measurement of consumption was made during the month before the game started, obtaining an average hourly consumption of 0.1535 kWh per player and 1.309 kWh per player per day.

Moreover, it has been measured that the working hours of each site were 7.68. During the remaining hours, devices were on standby, obtaining an hourly stand by consumption of 0.018 kWh per player and 0.2937 kWh per player a day. With these data, the average hourly consumption measured for each player during one month was 0.1715 kWh.

- *Meeting rooms:* they were used by 15 users, who were organized in five meetings, lighting systems were used during all meetings and three of them made use of the HVAC system.
- *Elevator:* on the other hand, each user goes up and down to and from the second floor at least four times a day: when arriving to work in the morning, at break time, at lunch time and when leaving work. Lab workers were monitored on the use of the elevator: 12 of them use the elevator in almost 90% of cases either going up or down, while six of them always use the stairs.
- *Leaving lab:* last users leaving the lab did not turn off the lights or HVAC. Lights are not switched off at the end of the day in 80% of cases while the HVAC system always keeps working when everybody has left the laboratory.

4.3. Experimental Results

The game was developed following the guidelines outlined in the previous sections. The 18 workers of the BISITE research group participated in the game during 30 working days in their laboratory. The data obtained from the monitoring desktop showed that the average total consumption per day of all the users at their workstations was 2.875 kWh, and the hourly energy consumption per player at his workstation was 0.1597 kWh. These results established that there were savings of between 6.6% and 6.9% with respect to the measurements made before the game.

Figure 6 shows the hourly kWh average consumption of each player's desktop during the 30 days of the game evolvement. This graph provides evidence that there were two different phases during the development of the game ($R^2{}_1 > R^2{}_2$ where the independent variable is the number of days during the game development): during the first three weeks of development, the linear approximation of the average consumption set a value of $R^2{}_1 = 0.47$, in which players were more motivated and learned about the game; during the last three weeks of the game, the linear approximation of the average consumption set a value of $R^2{}_2 = 0.01$, indicating that the consumption remained more stable, always below the baseline of average consumption acquired in the data collection phase. The result indicates that, in the first phase, the players learned how to play the game, and, in the second phase, they maintained the good habits acquired, showing that the use of the social machine was effective.

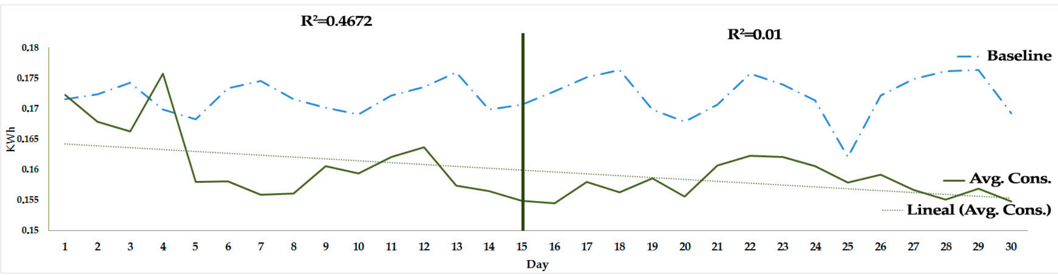


Figure 6. The graph of the hourly kWh average consumption of the desktop of each player provides evidence that there was a first phase in which players learned how to play the game and a second phase in which they maintained the good habits acquired, proving the effectiveness of the social machine.

Moreover, according to the hourly kWh baseline consumption per player, the use of the social machine in the game permitted an average of 7% energy savings per player and desktop. These savings were calculated as follows:

$$Savings = \frac{Baseline\ consumption - Reported\ consumption}{Baseline\ consumption}. \tag{2}$$

Consumption is given in kWh when measuring electric consumption or in the number of times that energy-efficient actions were recommended and carried out.

On the other hand, we analyzed the energy consumption habits when using the meeting rooms. During the 30 days of game progress, it was observed that the use of artificial lighting was reduced by 56% and the use of the HVAC system by 82%. These savings were mostly through playing the game, an argument that is confirmed with the results of the performed Student's t-test, reporting a mean of 2.15 times per day that lighting was used during the game, in comparison to the mean of 5.071 before the development of the game, and a p-value of 0.001, as can be seen in Table 2.

Table 2. Results of the Student's t-test and Levene's test performed to assess the difference of means and variances between the baseline usage data and the data collected during the game development. In all cases the percentage of use after the game is notably lower, with p-value always under 0.05, which shows that there is energy saving and behavioural change thanks to the game.

	Baseline		Game					
Variables	**Mean**	**Stdr. Deviation**	**Mean**	**Stdr. Deviation**	t	**p-Value (2-Tailed)**	**F**	**p-Value**
Meeting room light [1] (# times per day)	5.071	2.200	2.150	1.200	4.357	0.001	5.717	0.024
Meeting room HVAC [2] (# times per day)	3.143	1.703	0.559	0.565	5.386	0.000	10.944	0.003
Light when leaving [3] (# times per day)	0.857	0.363	0.142	0.363	4.298	0.000	0.934	0.343
HVAC when leaving [4] (# times per day)	1.000	0.000	0.142	0.363	11.787	0.000	12.480	0.002
Use of elevator [5] (# times per day)	44.774	2.355	4.933	8.035	17.803	0.000	4.598	0.042

[1] Meeting room light: # times light is used while a meeting is taking place and illumination conditions are optimal; [2] Meeting room HVAC: # times HVAC is used while a meeting is taking place and temperature conditions are optimal; [3] Light when leaving: # times lights are not switched off when the last player leaves the laboratory; [4] HVAC when leaving: # times HVAC is not switched off when the last player leaves the laboratory; [5] Use of elevator: # times the elevator is used.

In addition, it was evident that all users were aware of turning off lights and thermostats if they were the last to leave the workplace, and this is largely due to the warning system integrated. During the 30 days period, both systems were turned off when the lab was closed except the first two days at the beginning of the game (see Table 2). These data indicate that the behavioural change promoted by the game was effective and significant; the mean and p-value values after performing Student's t-test affirm this statement: the mean of the number of times per day that lights were not switched off when the last player left the laboratory decreased from 0.857 to 0.142, and reported a p-value of 0.000. Similarly, the mean of the number of times that HVAC was not switched off was reduced from 1 to 0.142, and reported a p-value of 0.000.

Finally, Table 2 shows that stairs were the option chosen in more than 88% of cases, as opposed to the 40% previously measured. In this case, a Student's t-test was performed to prove the decrease in the number of times the lift was used; a mean of 4.933 was obtained for the number of times the elevator was used per day during the game, in comparison to the mean of 44.774 times before its development.

From the results, it is clear that the game is a powerful tool to create a habit whose outcome is huge energy savings and, in addition, healthy habits, thanks to the incentive to achieve better results in the game.

5. Conclusions

This paper presents a serious game based on the social computing paradigm that integrates advanced technologies through the CAFCLA framework, including wireless sensor networks and real-time locating systems. The inclusion of these technologies allows for having a contextual characterization of the environment as precisely as required, since they favor the integration of any type of sensors, actuators and, thanks to the RTLS, the position, tracking and activity monitoring of the players. In addition, the game integrates Virtual Organizations of agents to create a social machine that personalizes recommendations for users. This integration enables resolving human–machine interaction and context-awareness issues and achieves the main goal of the game: that users acquire good energy saving habits in public buildings, such as the work environment.

The game has been developed in one of the BISITE research group laboratories, compared to other similar games. We can asseverate that the use of the provided framework presents a great potential for the development of systems that are intended to promote a behavioural change in the energy consumption habits in users. The case study showed that social interactions foster growth of interest in improving individual performance through competition among players. Moreover, the acquisition of good energy habits was encouraged to benefit the group in places where awareness of energy consumption is often absent, such as the working environment. Finally, the simple game that has been developed has demonstrated the potential of the framework for the development of these kinds of solutions. This work has encouraged the authors to improve their work in progress by designing and developing more complex serious games in which their potential is exploited more comprehensively.

The implementation of the proposed systems will be easier to develop in the near future thanks to the increase of devices and gadgets with sensing capabilities available in the market. Technologies that provide context-awareness information, such as thermostats or lighting sensors, are becoming more accessible, including the indoor location systems. This allows for implementing the proposed solution with more functionalities, less difficulty of development and at affordable prices. Moreover, social networks and games over the Internet are becoming more popular. However, a relevant issue in this aspect will be the coordination between promoters, developers and technology manufacturers, guaranteeing data privacy and security, and getting good user engagement.

Moreover, after the experimentation, it has been detected that the behavioural change has been maintained by the users after the end of the game. Users have continued with good habits in the use of the elevator, lights and HVAC in the meeting rooms and when leaving the workplace. However, some aspects such as the optimization in the use of energy in the job site has not been maintained as expected, since the level of savings are lower to those that were obtained during the performance of the experimentation.

Finally, it is important to note that the flexibility of the CAFCLA framework is an added value in comparison to other solutions. This is because the integration of multiple technologies and communication protocols can substantially improve context-awareness, meeting the requirements of a large number of potential cases of use that could be implemented.

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5.6. A framework to improve energy efficient behaviour at home through activity and context monitoring

NOTA: el artículo que se presenta en esta sección se encuentra en su segunda ronda de revisiones en al revista *Sensors*. Sin embargo, se ha decidido incluirlo en esta memoria debido a la relevancia del caso de uso que presenta en esta Tesis Doctoral.

Los sistemas de localización en tiempo real han sido postulados como una de las tecnologías más apropiadas para desarrollar aplicaciones que generen servicios personalizados. Su capacidad para proporcionar localización y trazabilidad de los usuarios permite, entre otras características, facilitar la identificación de patrones y hábitos de comportamiento. Además, la implementación de políticas para fomentar el ahorro energético en los hogares es una tarea compleja que utiliza este tipo de sistemas. Aunque hay múltiples propuestas en esta área, la implementación de frameworks que combinan tecnologías y utilizan la Computación Social para influir en el comportamiento de los usuarios no ha alcanzado aún ahorros energéticos importantes. A lo largo de este trabajo se utiliza el framework CAFCLA para desarrollar un sistema de recomendaciones para usuarios domésticos. El sistema optimiza el consumo de energía, como resultado de la integración de un sistema de localización en tiempo real y redes inalámbricas de sensores para desarrollar aplicaciones bajo el paraguas de la Computación Social. La implementación de un caso de uso experimental ha logrado un uso más eficiente de la energía, consiguiendo ahorros hasta un 22 %. Además, también se ha logrado la adquisición de buenos hábitos de consumo energéticos por parte de los usuarios, gracias a la provisión de recomendaciones personalizadas en tiempo real generadas mediante el uso de localización en tiempo real e histórica, seguimiento de los usuarios, y datos contextuales de estos y de la casa.

