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Departamento de Ingeniería Cartográfica y del Terreno



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Mención Industrial

*Análisis y caracterización de materiales compuestos y aditivos a través de
fotogrametría, termografía y métodos numéricos*

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de fotogrametría, termografía y métodos numéricos**

-Tesis Doctoral con Mención Industrial-

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Listado de artículos publicados

La presente Tesis Doctoral está constituida por un compendio de seis artículos científicos, publicados en revistas internacionales de alto impacto indexadas en el Journal Citation Report (JCR). A continuación, se enumeran estas publicaciones.

1. A Comparative Study of 2D and 3D Digital Image Correlation Approaches for the Characterization and Numerical Analysis of Composite Materials.

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2. Surrogate Metamodels From Digital Image Correlation for Testing High-Performance Composite Vessels

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3. Step Heating Thermography Supported by Machine Learning and Simulation for Internal Defect Size Measurement in Additive Manufacturing

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4. Flash Thermography to Detect and Evaluate Impacts in Polycarbonate Parts Produced by Additive Manufacturing

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5. Smartvessel: A New Extinguisher Prototype Based on New Materials and IoT Sensors

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*“La duda es la madre de las ideas;
sólo los ignorantes y los fanáticos no vacilan nunca.”*

Stefan Zweig

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La culminación de una Tesis Doctoral supone un paso importante en la vida personal y académica de cualquier persona. Sin embargo, aunque en cualquier documento aparezca un único autor, es bien sabido que no es un trabajo únicamente individual. Detrás de toda Tesis, hay un equipo, tanto de trabajo como personal, que ayuda a su consecución.

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La presente Tesis Doctoral con mención internacional, titulada “*Análisis y caracterización de materiales compuestos y aditivos a través de fotogrametría, termografía y métodos numéricos*”, presentada por D. Javier Pisonero Carabias, queda integrada en la línea de investigación *Análisis de materiales y soluciones industriales a través de correlación digital de imágenes y termografía activa* del grupo de investigación, afiliado a la Universidad de Salamanca, TIDOP (<https://tidop.usal.es/>).

Fruto de la actividad investigadora desarrollada por el doctorando, durante el periodo de elaboración de la Tesis Doctoral, diversos trabajos científicos han sido publicados en revistas internacionales de prestigio. Asimismo, el doctorando ha realizado trabajos y estudios relacionados con las técnicas desarrolladas en su Tesis Doctoral en la empresa Consorcio para el Diseño, Construcción, Equipamiento y Explotación del Centro de Láseres Pulsados Ultracortos Ultraintensos, a través de un contrato laboral Investigo, por el cual ha explotado en un ambiente científico-industrial la técnica de la correlación digital de imágenes.

En lo referente a las publicaciones mostradas en el presente documento, y a fin de corroborar la validez y robustez de los trabajos científicos desarrollados, los artículos científicos fruto de dichos trabajos fueron publicados en 5 revistas científicas impacto, algunas de ellas con un alto factor de impacto y posicionadas en primer cuartil, Q1. Éstas, por orden de aparición en la Tesis Doctoral, se distribuyen del siguiente modo:

1. El artículo científico: *A Comparative Study of 2D and 3D Digital Image Correlation Approaches for the Characterization and Numerical Analysis of Composite Materials*. Publicada en la revista IEEE Access indexada en el Journal Citation Report y emplazada en el segundo cuartil, Q2, de las categorías: *Engineering, Electrical & Electronic*. Ocupando la posición 119, en factor de impacto, de las 353 revistas indexadas. DOI: <https://doi.org/10.1109/ACCESS.2021.3132393>
2. El artículo científico: *Surrogate Metamodels From Digital Image Correlation for Testing High-Performance Composite Vessels*. Publicada en la revista *Heliyon*. Dicha revista, indexada en el primer cuartil, Q1, de la categoría *Multidisciplinary Sciences*, ocupando la posición 28 de 134 revistas. DOI: <https://doi.org/10.1016/j.heliyon.2024.e29525>
3. El artículo científico: *Step Heating Thermography Supported by Machine Learning and Simulation for Internal Defect Size Measurement in Additive Manufacturing*. Publicada en la revista científica *Measurement*, indexada y emplazada en el primer cuartil, Q1, de la categoría *Engineering, Multidisciplinary* ocupando la posición 17 de 181 revistas, en términos de impacto. DOI: <https://doi.org/10.1016/j.measurement.2022.112140>
4. El artículo científico: *Flash Thermography to Detect and Evaluate Impacts in Polycarbonate Parts Produced by Additive Manufacturing*. Publicada en la revista científica *NDT & E International*, indexada y emplazada en el primer cuartil, Q1, de la categoría *Material Science,, Characterization & Testing* ocupando la posición 5 de 38 revistas, en términos de impacto. DOI: <https://doi.org/10.1016/j.ndteint.2024.103163>.
5. El artículo científico: *Smartvessel: A New Extinguisher Prototype Based on New Materials and IoT Sensors*. Publicada en la revista *Sensors*. Dicha revista, indexada en el segundo cuartil, Q2, de la categoría *Engineering, Electrical & Electronic*, ocupando la posición 122 de 353 revistas. DOI: <https://doi.org/10.3390/s23063134>

A tenor de los requerimientos para la presentación de la Tesis Doctoral por compendio de artículos establecidos por la Universidad de Salamanca (https://posgrado.usal.es/TESIS%20NUEVA%202012/Formato_Tesis_compendio.pdf), se

considera que los artículos principales, así como los méritos adicionales de la misma, se ajustan de modo óptimo a dichas necesidades, quedando así validadas las metodologías, resultados y conclusiones presentadas en este documento.

Los resultados arrojados durante la elaboración de la Tesis Doctoral han permitido avanzar en la integración de técnicas de correlación digital de imágenes y termografía activa sobre nuevos materiales, tanto compuestos como de fabricación aditiva, añadiendo un valor a la metodología actual para implementarlos en la industria.

La Tesis Doctoral concluye con el correspondiente apartado de Conclusiones en el que de forma precisa y concreta se especifican las principales aportaciones realizadas de tal manera que puedan ser objeto de crítica y de proyección hacia el desarrollo de futuros trabajos integrados en líneas de investigación.

Lo que firman, a todos los efectos oportunos, en Ávila, a 3 de Febrero de 2025.

Dr. Diego González Aguilera.

Firmado por GONZALEZ
AGUILERA DIEGO -
***8000** el día
03/02/2025 con un

Dr. Roberto José García Martín

Firmado por GARCIA MARTIN
ROBERTO JOSE - ***5980**
el día 03/02/2025 con un
certificado emitido por
AC FNMT Usuarios

Resumen

A lo largo de la historia, la industria ha ido evolucionando de manera escalonada de cara a la mejora de los procesos de fabricación y calidad de los productos, así como la eficiencia de estos. Cuando aparece un desarrollo que cambia drásticamente estos procesos se denomina revolución industrial. Actualmente, la industria está inmersa en la cuarta revolución industrial, también conocida como Industria 4.0, en la que aparecen una gran cantidad de elementos que, en su conjunto, forman una evolución notable tanto en procesos de fabricación, como en la calidad del producto y también en la relación humano-máquina.