Objetivos
Los objetivos perseguidos en esta publicación son los siguientes:

- Fomentar el ahorro energético en los hogares así como conseguir la adquisición de buenos hábitos energéticos por parte de los residentes.
- Utilizar información contextual proveniente de sensores y localización en tiempo real para identificar las actividades que se están llevando a cabo en el hogar en un momento dado, así como el consumo energético que conllevan.
- Emplear técnicas de Computación Social para fomentar la colaboración entre los usuarios y la relación de estos con los dispositivos.
- Proveer de inteligencia al sistema mediante el uso de organizaciones virtuales de agentes.
- Diseñar e implementar un sistema de recomendaciones que, mediante el uso de Computación Social, sea capaz de identificar situaciones en las que existe un ahorro energético potencial y recomendar medidas de ahorro a los usuarios.

Resultados

La experimentación realizada ha supuesto el despliegue de la infraestructura necesaria en 5 viviendas de distinta tipología y la participación de 11 usuarios. Los resultados obtenidos señalan que el uso combinado del sistema de localización, la red inalámbrica de sensores y la máquina social, permite determinar con alta precisión el contexto que rodea a cada usuario. La gestión inteligente de esta información facilita la identificación de situaciones en las que surgen ahorros potenciales de energía e inmediatamente genera y envía recomendaciones personalizadas para alentar a los usuarios a llevarlas a cabo. El análisis de los resultados obtenidos mostró que las recomendaciones más frecuentes consideradas fueron las relacionadas con el uso de calefacción (77 %), iluminación (84 %) y apagado de dispositivos para evitar el consumo en espera (92 %). Sin embargo, las recomendaciones sobre la optimización en el uso del cuarto de baño (4 %) o cocinar al mismo tiempo (17 %) no tuvieron un gran efecto, lo que demuestra que la máquina social ha funcionado más efectivamente en las relaciones máquina-humano que en las relaciones entre humanos.

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A framework to improve energy efficient behaviour at home through activity and context monitoring

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Abstract: Real-time localization systems have been postulated as one of the most appropriated technologies for the development of applications that generate customized services. These systems provide us with the ability to locate and trace users and among other features, they help identify behavioral patterns and habits. Moreover, the implementation of policies which will foster energy savings at homes is a complex task which involves the use of this type of systems. Although there are multiple proposals in this area, the implementation of frameworks that combine technologies and use social computing to influence user behavior have not yet reached any significant savings in terms of energy. In this work the CAFCLA framework is used to develop a recommendation system for home users. The system optimizes energy consumption, it is integrated with real-time localization systems and wireless sensor networks in order to develop applications under the umbrella of social computing. The implementation of an experimental use case has achieved a more efficient use of energy and obtained savings of up to 22%. Moreover, good energy consumption habits have also been acquired, thanks to the provision of real-time customized recommendations generated from real-time and historical localization, tracking and contextual data from the users and the house.

Keywords: real-time localization system; wireless sensor networks; energy behaviour; energy savings; social computing; recommendation system; virtual organization of agents.

1. Introduction

During the last decades, the efficient use of energy resources has been established as one of the most concerning problems for our society and more resources are being allocated for its resolution [1]. For the European Union (EU), energy efficiency is a key strategy for the sustainable growth of our planet, for this reason it set a clear objective: in 2020 the consumption of traditional energy and greenhouse emissions should be reduced by 20% [2]. Within this broad framework, energy savings and energy efficiency policies must be applied at all levels and sectors, to achieve a global awareness of the problem. Further, the optimization of energy resources has to be considered for all uses, regardless of the punctual impact of each action on the total energy consumption.

One of the sectors in which proposals for the optimization of energy consumption have a wide impact are households, in 2015 this sector consumed 33% of total energy [2]. The EU recognized this issue and determined around 650 action measures in the residential sector. Some of these measures included the use of smart meters, information campaigns or the encouragement to change user behaviour [1]. Currently, household energy consumption within the EU is around 25% of total consumption and, although around 1.8% annual reduction in consumption has been achieved since 2000 in this sector [2], there is still a lot of room for improvement. Much of this decline in consumption has been driven by both technical improvements in devices and by the increase in the price of energy. However, the effect of policies that seek to influence and change consumer behaviour should not be overlooked [1].

Numerous studies have been conducted to measure the impact of home occupants' behaviour on energy consumption [3-7]. The determination of behaviour patterns, which provide feedback and guidelines to users, is one of the most widespread topics [8]. Two main lines of work are well differentiated within this area: on the one hand, works focused on the simulation of behaviour to obtain patterns [6-9] and on the other hand, the works that use real data for gathering behaviour patterns [5,10-12]. The former does not obtain good results since simulations do not consider spontaneous and unplanned modifications in environmental conditions. However, systems that use real-time data, either from user tracking or contextual information, even price of energy, make this data available to users, allowing for a substantial improvement in the effectiveness of the designed solutions [13-19].

Technology therefore, plays an essential role in the acquiring of real-time information that surrounds the residents at all times. The design, deployment and use of context-aware systems allows to determine what factors relate to energy consumption at a given time, including the location of the occupants, the use of domestic appliances or devices (open window, light on, TV off, etc.) or environmental conditions (temperature, humidity, time, lighting, etc.). Wireless sensor networks (WSN) and real-time localization systems (RTLS) are then posited as powerful tools that collect essential data in this kind of solutions [20-23].

Some of the most common solutions in this area are focused on the search for patterns in the use of lighting, windows, blinds or heating [3,15]. Some works go further and use the position of users to determine richer and more accurate behaviour patterns [16,18]. Moreover, the implantation of smart meters in homes is becoming universal [16,24]. These devices allow to determine energy consumption at home in real-time, which means that they are able to offer extensive feedback to users, while other solutions give recommendations to users to help them reduce consumption on the basis of historical data and not by considering current activity [24].

Furthermore, the penetration of social networks in our daily life has opened up new possibilities of improving energy consumption by influencing people's behaviour [25]. In this sense, social computing is an area of computer science which supports works focusing on collective and collaborative actions [26]. Thus, some solutions use social tools to foster the use of energy saving systems [27,28] and others use social information to aid decision-making or to share energy saving information [29,30].

Despite all the above, there is a great lack of works which would combine the obtaining of contextual information in real-time, through wireless sensor networks and indoor positioning systems, and the use of social computing. Moreover, there are very few studies that cover the problem in a global way, offering solutions that consider the great number of aspects which influence home residents' behaviour. Finally, this paper analyses several experimental systems designed to improve energy consumption. All of them attain savings of 10% and 15%, which is still far from the EU 20% objective.

In order to cover this gap, this work presents the CAFCLA framework (Context-Aware Framework for Collaborative Learning Applications) as a basis for the rapid and effective development of activities focused on improving users' energy consumption habits. The framework, designed from the perspective of social computing, is used as the basis for the implementation of applications that include context-aware, localization, and social functionalities.

To validate its conceptualization and design, the framework is assessed by an experimental use case, which emphasizes the effectiveness of the use of real-time localization systems and wireless sensor networks. They are used for the development of a social machine (recommendation system) that allows to improve energy savings at homes, as well as to positively influence the behaviour of users, thanks to the monitoring of their activities and their tracking.

The rest of the paper is organized as follows: Section 2 describes previous works surrounding context awareness for energy activity monitoring, RTLS for energy saving, and social computing for energy efficiency. After this, Section 3 presents CAFCLA and how it is used to achieve the objectives of the work: Section 3.1 describes the problem and the framework, Section 3.2 approaches the RTLS, Section 3.3 depicts how location is enhanced and how it is integrated within CAFCLA and Section

3.4 includes all the information of the social computing recommendations systems that makes use of the framework for its implementation. After explaining all the components of our solution, Section 4 presents the case study, the experimentation and discuss the results obtained. Finally, Section 5 depicts the conclusions reached after research and experimentation and considers possibilities for future work.

2. Related work

The work presented in this paper deals with the benefits of monitoring and precise localization of home residents, as well as real-time context-awareness, which offer possibilities for the development of systems and applications that foster energy efficiency. Those technologies also present a great potential for the development of social computing tools which would promote energy saving and good energy consumption habits. The main feature of this type of solutions is the collection of data through sensors [3]. This section of the paper outlines different proposals which are focused on the optimization of energy consumption through context-aware systems in households. Moreover, indoor Real Time Localization Systems used for energy saving solutions are analysed. Finally, the section identifies and analyses related works which employ social computing for efficient energy consumption.

2.1. Activity monitoring and contextual information for energy efficiency

Nowadays, with the boom of the Internet of the Things (IoT) solutions, context-aware systems have become more commonly implemented in our surroundings, this is due to their reduced cost, ease of use and integration [13]. Furthermore, sensor networks are widely used to collect environmental parameters at homes, they are a source of information which supports the decision-making process [31] and, in particular, aid energy optimization and learning [20].

In the literature we find multiple works that use sensors to contextualize environments for the purpose of saving energy. Temperature, lighting and electrical consumption monitoring systems are the most commonly used. Among them, we find the system proposed by Thomas *et al.* which determines activity at homes by integrating motion, door, lighting and temperature sensors [15]. Additionally, their system allows to customize services depending on the detected behavior patterns. Moreover, Hong *et al.* use presence, lighting and window status sensors in their work to model residents' behavior, demonstrating that they are able to decrease energy consumption by up to one third [3].A simpler work conducted by , Asif *et al*. analyzes the importance of lighting control and the presence of users for energy savings at homes [32]. We can also find commercial products such as nest Thermostat [33], a smart thermostat designed by Google that allows to manage house temperature remotely. Thanks to its connection with the smartphone, the system is also able to determine the number of people in the house, to stop the heating system, calculate the duration of a fixed temperature in the home, or register the users' favorite temperatures. To promote energy saving, it provides feedback to users and offers a rewards system (leaf reward) to encourage a more responsible energy use. However, the solution still has some limitations; it only takes into account the main user, it does not generate recommendations on consumption and does not learn from the behavior of users nor does it integrate social functionalities. Another approach, presented by Morales *et al.*, uses a complex device to monitor, control and manage electrical loads at homes to favor energy savings [14].