Dentro de esta revolución unas de sus bases son los nuevos materiales y métodos de fabricación avanzados, como es la fabricación aditiva, donde la Comunidad Científica se está volcando para mejorar su eficiencia y poder integrarlos en la industria. Estos sistemas cuentan con diferentes aspectos clave a tratar para su mejora. Dentro del campo de los nuevos materiales, aparecen los materiales compuestos combinando resinas poliméricas con fibras de alto rendimiento como pueden ser las de aramida, carbono y vidrio. Estos materiales dependen de múltiples variables, como son las constantes elásticas o valores límite, cuya configuración afecta notablemente al desempeño final, donde aparece un material heterogéneo y anisótropo difícil de caracterizar mecánicamente. Además, el diseño mecánico con este tipo de materiales también ha evolucionado, ya que tradicionalmente se aplicaba un enfoque determinista, el cual no es válido ni eficiente debido al alto grado de variabilidad del mismo.

Por otro lado, las técnicas de fabricación aditiva, y concretamente, la deposición fundida, están viviendo un auge para conseguir posicionarse como técnicas importantes en la nueva industria, lo cual resulta especialmente relevante en un contexto donde la sociedad está cada vez más concienciada con el medio ambiente, y el aprovechamiento de material es una pieza clave en este sentido. Este tipo de fabricación permite que el deshecho sea mínimo o incluso nulo, a diferencia de otros métodos más tradicionales de fabricación en el que se elimina material. Sin embargo, al ser una técnica novedosa, sigue presentando diferentes problemas en la fase de fabricación. En ciertos casos, aparecen defectos de carácter interno, por lo que la inspección visual no sería efectiva. También, esta fabricación emplea generalmente materiales poliméricos que son interesantes en diversas aplicaciones, siendo una de ellas la conformación de productos dedicados a la absorción de impactos. Si estos impactos se generan en zonas de difícil acceso, tampoco sería sencillo caracterizar dichos defectos provocados, por lo que es necesario aplicar técnicas que permitan detectar defectos sin poder acceder a la superficie afectada.

Para ambos casos, las técnicas visuales de campo completo son idóneas para poder caracterizar mecánicamente los materiales compuestos y poder detectar defectología en piezas fabricadas por deposición fundida. Siendo diferentes espectros los que se registran, visible e infrarrojo, es necesario el uso de cámaras y procesados de imágenes para ambos casos. Para la caracterización mecánica, la Correlación Digital de Imágenes dentro del espectro visible permite realizar una caracterización de campo completo para materiales compuestos. Para la detección de defectos e impactos, la técnica de termografía activa infrarroja es idónea de cara a poder localizarlos sin que estén en la superficie visible o estando en un punto interno del material.

Aunque estas técnicas no destructivas son muy útiles para la caracterización mecánica y defectológica de materiales, no son suficientes para poder llevar a cabo diferentes tareas de diseño o de metrología. Para completar esta carencia, otra de las bases de la industria 4.0 es la simulación numérica. El Método de los Elementos Finitos es uno de los más respaldados por la Comunidad Científica debido a su capacidad de simplificar sistemas complejos en pequeñas partes discretas, facilitando cálculos precisos y eficientes. Sin embargo, en ocasiones debido a la complejidad del

comportamiento y la naturaleza heterogénea de determinados materiales, se tiene que recurrir a métodos probabilísticos o estocásticos más complejos basados en la metamodelización.

En la presente Tesis Doctoral, se presenta una investigación en la que se tiene en cuenta todo lo anteriormente presentado para intentar dar una respuesta a esta problemática incipiente en la industria moderna. Por un lado, se presenta una validación de la metodología de correlación digital de imágenes para caracterizar mecánicamente materiales compuestos, seguido de un método de simulación numérica estocástico para realizar un diseño optimizado, basado en la ingeniería robusta aplicable a cualquier producto fabricado con este tipo de materiales.

Por otro lado, se presenta un estudio sobre diferentes técnicas de termografía activa en diferentes productos conformados por fabricación aditiva por deposición fundida realizados con diversos materiales para poder caracterizar defectos. El uso de algoritmos de Machine Learning y modelos numéricos permite no solo detectar estos defectos, sino también cuantificar geométricamente los mismos.

Finalmente, la combinación de todas estas técnicas se aplica en entornos industriales reales, fabricando un prototipo de recipiente para elementos presurizados de altas prestaciones que permita mejorar el desempeño en comparación con otros recipientes tradicionales añadiendo una mejora de portabilidad. También, se integran en este prototipo sensores procedentes del internet de las cosas, permitiendo su monitorización en tiempo real, lo que facilita las labores de mantenimiento, implementando técnicas avanzadas en este campo como es el mantenimiento predictivo.

Abstract

Throughout history, industry has evolved in stages in order to improve manufacturing processes and product quality, as well as product efficiency. When a development appears that drastically changes these processes, it is called the industrial revolution. Industry is currently immersed in the fourth industrial revolution, also known as Industry 4.0, in which a large number of elements appear which, as a whole, form a notable evolution in manufacturing processes, product quality and also in the human-machine relationship.

Within this revolution, one of its bases are the new materials and advanced manufacturing methods, such as additive manufacturing, where the scientific community is working to improve their efficiency and to be able to integrate them into industry. These systems have different key aspects to be addressed in order to improve them. Within the field of new materials, there are composite materials combining polymer resins with high performance fibres such as aramid, carbon and glass. These materials depend on multiple variables, such as elastic constants or limit values, whose configuration notably affects the final performance, where a heterogeneous and anisotropic material appears that is difficult to characterise mechanically. In addition, mechanical design with this type of materials has also evolved, as traditionally, a deterministic approach was applied, which is neither valid nor efficient due to the high degree of variability of the same.

On the other hand, additive manufacturing techniques, and specifically fused deposition, are experiencing a boom in order to position themselves as important techniques in the new industry. Society is becoming increasingly aware of the environment, and the use of materials is a key factor in this regard. This type of manufacturing allows waste to be minimal or even non-existent, unlike other more traditional manufacturing methods in which material is eliminated. However, as a new technique, it still presents a number of problems in the manufacturing phase. In certain cases, defects of an internal nature appear, making visual inspection ineffective. Also, this manufacturing technique generally uses polymeric materials that are of interest in various applications, one of them being in the manufacture of products dedicated to shock absorption. If these impacts are generated in areas that are difficult to access, it would not be easy to characterise the defects caused, so it is necessary to apply techniques that allow defects to be detected without being able to access the affected surface.