In relation to the monitoring of activities, different criteria have been used when dealing with this problem. Nguyen performs an important classification in his work [4] which identifies the most relevant information to be monitored: occupation, preferences, prediction of occupation and detailed activities. Real-time occupation in rooms is the information that is taken as the basis of multiple works. Thus, in [34] the lighting is controlled according to occupancy, in [35] temperature is automatically reduced when there is no occupancy and in [36] both are combined, controlling lighting and air conditioning depending on the occupancy of meeting rooms. The inclusion of users' preferences enriches the systems that use occupancy to improve energy efficiency. Thus, some systems use timers to turn off lighting when the last movement has been detected [4]. Other systems, such as [37], follow users to find a balance between lighting preferences and minimization of electricity consumption. Grouping more preferences, in [38] users are tracked and their preferences for lighting, temperature and ventilation are collected.

Predictive models are a resource that aim to optimize the efficiency of the actions taken [4]. This reduces the response time when automating actions, such as changing the temperature or turning off lights. There are multiple works in this area, such as ACHE [39], which predicts occupancy with hours in advance, entrance areas or hot water consumption. Other works, such as [40], predict the hours of entry and exit from home. Finally, works like [41] combine occupancy prediction with weather forecasting to optimize temperature.

Finally, the activities that usually take place in the homes are a good guide for optimizing energy consumption (watching TV, cooking, use of washing machine, etc.). In this sense, in [42] three activities are identified (sleeping, working or leisure) to determine their needs and to adjust temperature and lighting. On the other hand, [43] recognizes typical activities in the offices and [44] identifies who is in an area of interest within the house and what activity they are doing, limiting these activities to three (watching television, using the coffee machine or using a lamp).

The analysis of these works helps to identify three main parameters that most influence energy consumption at homes: temperature, lighting and plug load [4]. Furthermore, the studies show that context-aware information favors the procurement of consumption patterns, as well as decision making, enhancing energy savings. Also, the literature approaches activity monitoring with interesting criteria, such as the prior identification of activities in which energy savings could be reached. However, most of the works only postulate the use of these systems, without actually applying them to real environments. Moreover, there is a lack of solutions that combine localization and tracking of users with the collection of context-aware data, especially those that use the same communication platform to carry out both tasks. Some of the solutions that include activity monitoring are limited to few predefined activities. The following section focuses on the benefits that real-time localization provides and analyses several works that use these systems to improve energy savings.

Finally, the use of intelligent techniques and the connection between different systems and users are not addressed in these works. Social computing paradigm offers the foundations for filling this lack, offering resources and techniques that support the active participation of both users and the systems deployed for data collection. These techniques allow for the prediction, adaptation and anticipation of users' actions, improving the energy saving system. Section 2.4 addresses the use of social computing in energy saving systems, explaining the advantages it provides in order to encourage the acquisition of good energy practices in households.

2.2. Real Time Localization Systems and energy savings

As stated in many studies, household occupancy is an important parameter that should be measured when trying to understand and identify the parameters that have an influence on energy consumption at homes [4,21], even when unoccupied [45]. Thus, indoor localization systems play an important role in the proposed solutions. In this section we present and analyse different types of indoor localization systems that have been used in previous works to approach this issue.

One of the most commonly used technologies for detecting users at home are motion sensors. Among which, Passive Infrared Sensors (PIR) are the most extended thanks to their ease of use and low cost. Some solutions, such as the one presented by Lee *et al*. in [46], uses this technology to detect residents at homes and monitor their presence. Some solutions aim to develop more accurate tracking, by including more elaborated detection algorithms in which household components, such as furniture, are included to obtain precise user location [47]. On the other hand, recent studies, such as that presented by Moreno *et al.*, combine this type of sensors with Radio Frequency Identification (RFID) systems to control different devices and improve localization [16]. In other cases, as in [48], door sensors and PIR sensors are used to detect occupancy at homes and to predict temperature control strategies. These solutions are generally good at detecting occupancy in rooms, they are easy to deploy and their binary operation facilitates data analysis. However, they present a high number of false positives and their localization accuracy is poor [49]. In addition, a parallel system is required for data transmission, storage and analysis.

The detection of occupation in buildings has also been approached through the use of video cameras. For example, Bemezeth *et al.* devised a system for tracking users through video cameras, taking into account points of interest, which can be used in energy-saving solutions [50]. This type of systems is a logical solution for buildings in which there is an existing CCTV system. However, it presents serious privacy problems. In addition, its implementation in homes supposes a very high price, both at economical and computational level.

In order to improve the accuracy of localization systems, some solutions use active RFID technologies to monitor residents. In these cases, users must carry a tag that allows them to be identified and located at any time. The SPOTLIGHT project prototypes a system that uses this technology to determine how close the users are situated to electrical appliances and thus determines the consumed energy depending on their position [51]. Wi-Fi networks are postulated to be great helpers when it comes to detecting occupation in buildings and homes. Consequently, the Sentinel project uses these networks in public buildings to determine their level of occupancy, achieving energy savings of up to 17.8% [52]. Other fingerprinting techniques require complex calibration processes and do not allow to combine sensing and localization systems with a single deployed infrastructure [8,53]. In other works, localization accuracy is calculated by using the measurements of the RSS (*Received Signal Strength*) and TOA (*Time Of Arrival*) received from the WLAN devices [54].

Recent trends use localization systems based on Bluetooth Low Energy (BLE) technology to locate users. Their installation costs are low and the system can integrate simple actions, such as the switching on and off the thermostats and lights [18]. Systems based on this technology require a slightly dense anchor infrastructure in the area in the area in which they perform, this density depends on the required accuracy. Furthermore, these technologies are starting to be integrated with different mobile technologies [55], as shown in the project [56], which uses iBeacons and Android systems to track users and achieve a 10% accuracy improvement and 15% of energy savings. Generally, all of them provide a very limited localization accuracy, offering in the best case, the use of active technologies like active RFID or BLE, which can find the position of users by determining the anchor that they are the closest to, these systems can generate a high number of false positives in small environments such as houses.

Finally, navigation systems based on inertial sensors are discarded since the drift problem causes them to be inaccurate [57].

To summarize, there is a lack of works that combine localization and contextual information in an efficient way, for the development of solutions that favour energy saving behaviour at home. CAFCLA combines sensors and real-time localization transparently, without the need for any calibration when deploying this single infrastructure, this provides a high level of accuracy and fast deployment [58].

2.3. Social computing for energy efficiency

The emergence of the social computing paradigm enhanced collaboration between humans and machines, solving social problems by using innovative sociotechnical tools [59]. Virtual organizations (VOs) of agents are postulated to be one of the most powerful tools for their support [60]. Some of the functionalities that make them a strong candidate, are their ability to control agent behaviours by the inclusion of normative regulations, their dynamism when forming agent groups and when managing the entry and exit of components, and their ability to describe functional behaviours and structural compositions [61]. The application of social computing techniques leads to the creation of Social Machines, entities that are managed by both technical and social practices. Examples of such entities are the Twitter dynamics prediction system which uses behavioural data [60], or the Amazon recommendation system [62].

Several solutions aim to promote energy savings by fostering consumers' engagement in good energy consumption practices [63-64]. Within this topic, Zhou and Yang propose a framework focused on different research areas (energy, social and information) to understand the social issues that affect energy consumption, including demand-response and intervention strategies for efficient consumption [64]. Barrios-O'Neill argues in [63] that consumer behavior can be influenced by strategic social interactions and, in order to improve this area, proposes a Socially Dynamic Communications Framework to foster effective engagement in the designed interactions.

Despite all of the above, there is no working infrastructure that would integrate different technologies, communications protocols, intelligent management and multiple ways of social interactions. Furthermore, the use of context-awareness and, especially, of localization systems is not addressed in depth, weakening human-machine interactions.

3. CAFCLA approach for activity monitoring and energy efficiency

From the analysis of the solutions presented above, we can reach to the conclusion that, contextual information, localization and social computing offer great potential for the development of energy saving systems. Consequently, this work makes use of CAFCLA [58], a framework based on localization, and context-awareness and which integrates social computing tools. CAFCLA serves as a basis for the development of an intelligent recommendation system that encourages responsible energy consumption in households.

3.1. CAFCLA description

The use of multiple technologies can help promote energy saving in households. The objective pursued in this work is to identify users' activities at homes through the use of wireless sensor networks and a real-time localization system for the collection of data. Once the activities are identified, thanks to the work done by a social machine that is responsible for data processing and analysis, a system of recommendations makes use of the data collected by the sensors, the localization system, the electricity consumption and the activities identified, to promote efficient energy usage among users. Figure 1 shows all the components involved in the system. The implementation of this type of solutions helps users to make a more efficient use of energy in their homes. Additionally, it helps to identify users' behaviour when consuming energy, this data can be used to research and develop solutions that allow us to save energy. .

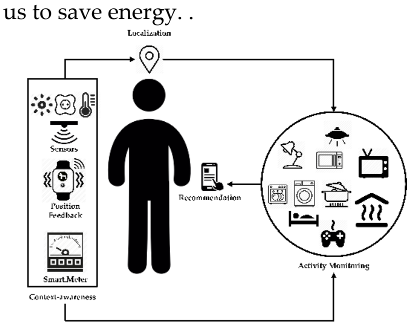


Figure 1. The presented model collects contextual information and users' location. These data, merged with the user activity monitoring, allow to generate recommendations that foster energy savings.

Although CAFCLA was conceived as a framework for the development of collaborative learning activities [58], its universality allows it to be applied to multiple domains, for both academic and non-academic environments. This is the case of the scenario shown in Figure 1, in which the framework is used to foster and enhance the acquisition of good energy habits at home by using a recommendation system. Despite not following a regulated learning process, by encouraging such habits, it creates a process that could be considered educational.

The best aspects of CAFCLA are its transparency and ease of use. This is because, these technologies can be used at any time without users having to worry about the difficulties that their integration entails. CAFCLA has been developed in C++ and supports the integration of different communication technologies and devices. Moreover, CAFCLA makes it easy to develop and deploy solutions such as the API, its offers can be accessed using Java, C# or .NET.

The biggest novelty of CAFCLA lies in the integration and combination of the following functionalities within the same structure:

- It obtains contextual information through the implementation of wireless sensor networks which collect data from multiple sources to define the environment. Among them, sensors that collect environmental parameters (temperature, humidity or illumination) or data on device usage (the switching of lights and even the status of blinds and windows).
- It implements a real-time localization system that allows users to be identified and tracked at all times. Users' positions permit to identify patterns of behaviour that help to describe good or bad energy consumption habits.
- It integrates a social machine that provides users with recommendations. The social machine uses virtual organizations of agents to provide the system with intelligence. Monitoring of all contextual parameters, localization and tracking of users, management of communications and data, as well as the generation of recommendations for users to encourage the efficient use of energy.

The CAFCLA design follows a scheme of layers, each layer offers a set technologies and tools needed to meet the functionalities of the system, as shown in Figure 2:

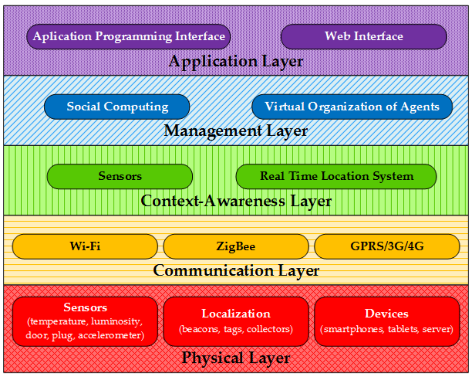


Figure 2. CAFCLA layers diagram and the devices and technologies implemented within each of them for this use case.

- *Physical layer:* it is made up of all the devices and infrastructure used by CAFCLA. They can be classified in three different categories:
  - *Sensors:* the infrastructure that collects all the information needed to characterize the environment. Includes temperature, lighting, door/window and electricity consumption plug sensors. It also integrates an accelerometer within the localization tag to better identify the level of users' activity. The wireless sensor network sends all the different physical measures gathered or the consumption of the monitored electrical points through the network.
  - *Localization*: the process of locating and tracking users requires a set of beacons (anchors) within the house and tags (targets) that identify each user individually. The target sends information with different parameters to the beacons. Similarly, the beacons resend it to the collectors which, in turn, send it to the server where the parameters are processed and the precise position of users is determined, as well as the level of their activity.
  - *Devices*: is all the equipment needed by the system that does not produce context-aware or localization data. This includes mobile devices such as smartphones or tablets which serve as an interface and are used to provide users with recommendations. Also, the server that is deployed to store data and run the management system, including the localization engine and the social machine. Finally, a protocol converter which acts as an intermediary between the sensor and localization infrastructure and the Internet.

- *Communication layer:* the CAFCLA design allows for the integration of any communication protocol that may be needed. In this case, the framework implements three communication protocols. The converters always implement two communication protocols. At one end, the ZigBee protocol (IEEE 802.15.4) which transmits signals and information to communicate with the localization and sensor infrastructure and, on the other, Wi-Fi or GPRS/3G/4G to send and receive data from the server. Finally, mobile devices receive and send information via Wi-Fi or GPRS/3G/4G protocol.
- *Context-aware layer:* Thanks to the use of CAFCLA and the integration of the n-Core platform [33], both the wireless sensor network and the real-time localization system can be deployed using the same physical and logical infrastructure, simplifying the development of the Context-aware Layer. The n-Core platform consists of a set of hardware devices (RadIOn as beacons (anchors), IOn-E devices as sensors and Quantum v2 as tags (targets), all of them from Nebusens) and software tools that integrate the ZigBee communication protocol. These devices form a mesh network whose devices collect both contextual information, through sensors, and localization information, through beacons and tags. This data feeds the recommendation system presented in Section 4. In addition, one of the major benefits of the platform is the duality of sensor nodes, as they can also act as localization anchors, which reduces the infrastructure of devices for the integration of any use case. Sections 3.2 and 3.3 provides all the details on the RTLS integrated by CAFCLA.
- *Management layer:* This layer provides the social, logical and intelligence aspects of the framework. One of its main tasks is to classify the contextual information and correlate this information with the monitored activities. Following the methodology of previous works, such as [42-44], eleven recommendations have been predefined to be delivered according to the identification of the users' activities. The recommendations that have been predefined within this development are as follows:
    - Turn off heating if the temperature is over 18°C.
    - Turn off lights if lighting is over 200 lux.
    - Turn off heating and lights when the last person leaves the house.
    - Turn off lights if there is no movement in certain areas, for example when sitting on the couch watching TV, playing, etc.
    - Turn off room lights with no occupancy.
    - Turn off heating if no movement is detected at night and the temperature is above 18°C.
    - Optimize the use of the heating schedule by identifying the times in which there are people at home.
    - Reduce the use of the washing machine by recommending an appropriate load and a low energy schedule.
    - Let's cook together: suggest cooking schedules or joint meals to users.
    - Organization of the bathroom: suggest a planned and serialized use of the bathroom to take advantage of the heat and the production of hot water.
    - Warn about stand-by consumptions in devices (televisions, consoles, computers, etc.).

- *Application layer*: this layer includes tools which configure all the sensors and define the areas of interest, such as beds (to identify when users are sleeping), couch (watching TV, reading, etc.), work areas (washing machine, cooker, etc.), front door, etc. Further, these tools also include mechanisms that define the activities which are to be identified or the conditions in which a recommendation should be triggered. Figure 3 shows the interface of the context-aware and localization systems, including the menu where new sensors in the system are registered.

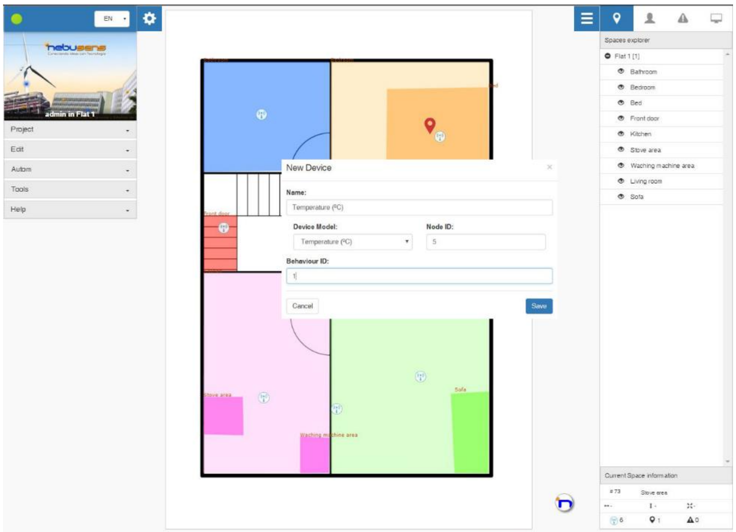


Figure 3. CAFCLA implements tools which, among other functions, define the areas of activity identification and configure sensors.

The information collected by sensors, in particular by smart plugs, permits to recognize and classify the activities performed by users. CAFCLA monitors temperature, lighting, electric consumption and users' movement. Thus, according to the level of lighting in a room, the temperature, the electric consumption of any of the monitored devices (washing machine, dishwasher, TV or PC) and the hour and day of the week, the system will be able to identify different user activities such as watching TV, having breakfast or using the bathroom. The RTLS is a perfect complement to the data collected by sensors [53] since it provides the location of users and their activity level, enabling to infer for example, who is watching the TV or putting on the washing machine. In this respect, CAFCLA integrates an RTLS with an accuracy of up to 1 meter and provides tools which, among other functions, define areas, place sensors, register users and define rules in order to generate and filter the information that is then processed intelligently, as explained in Section 4.

Having depicted the structure of the CAFCLA framework, the following section focuses on the techniques used to optimize localization accuracy and details the integration and performance of the RTLS within CAFCLA. Thus, the combination of localization and context awareness under a single infrastructure provides added value to the systems that address this topic.

3.2. Real-time localization via multilayer perceptron

The main objective for the implemented RTLS is to obtain the position of a target, $\boldsymbol{x}_{t\in\mathbb{N}} \in \mathbb{R}^2$, on each frame of time, $t \in \mathbb{N}$, by using measurements given by the received signal strength indicator (RSSI), $\boldsymbol{z}_{t\in\mathbb{N}} = \boldsymbol{r}_{t\in\mathbb{N}} \in \mathbb{R}^{N_t}$, where N_t is the number of anchors with known positions, $\boldsymbol{p}_{i\in 1,2,\ldots,N_t}$, that transmit to the target at time t.

To reach this objective, the process is divided in two steps:

- *Distance estimation:* during the first phase, the distance between the target and each anchor, $\left\|\boldsymbol{x}_t - \boldsymbol{p}_i\right\|_{i\in 1,2,\dots,N_t} \in \mathbb{R}$, is obtained by using real-time RSSI values, $\boldsymbol{z}_{t\in\mathbb{N}}$.
- *Position estimation:* during second phase, the position of the target, $\boldsymbol{x}_{t\in\mathbb{N}}$, is obtained by using the distance estimates, $\boldsymbol{p}_{i\in 1,2,\dots,N_t} \in \mathbb{R}^{N_t}$, makes use of $\boldsymbol{d}(N_{i,t})$ and the position of each beacon within the environment $\boldsymbol{x}(N_i)$.