For both cases, full-field visual techniques are ideal to mechanically characterise composite materials and to detect defectology in parts manufactured by fused deposition. As different spectra are recorded, visible and infrared, the use of cameras and image processing is necessary for both cases. For mechanical characterisation, Digital Image Correlation within the visible spectrum allows full-field characterisation of composite materials. For the detection of defects and impacts, the technique of active infrared thermography is ideal in order to locate them without them being on the visible surface or being in an internal point of the material.

Although these non-destructive techniques are very useful for the mechanical and defectological characterisation of materials, they are not sufficient to carry out different design or metrology tasks. To fill this gap, another of the foundations of Industry 4.0 is numerical simulation. The finite element method is one of the most widely supported by the scientific community due to its ability to simplify complex systems into small discrete parts, facilitating accurate and efficient calculations. However, sometimes, due to the complexity of behaviour and the heterogeneous nature of certain materials, it is necessary to resort to more complex probabilistic or stochastic methods based on metamodeling.

In this Doctoral Thesis, research is presented which takes into account all of the above to try to provide an answer to this incipient problem in modern industry. On the one hand, a validation of the digital image correlation methodology is presented to mechanically characterise composite

materials, followed by a stochastic numerical simulation method to carry out an optimised design, based on robust engineering, applicable to any product manufactured with this type of materials.

On the other hand, a study is presented on different techniques of active thermography in different products formed by additive manufacturing by fused deposition made with different materials in order to characterise defects. The use of Machine Learning algorithms and numerical models allows not only to detect these defects, but also to quantify them geometrically.

Finally, the combination of all these techniques is applied in real industrial environments, manufacturing a prototype vessel for high-performance pressurised elements that improves performance compared to other traditional vessels by adding an improvement in portability. Also, sensors from the internet of things are integrated in this prototype, allowing real-time monitoring, which facilitates maintenance work, implementing advanced techniques in this field such as predictive maintenance.

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Glosario

AFRP	Aramid Fiber Reinforced Polymer
ASTM	American Society for Testing and Materials
CC	Cross Correlation Criterion
CFRP	Carbon Fiber Reinforced Polymer
CNC	Computer Numerical Control
COPV	Composite Overwrapped Pressure Vessel
CPA	Chirped Pulse Amplified
DAC	Differentiated Absolute Contrast
DIC	Digital Image Correlation
DLT	Direct Linear Transformation
FEM	Finite Element Method
FRP	Fiber Reinforced Polymer
FW	Filament Winding
GFRP	Glass Fiber Reinforced Polimer
IC-GN	Inverse-Compositional Gauss-Newton
IoT	Internet of Things
LVDT	Linear Variable Differential Transformer
MIG	Mean Intensity Gradient
PCE	Polynomial Chaos Expansion
PDF	Probability Density Function
PIV	Particle Image Velocimetry
PLA	Polylactic Acid
PSSD	Parametric Sum of Squared Differences
PSSD	Parametric Su of Squared Differences
RBDO	Reliability Based-Design Optimization
RG-DIC	Reliability-Guided Digital Image Correlation
RHTT	Ring Hoop Tensile Test
ROI	Region Of Interest
RW	Roll Wrapping
SAD	Sum of Absolute Differences Criterion
SFEM	Stochastic Finite Element Method
SNR	Signal to Noise Ratio
SSD	Sum of Squared Differences
TSR	Thermal Signal Reconstruction
ZNCC	Zero-Mean Normalized Cross Correlation

ZNSSD

Zero-mean Normalized Sum of Squared Differences

CAPÍTULO I

INTRODUCCIÓN

1.1 Introducción

La aparición de la máquina de vapor marco el inicio de una carrera innovadora que sigue avanzando sin señales de detenerse. Esta máquina fue clave para la Primera Revolución Industrial, al permitir la sustitución de la mano de obra humana en ciertas labores mediante automatizaciones mecánicas, impulsando así la producción y el desarrollo industrial. Este impulso inicial sentó las bases para sucesivas transformaciones, cada una marcada por avances tecnológicos. La Segunda Revolución Industrial se basó en la producción en masa, posible gracias a la cadena de montaje y la incorporación de la energía eléctrica, que permitieron una fabricación más rápida y eficiente. En la Tercera Revolución Industrial, la incorporación de la electrónica y las computadoras revolucionó nuevamente la industria, facilitando la automatización de procesos repetitivos y aumentando la precisión en el control de la producción. En la actualidad, el concepto de Industria 4.0 representa la Cuarta Revolución Industrial, una transformación digital centrada en sistemas ciberfísicos, la interconexión de dispositivos a través del Internet de las cosas y el análisis avanzado de datos. Esta revolución conecta y optimiza todos los sistemas productivos, marcando una nueva era en la que la tecnología digital redefine la industria y nuestras formas de trabajo (Figura 1).

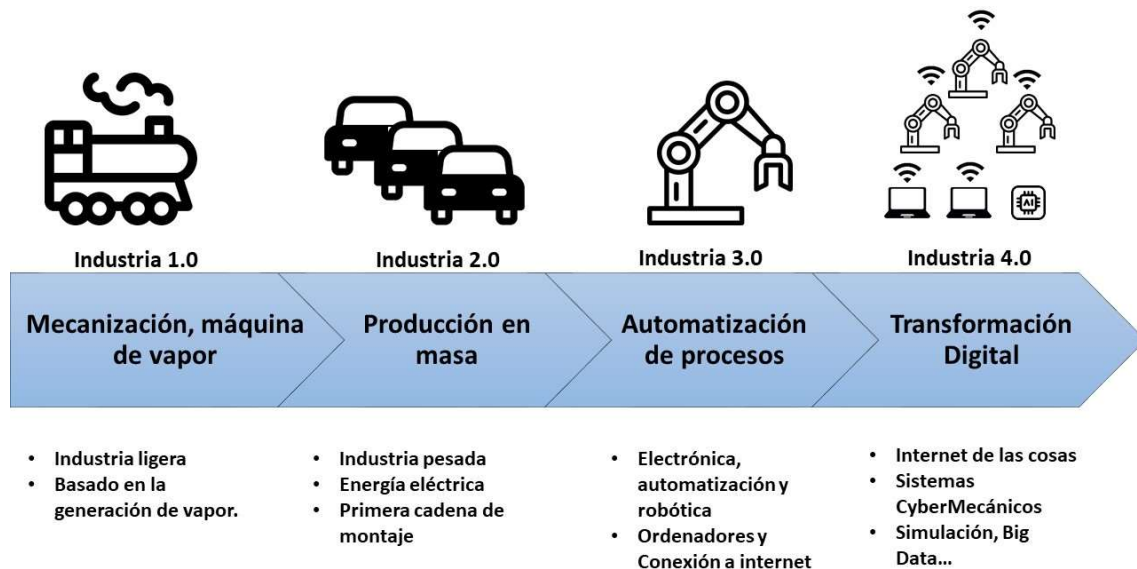


Figura 1. Evolución de las diferentes revoluciones industriales.

Sin embargo, definir esta cuarta revolución a partir de esos puntos dejaría muchas otras actividades y desarrollos importantes sin tener en cuenta. El progreso en las técnicas de fabricación aditiva es otro de los puntos clave de esta revolución, ya que permite la producción personalizada, reduce desperdicios y acelera los ciclos de desarrollo de productos. Su capacidad para crear geometrías complejas directamente a partir de diseños digitales está transformando la industria al hacer posible una manufactura más ágil y sostenible. En la misma línea, el desarrollo de la visión artificial y el uso de métodos no destructivos combinados con simulaciones numéricas, han asegurado una mayor precisión y eficiencia en los procesos industriales, mejorando la seguridad y la sostenibilidad y optimizando considerablemente el uso de material. De hecho, los materiales avanzados, tales como las fibras reforzadas con resina u otros polímeros para la impresión 3D por deposición, están consiguiendo alcanzar unos niveles de desarrollo en los cuales se pueden modificar sus características en fabricación para conseguir unas prestaciones personalizadas. Esto abre nuevas posibilidades en el diseño de productos con propiedades específicas y optimizadas para cada aplicación.

En la presente Tesis Doctoral se presenta una investigación en diferentes ámbitos de la Industria 4.0. Los materiales avanzados dan pie a nuevos procesos de fabricación aditiva, cuyos productos

necesitan herramientas de caracterización de campo completo, basadas en imagen. Tras ello, modelos numéricos se nutrirán de los datos obtenidos para generar modelos estocásticos probabilísticos. Concretamente, los materiales a estudiar van a ser materiales compuestos basados en fibra de carbono combinados con resina epoxy, y polímeros empleados en impresión 3D tales como el ácido poliláctico (Polilactic Acid-PLA), el policarbonato o el nylon. Las técnicas de imagen que se desarrollan son la Correlación Digital de Imágenes (Digital Image Correlation-DIC) para el análisis mecánico de los materiales compuestos, y la inspección por termografía activa sobre los polímeros para la auditoria de defectología. Los modelos numéricos a estudiar se basan en el Método de los Elementos Finitos (Finite Element Modeling-FEM) combinados con modelos estocásticos tales como el Polynomial Chaos Expansion (PCE) y simulaciones de Montecarlo (MC). La combinación de estas técnicas genera los métodos de los elementos finitos estocásticos (Stochastic Finite Element Modeling-SFEM). Todo ello se recoge en la Figura 2 y se irá desarrollando con más detalle a lo largo de la Tesis Doctoral.

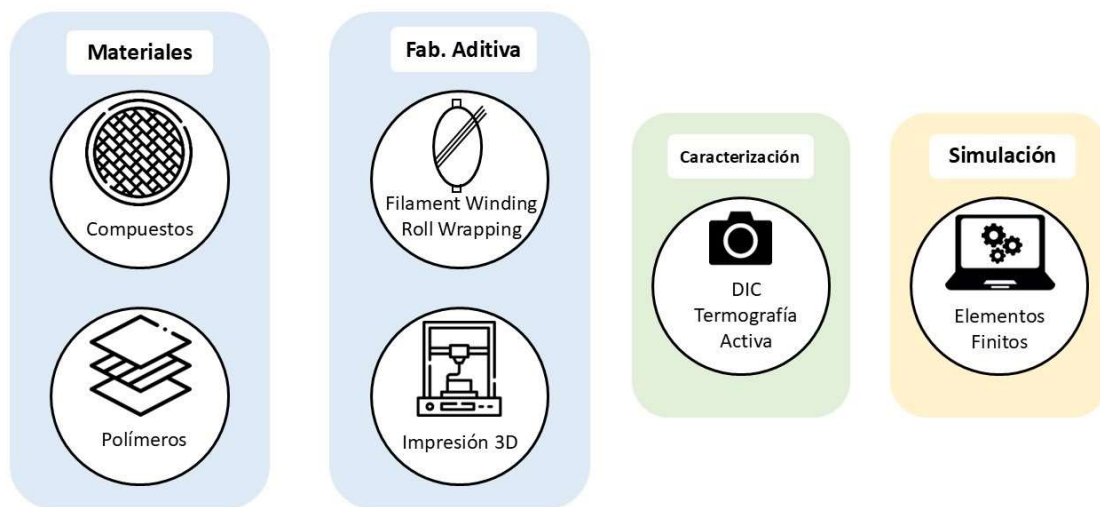


Figura 2. Elementos a tratar en la Tesis Doctoral correspondientes a la Industria 4.0.

1.1.1 Materiales y fabricación

Tipos de materiales

Los materiales empleados en la industria se dividen principalmente en: cerámicos, compuestos, poliméricos y metálicos [1,2]. Cada uno de estos tipos de materiales cuenta con unas características particulares que los hacen idóneos para diferentes aplicaciones. Las nuevas demandas de la industria hacen que los materiales compuestos y los poliméricos empleados en impresión 3D estén ganando un peso mayor.

Es en los materiales compuestos hacia donde la tecnología está centrando sus mejoras, ya que por su propia naturaleza es posible configurar prácticamente la totalidad de las propiedades mecánicas del producto [3]. Existen diferentes posibilidades de producir materiales compuestos, pero una de las más comunes y aplicadas en la industria es a partir de una matriz polimérica en forma de resina y una fibra como refuerzo. Esta configuración da como resultado los denominados Fiber Reinforced Polymer (FRP). La resina más empleada es la resina Epoxy, mientras que las fibras más empleadas en industria son las de: aramida, vidrio y carbono. Las fibras de aramida dan como resultado los Aramid Fiber Reinforced Polymer (AFRP), y son empleadas sobre todo para la fabricación de vestimenta técnica. Por su parte, las fibras de vidrio y carbono dan como resultado los denominados Glass Fiber Reinforced Polymer (GFRP) y Carbon Fiber Reinforced Polymer (CFRP), siendo estos materiales de muy altas prestaciones empleados en aplicaciones muy exigentes como puede ser la industria aeronáutica, recipientes a presión avanzados o la industria automovilística [4,5]. Una de las principales ventajas de estos GFRP y CFRP son los índices de comportamiento como el buen ratio resistencia/peso como se observa en la Figura 3, con un peso muy inferior en proporción a otro tipo de materiales como pueden ser los metálicos se consigue una resistencia y desempeño igual o superior a los materiales metálicos [6]. Las propiedades individuales de estos componentes darán como resultado las propiedades del compuesto a partir de las ecuaciones de la regla de las mezclas y sus sucesivas iteraciones teniendo en cuenta diferentes características intrínsecas de estos materiales [7]. Sin embargo, la propia fabricación y los materiales cuentan con un alto nivel de heterogeneidad y anisotropía, generando una gran incertidumbre, por lo que la caracterización y cálculo de propiedades por estos métodos no es válido. Es necesario utilizar caracterizaciones de campo completo que tengan en cuenta todas estas variaciones. De la misma manera, no se pueden emplear técnicas de diseño deterministas debido al alto grado de variación de estos materiales, por lo que todo lo anterior debe tenerse en cuenta de cara a la utilización de estos.