In this work, target and anchors are responsible to send the information needed to calculate the position of the first one, $\boldsymbol{x}_t$, within the *Physical* and *Context-awareness Layers*. To calculate its position, the target sends information related to the RSSI (*Received Signal Strength Indicator*) of the signal, $\boldsymbol{z}_t$. This information is sent every second if the user is in motion, being determined this state by a positive value of the accelerometer. This data, once on the server is processed by the localization engine which estimates the position of the tag in the mentioned two phases:

- *Distance estimation:* during the first phase, the engine calculates the most probable distance between the target and the anchors, $\widehat{\boldsymbol{d}}_t = \|\widehat{\boldsymbol{x}_t - \boldsymbol{p}}_i\|_{i\in 1,2,\dots,N_t}$, based on the RSSI level, $\boldsymbol{z}_t$**.** These values are calculated by using time series applied to ANN. ANNs permit for the use of time series, making it easier to forecast in situations where the estimation of the position from non-independent values with consecutive samples is not possible. Thus, the ANN is able to forecast a value according to the historical records. More concretely, an MLP is used to provide a value according to the historical values [65]. Therefore, the neural network in this study is fed with both the current detected RSSI value and the RSSI values detected in previous time instants,$\boldsymbol{z}_{t-l:t}$. The ANN has been trained considering several anchors at the same time to avoid the multipath effect. It is formed by $(l+1)$ input neurons, with l the lag or number of previous times recorded. The intermediate layer of the Neural Network uses $2(l+1)+1$ neurons and is configured following the *Kolmogorov Theorem* [66].

  Figure 4 shows that the ANN includes a number of input groups equal to the number of anchors considered in the estimation. Finally, the classification of the groups of input neurons is made attending to the current RSSI signal, with the first neuron corresponding to the reader that receives a higher RSSI and the last, the one that receives the lowest.

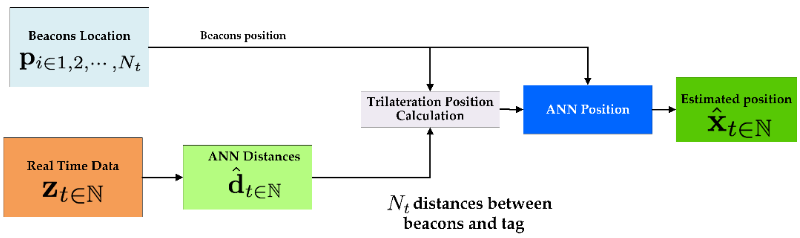


Figure 4. Architecture of the Multi-Layer Perceptron Neural Network used to calculate the distance between the anchors and the target within the system.

- *Position estimation:* the second phase calculates the positon of the target, $\boldsymbol{x}_t$, by using the distances calculated in the first phase, $\widehat{\boldsymbol{d}}_t$, and the beacons' fixed location within the environment, $\boldsymbol{p}_{i\in 1,2,\dots,N_t}$. The distance estimates and anchors' positions are introduced in the second ANN (MLP) that estimates the target's position from the input data [65,67]. This ANN has been trained by an *error back propagation algorithm* with positions obtained by the application of a trilateration algorithm to the distance estimates. This algorithm calculates the maximum likelihood (ML) of adaptive distributions based on kernel mixtures [54]:

$$\hat{\mathbf{x}}_t = \arg\max_{\mathbf{x}_t} p\left(\hat{\mathbf{d}}_t \middle| \mathbf{x}_t\right) = \arg\max_{\mathbf{x}_t} \prod_{i=1}^{N_t} p\left(\hat{\mathrm{d}}_{i,t} \middle| \mathbf{x}_t\right) \quad (1)$$

where $p\left(\hat{\mathrm{d}}_{i,t} \middle| \mathbf{x}_t\right)$ is the likelihood function of the target's position for the distance estimate with respect to the ith anchor where, for one kernel:

$$\boldsymbol{p}\left(\widehat{\boldsymbol{d}}_{i,t} \middle| \boldsymbol{x}_t\right) \approx \frac{1}{h}\boldsymbol{K}\left(\frac{\|\boldsymbol{x}_t - \boldsymbol{p}_i\| - \widehat{\boldsymbol{d}}_{i,t}}{h}\right) \quad (2)$$

where $K(\cdot)$ is a kernel function with bandwidth h [68].

For the trilateration algorithm, we use a Gaussian kernel due to the tractability constraints of the ML. However, by using the ANN, we avoid the high processing times required by other kernels, by dealing with the complexity vs. accuracy trade-off. The number of neurons of the ANN is n in the input layer, $2n+1$ in the hidden layer, and 1 in the output layer.

Figure 5 shows how the problem is resolved in a schematic way. This model will provide the position of the tags within the localization environment, at every second.

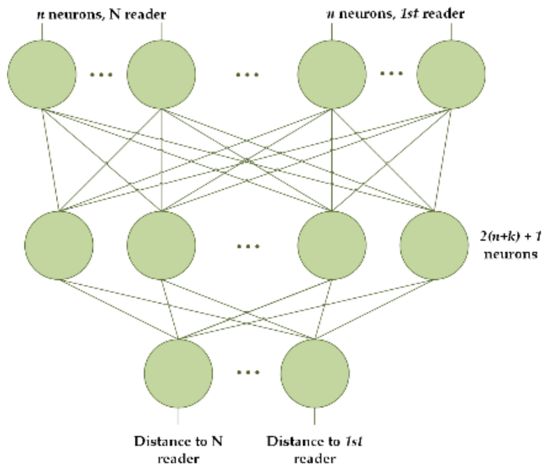


Figure 5. A schematic diagram of the two paths that follow the training and the real-time data: the calculation of the distances between anchors and targets and the calculation of the final estimated position.

3.3. Integration within CAFCLA and performance of the RTLS

In this section, we assess the performance of the localization system in comparison with conventional techniques. Note that the devices have been designed by the authors for the purpose of localization and the results obtained with novel techniques will outperform those obtained with conventional, off-the-shelf devices.

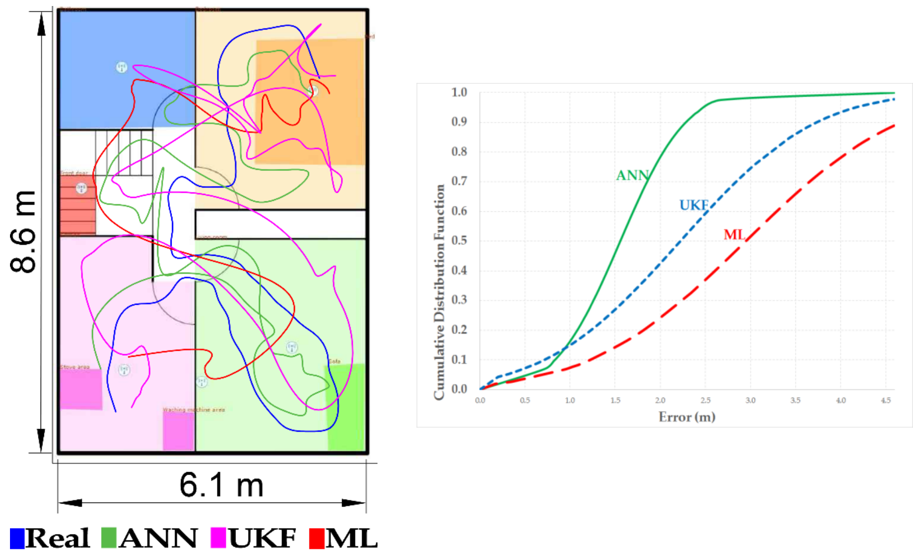
As introduced in Section 3.1, CAFCLA integrates the functionalities of an RTLS based in the ZigBee communication protocol. The deployment of the integrated localization system requires a number of beacons (anchors) to be distributed in the scenario, directly proportional to the required accuracy. Those beacons are Sirius RadIOn devices, part of the *Physical Layer* of the framework. They transmit in the 2.4 GHz frequency band with a transmission power of 3 dBm and patch antennas. In addition to placing and locating each of the anchors in the houses, the software allows to determine the different areas within the house with high granularity, as they are not only defined at the room level, but more precisely such as the stove area, the washing machine, the sofa and the armchairs, the different tables, the beds and the front door. This information is very useful for identifying the activity that the user is performing at a given moment and thus, provide a recommendation accordingly.

The target carries a mobile tag (Quantum v2, also part of the *Physical Layer*) with an integrated accelerometer, a vibrator to receive warnings and a button that allows to send feedback on the recommendations sent by the system. This tag transmits a set of signals to the beacons with their RSSI values. All the information acquired by the devices in the *Physical Layer* is transported via ZigBee, in the communication between readers, and Wi-Fi or 3G/4G from each house to the server. Within the server all the functionalities that make up the *Context-Awareness*, *Management* and *Application Layers* are running to perform all the services offered by CAFCLA. Within the *Context-Awareness Layer*, the received RSSI signals are organized to serve as input data for the localization model within the

Management Layer. Here, the position of each user within the house is estimated by means of the described localization model.

Figure 6 shows the result of a case-study where a target is localized on the basis of signals transmitted to 6 anchors at every second. We compare the results with conventional techniques based on ML and Bayesian filtering. We call:

- ANN: the proposed localization approach based on the two MLP stages.
- UKF: a conventional Unscented Kalman filter (UKF) based on the likelihood shown in (2) [69].
- ML: a trilateration algorithm based on the likelihood function shown in (2) [54].



(a) (b)

Figure 6. The presented localization algorithm remarkably outperforms conventional localization techniques based on UKF and ML.

As Figure 6 points out, the proposed two-step ANN obtains lower errors than conventional techniques, obtaining a root mean squared error (RMSE) of 1.66 m for the ANN, 2.53 m for the UKF and 3.26 m for the ML approach. This level of accuracy is highly useful for determining the position of each user inside the house, identifying when they are sitting on the sofa, cooking or at the front door ready to leave.

Next section addresses the use of social computing in energy saving systems, the development of the designed recommendation system, as well as the inclusion of social computing and virtual organizations of agents as cornerstones of intelligent and efficient management in the system.

3.4. Energy efficiency based on social computing

The great utility of localization and sensing data for the monitoring of users' activities in their households, requires a system that is able to manage this information efficiently and intelligently. As the title of this section suggest, social computing is postulated as a paradigm that maximizes the functionality of this information and allows to simplify and improve relationships between machines and humans.

The development of a recommendation system such as the one presented in this work requires a set of functionalities which are difficult to merge, as shown in the following.

The main objective of the recommendation system is to achieve a substantial reduction in energy consumption in households and improve the demand response through the promotion and acquisition of energy-efficient habits.

This work is based on three technological pillars: first, a precise localization system that allows to monitor users and their level of activity at all times; second, a scalable sensor network that gathers environmental parameters to characterize the environment in real-time; and third, a social machine that provides intelligence to the system. CAFCLA allows to implement intelligence techniques through the *Management Layer*, which is responsible for covering all the social, logical and intelligence needs of the system. For this reason, this layer implements the VO-based social machine that supports the recommendation system. The implementation of the VO has been developed using the JADE platform and the Jadex tool [70], an extension that provides a BDI architecture to the JADE agents. Thus, Jadex agents work with concepts such as beliefs, goals and plans. Jadex has the advantage of allowing the programmer to introduce their own deliberative mechanisms. The platform allows to implement open multi-agent systems easily by using different tools to create, manage and control virtual organizations, including organizational aspects.

Figure 7 shows the different VOs included in the designed architecture:

- *Localization VO*: it collects the RSSI information and implements the localization algorithm. It is coordinated with de *Data management VO* to update the position of each user in real-time.
- *Context-aware VO*: it manages all the information gathered by the sensors. It is coordinated with the *Data management VO* to update the information collected by the sensors.
- *Data gathering VO*: it is in charge of the management of the data sources and the control of heterogeneous systems such as the localization system, the WSN and other data sources.
- *Data management VO:* it includes data reception, classification, storage and delivery. It classifies users' preferences, identifies habits and patterns or the correlation among context-awareness and predefined activities, among others.
- *Social machine VO*: it manages the interaction among all the agents of the system and the social information extracted from them. The agents implemented in this VO are as follows:
    - *User agent*: it is responsible for user-user and user-machine interactions. They register all the information that is relevant to the recommendation system.
    - *Preferences agent*: it analyses the information stored by the data management layer and identifies and classifies energy preferences for each user and their energy savings habits.
    - *Reputation agent*: it manages the reputation of energy-efficient actions. This reputation is calculated using a Bayesian system that takes binary ratings as inputs [71]: when a recommendation is sent and accepted by the user, if it implies energy savings, then positive rating increases by 1 unit (α) and, if it does not imply energy savings, negative rating increases by 1 unit (β). The reputation $\mathbb{E}\{p_i\}$ of the ith recommendation is calculated using beta probability density function (pdf) and its score is represented by the expected value of the beta pdf. Thus, the beta pdf is expressed using the gamma function, $\Gamma(\cdot)$, as:

$$f(p_i;\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} {p_i}^{\alpha-1}(1-p_i)^{\beta-1} \quad (3)$$

$$\begin{aligned} s.t. \quad & 0 \le p_i \le 1 \\ & \alpha,\beta > 0 \\ & p_i \ne 0 \; if \; \alpha < 1 \\ & p_i \ne 1 \; if \; \beta < 1 \end{aligned}$$

Then, the expected value of the beta distribution is calculated as follows:

$$\mathbb{E}\{p_i\} = \frac{\alpha}{\alpha+\beta} = \frac{1}{1+\frac{\beta}{\alpha}} \quad (4)$$

- *Recommendation VO:* it generates personalized recommendations which are sent to users to engage them in using energy more responsibly. It receives information from the reputation agent.

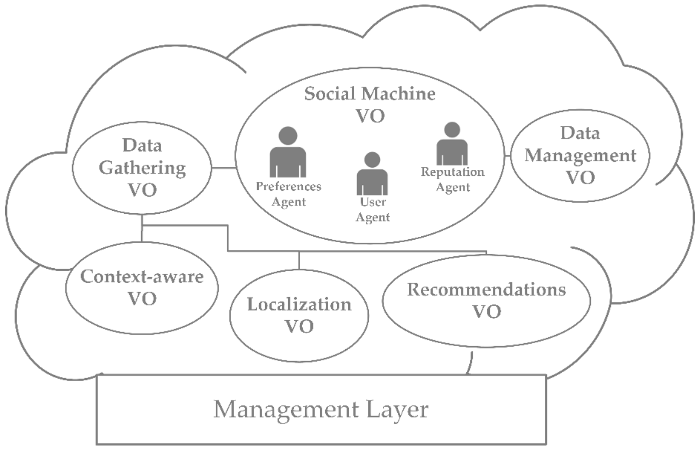


Figure 7. The social machine is supported by the VOs' that manage the localization and tracking of users, the contextual information and the generation of recommendations which help foster good energy saving habits.

Next section describes the implementation of a case-study in which the recommendation system is used to promote energy saving in households.

4. Case-study: recommendation system for the enhancement of energy savings in homes

This section describes the experimental set-up and the results of a case-study designed to assess the performance of the presented framework for energy efficiency in households. First, it presents the recommendation system, its objectives and the recommendations that are provided to the users. Next, it shows the consumption results before and after the implementation of the recommendation system.

4.1. Description of the case-study

The proposed system has been deployed in 5 houses with 3 different typologies: Type I, a 1-bedroom flat with one user; Type II, are two 2-bedroom flats with two users; Type III, are two 3-bedroom flats with three users. All the houses have a kitchen, a living room and a bathroom except the 3-bedroom dwellings, which have two bathrooms. As a whole, 11 users participated in the experimentation. An example of deployment can be seen in one of the flats in Figure 3.

Moreover, the deployed WSN consists of a temperature and a lighting sensor in each room of every flat, in the kitchen, in the bathrooms, in the living room and in the front door area, which implies a total of 5 measurement points for Type I, 6 for Type II and 8 for Type III. These points are formed by an IOn-E device [72] connected through a digital I2C port to a RadIOn communication device. The IOn-E device integrates a light sensor model TSL2561 (AMS, Stiria, Austria), whose measuring range is between 0.1 and 40.000 lux. The brightness measurement is sent every 60 seconds to the server. The IOn-E device also integrates a high-precision temperature sensor SHT25 (Sensirion, Staefa, Switzerland). This sensor is capable of recording measurements between -20°C and 100°C with an accuracy of ±0.1°C. For the purpose of this work, the sensors send the temperature to the server when a variation of ±0.5°C occurs.

Electric consumption is gathered from smart plugs in the living rooms and the bedrooms of each house in order to identify the use of devices such as TV, computers, lamps and others. We use Cloogy plugs [73] in the living room and bedrooms. They include an electrical consumption sensor, that registers the consumption every 15 minutes, with an accuracy of ±1% ± 0.5W, and ZigBee communication capability to provide data consumption. The data are collected by a crawler that accesses the web service where the consumption measured by each sensor is published. Every day, a different crawler obtains the aggregated hourly consumption data of each household from the API of the DSO connected to the smart meter, to which all the users have access.

One RadIOn device per room and a Quantum device will act as anchors and target for the localization system, which enrich the system thanks to its great accuracy.

The social machine implemented in this experiment receives real-time data from both the localization system and the WSN (see Figure 8). This data allows to identify patterns such as predefined actions, bad energy uses or potential improvements by giving the instantaneous situation of the users and their surrounding environment. Moreover, the social machine calculates the reputation of each of the actions in order to recommend them to the users. These recommendations are sent through emails, when a behaviour pattern is detected, explaining their benefits, their use by the rest of the participants, the improvements achieved and, above all, with an explicit subject that permits them to be carried out quickly. Further, users receive a vibration on the localization tag they carry to inform them that a recommendation has been sent. If they take it into consideration, they only have to push the tag button and the system interprets this signal as positive feedback.

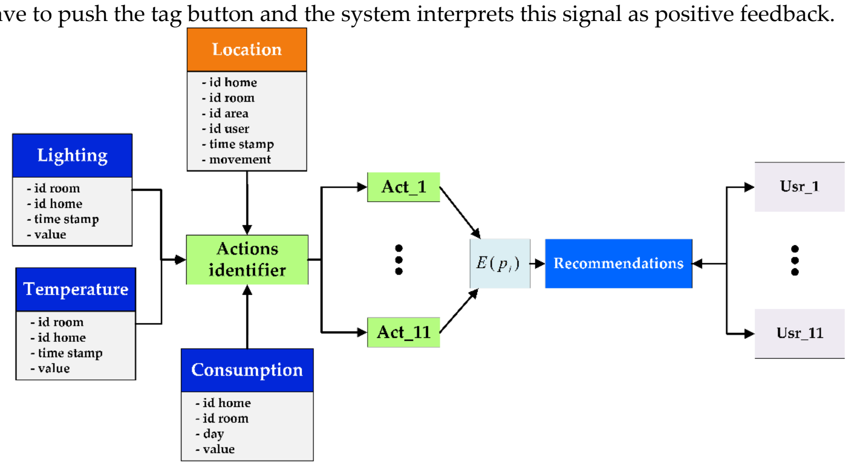


Figure 8. The social machine receives data from the localization engine and the sensor network to identify the actions that are being carried out. With the current and historical data gathered, the social machine calculates the reputation of each action to provide customized recommendations to the users.

The next section describes the results obtained during the experimentation and also compare baseline consumption data.

4.2. Experimental results

The experiment was performed during two consecutive months. During the first month, the daily consumption data was collected for each flat in order to create a baseline consumption and compare it with the results of the experiment in the second month. The month of April was chosen for collecting baseline data and the month of May to perform the experiment, seeking to minimize the differences in weather conditions, pluviometry and sunlight that could affect the results, avoiding the months with extreme hot or cold. Moreover, these months were chosen because they are considered the most standard months in terms of work and daily life, this means that the participants were at home (and not on holidays).

To obtain the baseline data and to determine the recommendations, the deployed system collected data without sending recommendations for 30 days, the obtained results are shown in Table 1, where savings are calculated as follows:

$$\boldsymbol{Savings} = \frac{\boldsymbol{Baseline\ consumption - Reported\ consumption}}{\boldsymbol{Baseline\ consumption}} \quad (5)$$

Table 1. Total consumption in kWh during the 30 days of baseline data collection, during the 30 days of the experiment, difference in the consumption and savings between the two periods.