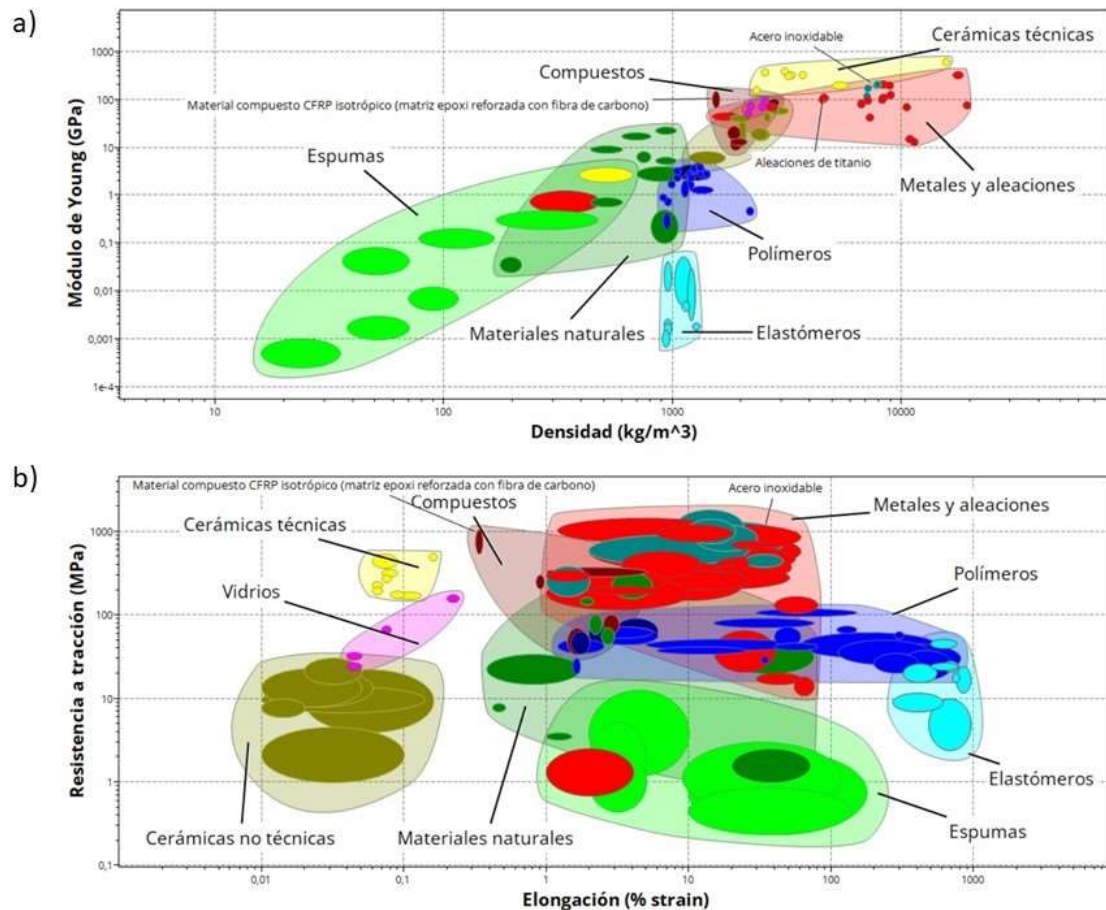


Figura 3. Diagramas Ashby de a) Módulo de Young vs Densidad y b) Resistencia a la tracción vs Elongación.

Por otro lado, los materiales poliméricos están viviendo su propia revolución gracias al desarrollo de la fabricación aditiva, siendo estos muy versátiles en cuanto a sus aplicaciones. En este sentido, la caracterización térmica es un punto clave para poder utilizar estos materiales, más si cabe de acuerdo con la metodología de fabricación, explicada posteriormente, que se basa en estos comportamientos. Estos materiales no son idóneos para soportar cargas mecánicas elevadas, pero, sin embargo, cuentan con un buen desempeño en cuanto a resistencia abrasiva o absorción de impactos. Esto se debe a que son materiales que se deforman elástica y plásticamente de manera considerable cuando sufren solicitaciones mecánicas, lo cual se traducen en una buena capacidad de absorción de energía.

A diferencia de los materiales compuestos, la caracterización mecánica es más simple, por lo que no necesita de sistemas avanzados. Por lo tanto, otros tipos de caracterizaciones, concretamente la caracterización térmica para diferentes aplicaciones es más interesante y supondrían un desarrollo más eficiente en este campo.

Fabricación aditiva

Dentro de la ya mencionada Revolución Industrial 4.0, la fabricación aditiva es uno de los ejes principales de desarrollo. La mayoría de los métodos de fabricación tradicionales tienen un carácter sustractivo de material para obtener la geometría diseñada. Esto hace que exista mucho residuo inutilizable y se necesite mucho más material del necesario. Sin embargo, la fabricación aditiva tiene como premisa todo lo contrario, ir añadiendo material para conseguir el producto final. Esto consigue, no solo que el deshecho sea menor y además reutilizable, sino que se pueden conseguir geometrías complejas que mejoren el comportamiento y optimice el diseño mecánico

de los productos [8,9]. Dentro de este tipo de fabricación el más conocido por el público general es la impresión 3D [10,11], pero existen otros tipos de fabricación que también son considerados como fabricación aditiva, como el Filament Winding (FW) [12,13] o la técnica Roll Wrapping (RW) [14].

Impresión 3D

La impresión 3D consiste en la adición de material fusionado a través de inyectores dando como resultado una geometría prediseñada por un software. A partir de sistemas basados en movimientos con un mínimo de tres grados de libertad, habitualmente desplazamientos lineales en los tres ejes espaciales, dicho sistema va depositando el material fundido en una posición determinada. Esto se realiza gracias a sistemas conocidos basados en Computational Numeric Control (CNC), similares a otros procesos de fabricación por mecanizado como puede ser el torneado o el fresado, basados en un lenguaje de programación denominado código G por el que a partir de comandos específicos el sistema describe los movimientos necesarios para conseguir la forma diseñada. Cabe destacar que existe la posibilidad de utilizar brazos robóticos con seis grados de libertad, en los que aparecen giros en los diferentes ejes espaciales además de los desplazamientos, en cuyo extremo estaría ensamblada la boquilla que va agregando el material.

Este material puede ser de cualquier tipo de los anteriormente descritos, en forma de bobina o de pellets, que van pasando por un sistema guiado hasta la boquilla donde este material es calentado, finalizando con la fusión y depositado en el mismo diseño. Por este motivo, uno de los tipos de material más común para este tipo de fabricación son los materiales poliméricos gracias a su fácil maleabilidad y punto de fusión para poder ser introducido por la boquilla.

Sin embargo, existen diferentes puntos críticos en este tipo de fabricación (Figura 4) [15]. El material fundido debe solidificar relativamente rápido para que la forma diseñada pueda ser fabricada. Por este motivo puede haber un desplazamiento del material, generando huecos internos o la aparición de pequeños hilos no deseados de material, denominado Stringing. Esto también puede ser generado por una heterogeneidad en el filamento o pellet haciendo que el material no se funda correctamente o aparezcan burbujas de aire donde debería haber material. Por otro lado, si la boquilla se obstruye o no funde bien el material este no podrá ser depositado generando defectología tanto de manera interna como externa. Otra posible causa de fallo es la base sobre la que se asienta el material. Dicha base debe estar a una temperatura adecuada para que el material pueda asentarse, en caso de que no sea así puede aparecer lo que se denomina Warping, que es un levantamiento de la primera capa que hará que los pasos posteriores no se realicen de manera óptima. Finalmente, como este tipo de fabricación se basa principalmente en ir incorporando capas en altura, puede suceder que aparezca una delaminación entre capas sucesivas.

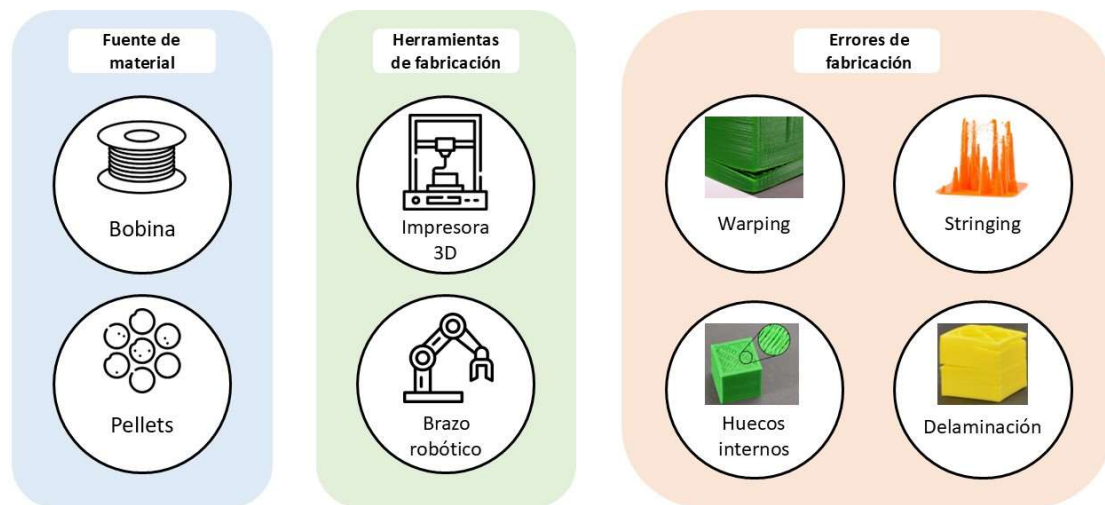


Figura 4. Esquema de metodología de fabricación por impresión 3D y posibles fallos del proceso.

Todos estos problemas pueden dar lugar a diferentes fallos en el comportamiento del producto final. Sin embargo, estos procesos tienen duraciones elevadas, de unas cuantas horas o incluso días, no siendo posible hacer un monitoreo continuo y eficaz del proceso, por lo que muchos de esos fallos no se podrían detectar. Si se producen en la superficie exterior, una inspección visual sería suficiente para detectar y caracterizar ese defecto, pero si es de carácter interno, sería necesario utilizar técnicas avanzadas, a poder ser no destructivas, para poder determinar la existencia y caracterización. La termografía activa se desmarca como una de las técnicas no destructivas idóneas para diagnosticar dichos materiales y procesos de impresión 3D y será objeto de investigación y desarrollo en esta Tesis Doctoral.

Filament Winding

La técnica Filament Winding es la más empleada para la fabricación de Composite Overwrapped Pressure Vessels (COPV). Es un sistema optimizado para emplear materiales compuestos a partir de fibras y conseguir un recipiente en forma de depósito esférico o cilíndrico apto para almacenar fluidos presurizados [16–18] (Figura 5).

Las fibras se van enrollando en un mandril de manera que quedaría un recipiente completo fabricado a partir de estos materiales. Previa deposición de la fibra se va preimpregnando con la resina, de manera que se consigue el material compuesto. En el mandril puede haber un molde que puede ser metálico, polimérico o simplemente un molde que finalmente se sustraerá. Este molde se denomina Liner y es el que define, junto al material de envoltura, el tipo de COPV tal y como se muestra en la Tabla 1.

Tabla 1. Tipos de COPV.

	Material del Liner	Material exterior	Kg/L	Aplicaciones
Tipo I	Aluminio	Aluminio	1.40	- Altos volúmenes en industria - Transporte de Gas Natural Licuado - Aplicaciones de vehículos pequeños
Tipo II	Aluminio	Fibra de vidrio	0.98	

				- Igual que tipo 1
Tipo III	Aluminio	Fibra de carbono	0.74	- Almacenamiento de combustible en vehículos - Transporte de Gas Natural Licuado - Transporte de hidrógeno - Aeroespacial - Pila de combustible
Tipo IV	Polímero	Fibra de carbono/Aramida	0.45	- Aplicaciones de alta portabilidad
Tipo V	-	Fibra de carbono/Aramida	0.32	- Aplicaciones militares y aeroespaciales avanzadas

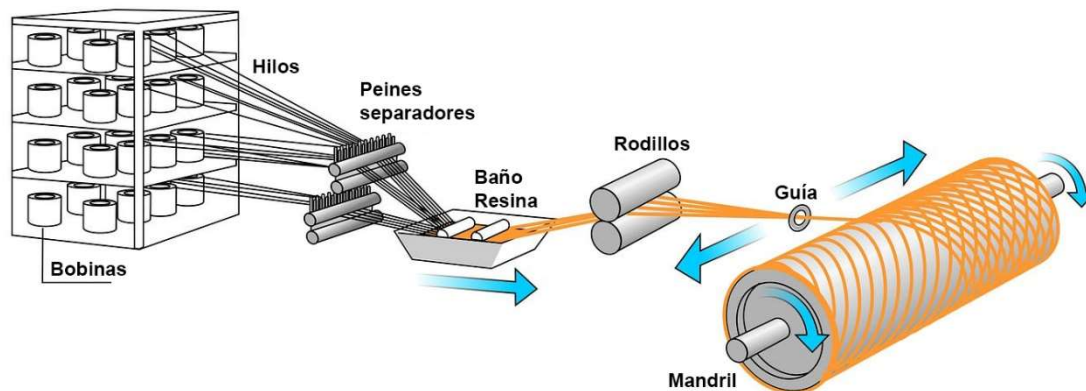


Figura 5. Esquema del proceso de fabricación aditiva por FW.