Consumption	Flat 1	Flat 2	Flat 3	Flat 4	Flat 5
Baseline (kWh)	496.56	561.66	545.40	601.35	654.73
Experiment (kWh)	387.41	470.92	470.24	493.57	549.04
Difference (kWh)	109.15	90.74	75.16	107.78	105.68
Savings (%)	21.98 %	16.15 %	13.78 %	17.92 %	16.14 %

As shown in Table 1, flat 1 displays significantly lower consumption during the development of the experiment in comparison to the monitoring phase in the first month, while the other flats experienced more moderate changes. Energy savings have oscillated between 13.78% and 21.98%. We can point out that the average energy savings per user were 17.08% (44.41 kWh) during the experiment.

Figure 9 shows daily consumption for each flat during the monitoring experimentation phases. The graphs show the levels of consumption for each day of the week. Levels increase during weekends, when users stay at home for longer and use the time to do the laundry, watch TV or cook. Furthermore, the negative tendency (dashed line) indicates that users are reaching energy savings thanks to the recommendations and acquiring good energy consumption habits. Finally, the accumulated savings in Fig. 9.(f) asseverate that the use of the social machine is effective.

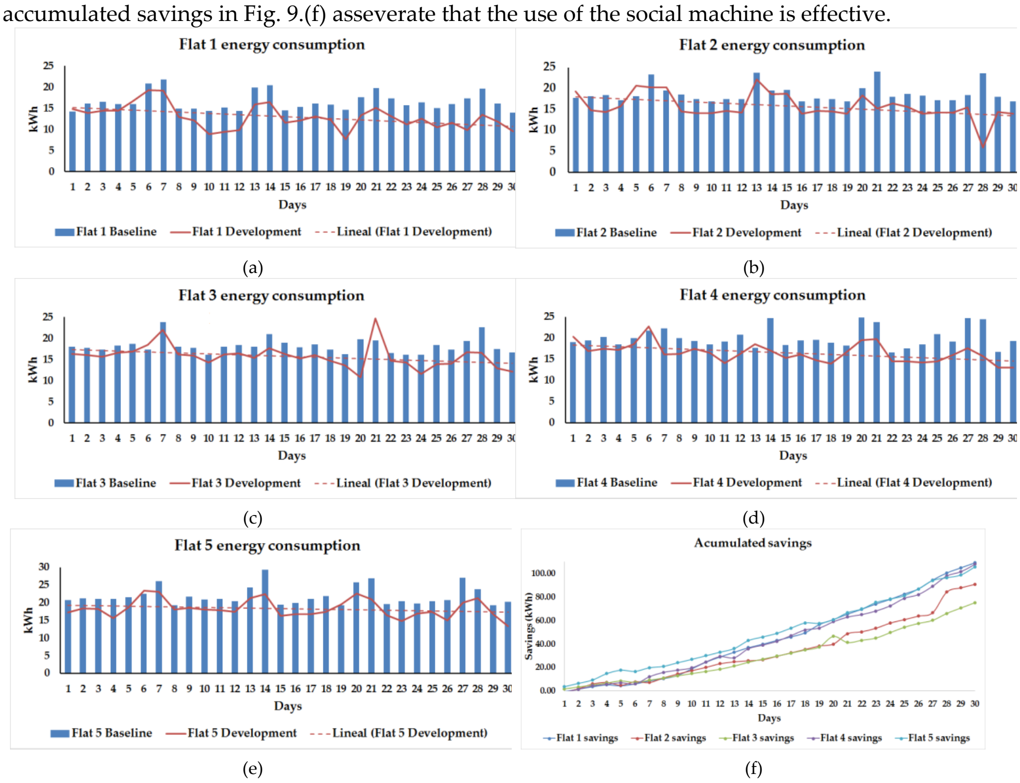


Figure 9. Daily energy consumption during the baseline and the experimentation periods in each flat (graphs a to e) and accumulated savings (f). The results demonstrate the reduction in consumption and the lineal tendency shows how players acquire good habits along the experimentation.

Table 2 shows the results of the Student's t-test and Levene's test. In this case, the difference between the reported average consumption during the monitoring and the experiment was significantly lower for the latter in all the cases, with a p-value of 0.000 in all cases for the mean differences, what demonstrates the effectiveness of the recommendation system in terms of energy savings and behavioural change.

Table 2. Results of the Student's t-test and Levene's test performed to assess the difference of means and variances between the baseline usage data and the data collected during the experimentation. All the flats present a lower percentage of energy usage after the experimentation.

	Baseline		Experiment					
Houses	**Mean**	**Std.**	**Mean**	**Std.**	**t**	***p*-value (2-tailed)**	**F**	***p*-value**
Flat 1 (kWh)	16.553	2.179	12.914	2.838	5.569	0.000	1.449	0.234
Flat 2 (kWh)	18.721	2.140	15.696	3.065	4.431	0.000	2.006	0.162
Flat 3 (kWh)	18.179	1.761	15.674	2.733	4.219	0.000	1.853	0.179
Flat 4 (kWh)	20.045	2.363	16.451	2.234	6.052	0.000	0.162	0.689
Flat 5 (kWh)	21.823	2.661	18.301	2.550	5.232	0.000	0.010	0.920

The analysis of the results showed that the most frequent recommendations taken into account were those related to the use of heating (77%), lighting (84%) and switching off devices to avoid stand-by consumption (92%). However, recommendations on the optimization in bathroom usage (4%) or cooking at the same time (17%) did not have a high response, which shows that the social machine has operated more effectively in human-machine than in human-human relationships.

5. Conclusions

This paper presents a recommendation system that identifies users' energy consumption behaviour patterns in their homes, for the purpose of promoting a more efficient energy usage. To achieve this aim, it uses the CAFCLA framework to integrate the infrastructure itself; a real-time localization system and WSNs. The design of the system makes use of Virtual Organizations of agents that enabled for the development of a social machine which personalizes the recommendations sent to each user. Thanks to the precise traceability of each user, the system is able to encourage them to acquire good energy habits.

The conducted experiment involved the deployment of the required infrastructure in 5 houses with different typology and had 11 participants in total. The obtained results point out to the fact that the combined use of the localization system with the WSN and the social machine, allows to determine the context that surrounds each user with high precision. The intelligent management of this information helps identify situations in which potential energy savings arise and, immediately, generate and send customized recommendations to encourage users to take energy saving actions.

More specifically, the proposed system attains energy savings that exceed 20%, higher than those achieved by the solutions analysed in the state of the art (between 10 and 15%). In addition, the proposed system provides greater flexibility than other solutions, this is because it combines context-awareness, localization and social computing techniques. Multiple solutions have approached these problems independently but none of them has faced them together.

However, the accuracy of the system makes its implementation in homes very expensive for users. In this regard, it is necessary to improve the accuracy of localization using more standard devices, such as mobile phones. Moreover, although it is becoming easier to implement these solutions due to the boom of contextualization devices, future work will require the coordination of different stakeholders (promoters, developers, manufacturers, etc.) in order to benefit from the integration of technologies coming from different sources. Finally, with the aim of further decreasing energy consumption, future works will integrate techniques that consider demand response information and the price of energy.

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6 Conclusiones

Durante esta Tesis Doctoral se ha presentado el framework CAFCLA para el diseño y desarrollo de actividades de aprendizaje colaborativo y las publicaciones a las que ha dado lugar. Este Capítulo final desarrolla las conclusiones y trabajo futuro más relevantes, resumiendo el objetivo general de investigación, las contribuciones propuestas y su evaluación. La Sección 6.1 presenta las conclusiones que se han obtenido tras la implementación de diferentes casos de uso utilizando CAFCLA y cuyos resultados nos llevan a concluir se han cumplido los objetivos de la Tesis Doctoral. La Sección 6.2 ahonda en las líneas de investigación futuras que han surgido durante la realización de este trabajo.

6.1. Conclusiones

El uso de las Tecnologías de la Información y la Comunicación en todas las áreas ha aumentado en los últimos años gracias a la emergencia en la sociedad de los dispositivos móviles, las redes de sensores y los sistemas de localización. Además, el fácil acceso a la tecnología existente y las múltiples características y funcionalidades que estos dispositivos presentan y ofrecen, como protocolos de comunicación y tecnologías sensibles al contexto, los convierten en herramientas de gran potencial para desarrollar aplicaciones. Sin embargo, es difícil desarrollar aplicaciones para exprimir al máximo la capacidad que ofrece la tecnología, sobre todo cuando el objetivo principal es el desarrollo de aplicaciones tecnológicas transparentes para los usuarios (como sugiere el paradigma de Inteligencia Ambiental), e inteligentes y que tengan en cuanta las relaciones entre humanos y máquinas (como sugiere el paradigma de la Computación Social).

El ámbito educativo no ha permanecido impasible ante estos avances tecnológicos. Gracias a ellos, y a su incorporación en el proceso educativo, a día de hoy existen un abanico de posibilidades para desarrollar procesos de aprendizaje impensable unos años atrás. El uso de recursos digitales, la posibilidad de comunicación ubicua o el acceso a información a través de dispositivos móviles han hecho que el aprendizaje pueda llevarse a cabo en cualquier momento y lugar. Además, las múltiples vías de comunicación que ofrece la tecnología a sus usuarios facilita el desarrollo de actividades de aprendizaje colaborativo, fomentando los lazos sociales entre los participantes en la actividad, considerando a éstos no solo a los humanos, sino también a los dispositivos y máquinas que en él participan.

A pesar de la abundante literatura que se encuentra en relación a estos temas, la investigación llevada a cabo en esta Tesis Doctoral ha evidenciado algunas carencias que deben resolverse para mejorar el uso de la tecnología en el ámbito educativo. De forma más concreta, no existe ningún framework horizontal que permita:

- Adaptar los procesos educativos a cualquier tipo de entorno: académico, no académico, aulas, parques, museos, edificios públicos, etc.
- Fomentar una participación activa de los estudiantes: las soluciones de aprendizaje tradicionales se han basado en métodos de aprendizaje pasivos donde el usuario era un mero receptor de información, un rol pasivo que no incentiva su motivación y fomenta malos resultados en el proceso de aprendizaje.

Para hacer frente a estas carencias, durante esta Tesis Doctoral se ha presentado el framework CAFCLA cuyo principal objetivo de diseñar y desarrollar un conjunto de herramientas que sirvan de base para implementar actividades de aprendizaje colaborativo basadas en Inteligencia Ambiental, la Computación Social y que utilicen información contextual. CAFCLA es un framework que integra diferentes tecnologías sensibles al contexto, como sistemas de localización en tiempo real, redes inalámbricas de sensores, múltiples protocolos de comunicación, e interfaces de programación. La integración de estos recursos se ha realizado con un objetivo claro: reducir tanto a los educadores como a los desarrolladores y técnicos la complejidad a la hora de crear actividades de aprendizaje colaborativo que hagan uso simultáneo de diferentes tecnologías. El desarrollo de CAFCLA se ha centrado en proporcionar un conjunto de herramientas y métodos para los profesores, desarrolladores y personal técnico con el fin de diseñar, desarrollar y desplegar fácilmente este tipo de actividades de aprendizaje, haciendo transparente al máximo su complejidad y ofreciendo recursos que facilitan y simplifican los procesos.

Desde su creación, CAFCLA ha sido diseñado siguiendo las directrices establecidas por la Inteligencia Ambiental y la Computación Social. La implementación de tecnologías sensibles al contexto ha permitido cubrir requisitos tales como la adaptación, la anticipación, las relaciones sociales o el razonamiento, siendo el framework capaz de cubrir una amplia gama de escenarios de aprendizaje. Su estructura en capas así como la incorporación de Organizaciones Virtuales de agentes lo han dotado de una mayor escalabilidad y capacidad de adaptación a diferentes entornos y situaciones de aprendizaje.

Gracias a la Computación Social, las personas se ven involucradas en la resolución de problemas ya sea por sus propios medios o mediante la colaboración con máquinas u otras personas. La inclusión de aspectos sociales como la motivación de los alumnos a través de recomendaciones personalizadas y desafíos, ha permitido conseguir mejores resultados en el proceso de aprendizaje y, lo que es más importante, mantenerlos en el tiempo. Para ello, se han integrado en CAFCLA tecnologías avanzadas para resolver problemas sociales educativos teniendo en cuenta las interacciones hombre-máquina, así como la sensibilidad al contexto.

Para comprobar su viabilidad y potencial, CAFCLA ha sido evaluado en diferentes casos de uso. De esta forma ha podido demostrarse la flexibilidad, capacidad de adaptación a diferentes contextos y utilidad de las funcionalidades que integra. A continuación, se resumen las conclusiones más importantes extraídas de cada uno de los despliegues.

El primer caso de uso se llevó a cabo en el Museo de las Escuelas Mayores de la Universidad de Salamanca. En él se desarrolló una actividad de aprendizaje colaborativo, tal y como se detalla en la Sección 3.4. En comparación con las soluciones existentes, pudieron valorarse de forma positiva las siguientes conclusiones a cerca de CAFCLA, ya que favorecen al proceso de aprendizaje a través de la creación de entornos atractivos que fomentan el compromiso y la participación de los estudiantes:

- CAFCLA permite a los profesores definir múltiples tipos de actividades a través de diferentes procesos y técnicas de aprendizaje.
- CAFCLA permite el desarrollo de actividades diseñadas para favorecer las relaciones sociales de los participantes, tanto entre sí como con las máquinas integradas en el proceso (por ejemplo, sensores).
- CAFCLA permite una descripción detallada y gran granularidad de la información contextual mediante sistemas de localización en tiempo real.
- CAFCLA permite a los docentes gestionar todas las interacciones que se producen durante la realización de la actividad, de manera que se fomente la cooperación y participación de todos los actores implicados en la actividad.
- CAFCLA ha permitido desarrollar un caso de estudio con el que se ha demostrado que proporcionando información contextual a través de la Computación Social en actividades de aprendizaje colaborativo, se mejora la adquisición de conocimientos, se fomenta la colaboración de los estudiantes, se fortalece los lazos sociales y se aumenta la satisfacción de los participantes.

El segundo caso de uso se llevó a cabo un juego serio basado en el paradigma de la Computación Social. Este juego integraba diferentes tecnologías a través de CAFCLA, incluyendo redes inalámbricas de sensores y un sistema de localización en tiempo real, tal y como se detalla en la Sección 3.5. La inclusión de estas tecnologías permitió tener una contextualización del entorno tan precisa como fuera necesaria, ya que se facilitó la integración de cualquier tipo de sensores, actuadores y, gracias al sistema de localización, la posición, seguimiento y monitorización de la actividad de los jugadores. Además, el juego integraba Organizaciones Virtuales de agentes para crear una máquina social que personalizara las recomendaciones ofrecidas a los usuarios. Esta integración permitió resolver los problemas de interacción hombre-máquina y de conocimiento del contexto, logrando el objetivo principal del juego: que los usuarios adquieran buenos hábitos de ahorro energético en los edificios públicos y el entorno de trabajo. El juego se ha desarrollado en uno de los laboratorios del grupo de investigación BISITE y, en comparación con otros juegos similares, podemos aseverar que:

- El uso de CAFCLA proporciona un gran potencial para el desarrollo de sistemas que pretenden promover un cambio de comportamiento en los hábitos de consumo energético.
- El caso de estudio mostró que las interacciones sociales fomentan el crecimiento del interés en mejorar el rendimiento individual a través de la competencia entre los jugadores.
- Además, se fomentó la adquisición de buenos hábitos energéticos para beneficiar al grupo en lugares donde la conciencia del consumo de energía es a menudo inexistente, como en el ámbito laboral o en los edificios públicos.
- El juego serio ha demostrado el potencial del framework para el desarrollo de este tipo de soluciones.
- La experimentación llevada a cabo ha conseguido un cambio de comportamiento hacia hábitos más eficientes energéticamente en el entorno de trabajo que ha sido mantenido a lo largo del tiempo.

El tercer caso de uso presentado llevó a cabo un sistema de recomendaciones que identificaba patrones de comportamiento energético de los inquilinos en sus casas. El objetivo principal era promover un mejor uso de la energía y fomentar el ahorro energético, así como la adquisición de buenos hábitos y el uso eficiente de los recursos energéticos. Para lograr este propósito, se integró en CAFCLA una única infraestructura que proporcionaba un sistema de localización en tiempo real y una red inalámbrica de sensores. Además, el sistema fue diseñado utilizando Organizaciones Virtuales de agentes que han permitido el desarrollo de una máquina social que personaliza las recomendaciones a cada usuario. Gracias a la trazabilidad precisa de cada inquilino, el sistema ha sido capaz de animarlos a adquirir buenos hábitos energéticos. La experimentación realizada ha supuesto el despliegue de la infraestructura necesaria en 5 viviendas de distinta tipología, con la participación de 11 usuarios. Los resultados obtenidos señalan que:

- El uso combinado del sistema de localización, la red inalámbrica de sensores y la máquina social, permite determinar con alta precisión el contexto que rodea a cada usuario.

- La gestión inteligente de esta información facilita la identificación de situaciones en las que se generan ahorros potenciales de energía e inmediatamente genera y envía recomendaciones personalizadas para alentar a los usuarios a llevarlas a cabo.
- La experimentación permitió generar ahorro energético a través de acciones individuales.
- CAFCLA no fue capaz de fomentar la realización de actividades conjuntas entre los inquilinos (por ejemplo, cocinar a la vez), tal y como se proponía.
- La flexibilidad de CAFCLA es un valor añadido en comparación con otras soluciones, ya que la integración de múltiples tecnologías y protocolos de comunicación puede mejorar sustancialmente el conocimiento del contexto, cumpliendo los requisitos de un gran número de casos de uso potenciales que podrían ser implementados.

6.2. Trabajo futuro

A lo largo del desarrollo de esta Tesis Doctoral han aparecido nuevas líneas de investigación y desarrollo que permiten continuar y diversificar el trabajo aquí presentado. La presente sección resume de forma breve las más relevantes. La flexibilidad y escalabilidad con la que CAFCLA ha sido diseñado desde su concepción, permitirá una integración sencilla y transparente de las tecnologías que resulten de estas líneas de trabajo futuro:

- **Localización:** CAFCLA necesita innovar en el desarrollo de sistemas de localización más precisos a través del teléfono móvil. Actualmente un amplio porcentaje de la población utiliza estos dispositivos de forma constante, acompañándonos a todas partes en todo momento. Sin embargo, la precisión de localización en interiores que se consigue actualmente, utilizando los protocolos de comunicación que ofrecen, no alcanza niveles que permitan dotar de una granularidad alta a las actividades de aprendizaje diseñadas haciendo uso de CAFCLA.
- **Sensorización:** la integración de diferentes tipos de sensores comerciales es otra línea de trabajo en el futuro. Gracias al auge de la IoT el mercado ofrece innumerables dispositivos que permiten monitorizar todo tipo de parámetros. CAFCLA debe prestar atención a las tendencias y estandarizaciones en este ámbito para ofrecer recursos totalmente actualizados a sus usuarios. Gracias a este auge, la implementación de los sistemas propuestos en el futuro será más fácil gracias a la mejor accesibilidad que presentan estas tecnologías, tanto a nivel de sensorización como de localización, permitiendo implementar las soluciones propuestas con más funcionalidades, menos dificultad de desarrollo y precios más asequibles.

- **Juegos Serios:** CAFCLA ha alentado a los autores a mejorar sus habilidades mediante el diseño y desarrollo de juegos serios más complejos que permitan explotar de forma más amplia el potencial que el framework ofrece. Estos juegos se enfocarán a diferentes ámbitos, prestando especial atención al ahorro energético. Además, estos juegos serios deberán enfocarse a público de diferentes edades y requisitos de aprendizaje.

- **Redes Sociales Distribuidas:** las redes sociales distribuidas son cada vez más populares. La integración en CAFCLA de funcionalidades que permitan hacer uso de ellas dotará al framework de una gran potencial de cara al futuro. En este asunto, hay varios aspectos relevantes que exigirán grandes esfuerzos de I+D+i: la coordinación entre promotores, desarrolladores y fabricantes de tecnología, garantizar la privacidad y seguridad de los datos, o conseguir una alta participación de los usuarios.

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