La evolución en la técnica de fabricación FW está permitiendo que los beneficios de los COPV tipo IV y V sean utilizados en las aplicaciones de tipos I, II y III con todas las ventajas que ello supone. Económicamente aún no están a la par, pero la distancia entre todos los tipos se va reduciendo, de manera que en un futuro no muy lejano los tipos I y II quedarán como soluciones cuasi obsoletas, siendo utilizadas en aplicaciones donde el ajuste económico sea muy elevado.

Como se ha podido observar, existe un alto grado de incertidumbre para la definición de las características mecánicas de estos materiales compuestos. Esta incertidumbre no es únicamente intrínseca al tipo de material, sino también al proceso de fabricación empleado. Por este motivo, el diseño mecánico tradicional no es el más indicado para este tipo de materiales. La influencia de las variables en cuanto al comportamiento final se encuentra descritas en la Tabla 2.

Tabla 2. Influencia (en %) de las 12 principales variables en la resistencia a presión interna de los COPVs a partir de la técnica FW.

Variable	% de influencia
Tensión del hilo	71
Variabilidad de la resistencia de la fibra	62
Secuencia de apilamiento	62
Etapa-B de la resina (curado latente)	57
Daño en la fibra durante el bobinado	57
Impregnado de la fibra	57
Gradiente de tensión en el bobinado	48
Contenido en resina	43

Tiempo total de bobinado	43
Tiempos de arrollamiento entre capas	43
Espesor de capas circulares	43
Capas helicoidales cortadas vs no cortadas	38

Roll Wrapping

La técnica de Roll Wrapping también consigue productos cilíndricos, como podría obtenerse en la técnica de FW. Sin embargo, en esta técnica no se combina resina y fibra durante el proceso, sino que primero se fabrica una plancha uniforme de material compuesto denominado prepeg, Figura 6. Tras ello, la plancha se enrolla sobre un mandril donde se cura el material a través de calor obteniendo el producto final. La lámina es muy maleable, por lo que se debe enrollar sobre el mandril y dejar curar y solidificar en este estado. En este sentido, la orientación de las fibras con respecto al mandril puede ser customizado, por lo que las propiedades mecánicas finales se ven afectadas directamente tanto por la configuración de la lámina como del propio proceso de fabricación. En la línea de reducir residuos en los procesos de fabricación, este tipo de técnica optimiza el uso de material, ya que la totalidad de la lámina enrollada puede ser utilizada sin necesidad de generar ningún tipo de residuo.

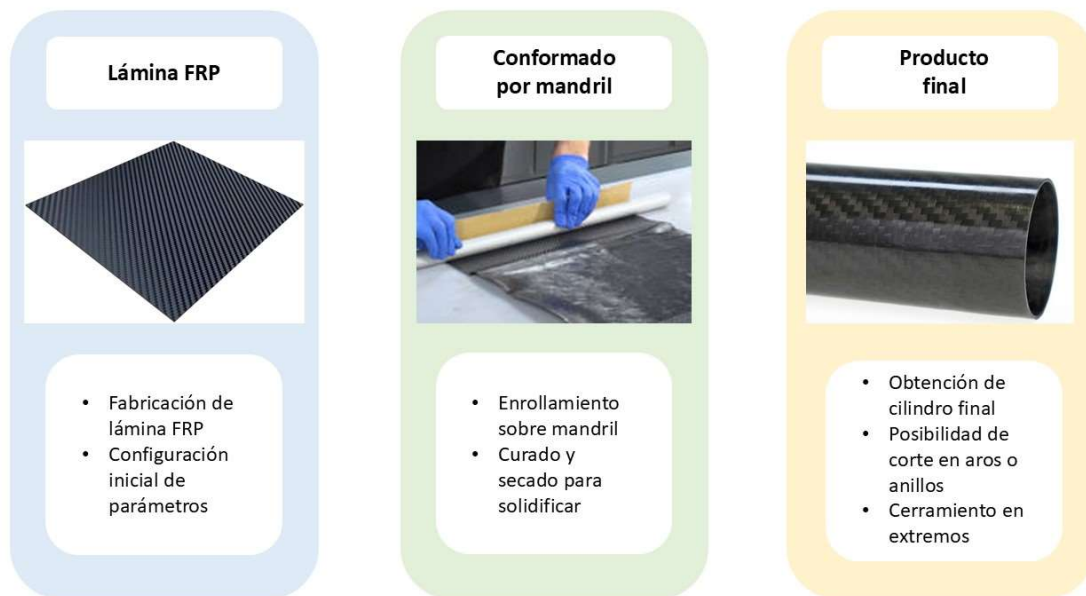


Figura 6. Esquema del proceso de fabricación aditiva por RW.

Caracterizar el material previamente, mientras está en fase lámina, no sería preciso a la hora de utilizar el diseño de algún producto con este tipo de materiales y técnica. Es por ello, que se están desarrollando nuevos métodos de caracterización que son modificaciones basados en la norma UNE-EN ISO 52924. En la familia de normas americana American Society for Testing and Materials (ASTM), se está considerando esta combinación material-proceso, y se ha desarrollado el ensayo Ring Hoop Tensile Test (RHTT) [19], en el que se realiza un ensayo a tracción donde la probeta no es plana, sino que es en forma de aro o anillo y unos útiles específicos aplican la carga simulando un ensayo a tracción. Además, este método puede funcionar como una simulación de presión, ya que la carga se distribuye uniformemente sobre la superficie interna del anillo, permitiendo una evaluación precisa del comportamiento del material bajo condiciones de presión interna.

1.1.2 Técnicas Visuales

Dentro del marco de la industria actual, la visión artificial o inspección a partir de imagen es una de las bases más importantes de desarrollo. Gracias a ello se están sustituyendo instrumentaciones más tradicionales o inspecciones visuales por métodos donde la repetitividad o su capacidad de análisis es más completa.

En este sentido se observan dos aplicaciones que destacan sobre el resto: (i) sustitución de instrumentación de medidas para analizar desplazamientos y deformaciones por técnicas visuales de campo completo [20,21], e (ii) inspección por termografía de daños o defectos en diferentes productos y materiales industriales [22–27]. En este sentido cabe destacar la Correlación Digital de Imágenes y la termografía activa.

Correlación Digital de Imágenes

Como se ha comentado anteriormente, la caracterización de ciertos materiales, como pueden ser los materiales compuestos, es compleja debido a la gran cantidad de variables que afectan al comportamiento del material. Para ello, se emplean ensayos de laboratorio sobre probetas normalizadas donde son sometidas a diferentes esfuerzos, como pueden ser tracción o compresión. Con ello se pueden conseguir las propiedades mecánicas comparando el esfuerzo medido por la propia máquina con los desplazamientos y deformaciones sufridos por el material. Para medir estos desplazamientos y deformaciones se han empleado normalmente elementos e instrumentos como Linear Variable Differential Transformer (LVDT), transductores, extensómetros o galgas extensiométricas [28]. Sin embargo, todas estas técnicas de contacto son susceptibles de producir errores de medida debidos a distintos factores o alteraciones, como pueden ser: (i) presencia de fisuras no esperadas [29]; (ii) carácter invasivo de estas instrumentaciones que pueden alterar el comportamiento de los materiales, o (iii) distribución de cargas desiguales. Además, estas técnicas tienen un carácter muy local, mientras que los materiales compuestos presentan una anisotropía donde una caracterización global es muy importante para poder dar una respuesta completa.

Asimismo, toda esta instrumentación dificulta enormemente la preparación de los ensayos y puede presentar distintos inconvenientes o imprevistos: (i) coste elevado asociado al uso de instrumentación adecuada en el caso de emplear galgas extensiométricas o fibras ópticas; (ii) posicionamiento incorrecto o desalineación con la carga; (iii) daño en los sensores o factores externos que alteran las medidas como puede ser la temperatura del entorno. Para evitar estas restricciones se han ido desarrollando métodos de no-contacto capaces de realizar estas medidas a lo largo de toda su extensión, como es la interferometría de Moiré [30,31]; Particle Image Velocimetry (PIV) [32–35] o el DIC [36–38], entre otras.

Para la caracterización mecánica a través de ensayos de tracción o compresión, la técnica DIC presenta las mejores características para ser empleada. Es una técnica óptica de no contacto que tiene como principio la comparación de una imagen de referencia con una serie de imágenes adquiridas durante el proceso de ensayo. Gracias a ello es posible calcular los desplazamientos y deformaciones en campo completo sufridas por el espécimen en entornos complejos sin alterar el propio desarrollo del ensayo o aplicación.

Este método tiene la particularidad de que puede ser empleado en forma 2D y 3D según las necesidades del usuario. La principal diferencia entre los métodos, es que para la DIC 2D solamente es necesaria una cámara situada perpendicularmente al plano de medida [39], mientras que la técnica DIC 3D necesita mínimo dos cámaras para garantizar estereoscopia [40]. Los esquemas de funcionamiento de las dos modalidades se registran en la Figura 7.

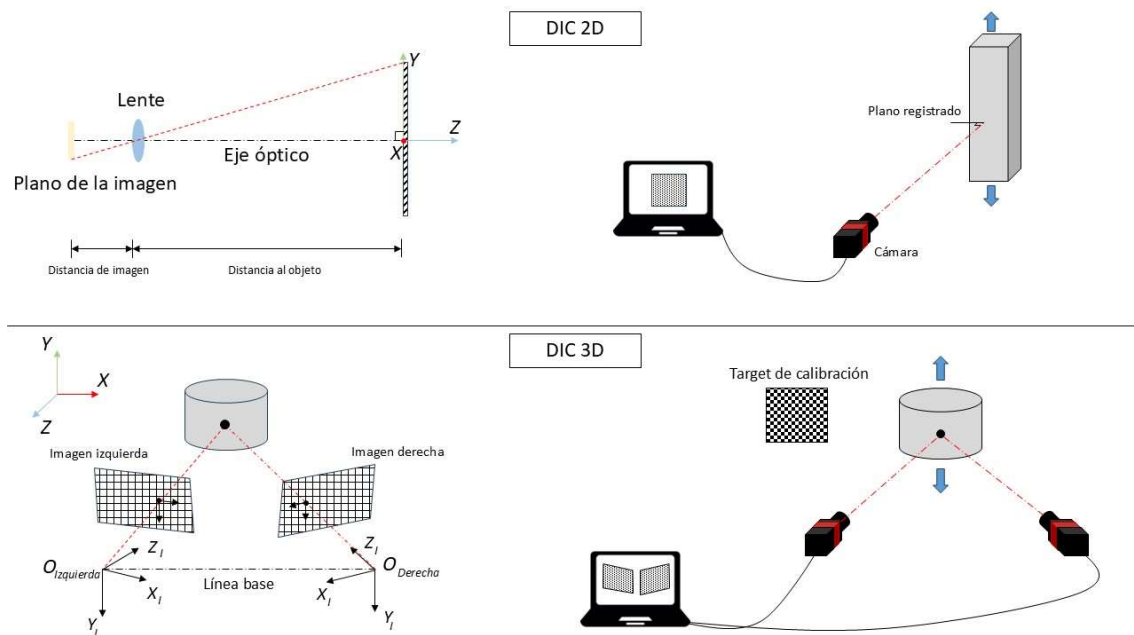


Figura 7. Esquema funcionamiento del DIC 2D (arriba) y 3D (abajo).

Correlación Digital de imágenes 2D

Para la caracterización mecánica sobre superficies planas esta técnica es idónea si se prevé un comportamiento heterogéneo del material. Como se ha explicado, esta técnica precisa de una cámara digital situada de manera perpendicular al plano a registrar, previamente preparado con un patrón denominado Speckle. En esta modalidad de la técnica, la calibración no es un punto tan sensible como se verá en la modalidad 3D, ya que, gracias a la distancia al plano y los parámetros intrínsecos de la cámara, los datos necesarios para tener medidas reales sobre la imagen están definidos.

El mencionado patrón Speckle consiste en una malla de puntos negros sobre un fondo blanco que mejora la precisión de la técnica. Este patrón tiene que cumplir con las siguientes consideraciones para ser efectivo [41–43]: (i) Aleatoriedad del patrón; (ii) Puntos circulares; (iii) Cobertura de entre el 40-70% de la superficie a registrar. Esta aleatoriedad permitirá una mejora de la correlación. Para evaluar el patrón, el algoritmo Mean Intensity Gradient (MIG) se emplea para asegurar su calidad. Este patrón se genera por computadora teniendo en cuenta todas esas consideraciones y se imprime con una impresora láser. Para poder colocarlo en la probeta a estudiar, primero se debe preimpregnar con pintura blanca y a través de gel-transfer se coloca el patrón.

Una vez colocado el patrón se lleva a cabo el ensayo donde se irán capturando imágenes sucesivas de la superficie a estudiar. Cabe destacar que previa actuación de cualquier carga, se debe tomar una imagen de referencia que será la base de comparación entre imágenes. Gracias al método desarrollado por Blaber [44] la comparación de imágenes puede llevar a conseguir precisiones subpíxel. Haciendo una combinación cámara-objetivo adecuada, es posible llegar a medir desplazamientos en el rango submicrométrico.

Los algoritmos de la técnica DIC dependen enormemente de la precisión con la que se encuentren los píxeles completos en los valores iniciales para el monitoreo del desplazamiento. Cuando el desplazamiento medido es muy elevado o excede el dominio de búsqueda, el tiempo de cálculo y el consumo de memoria de los algoritmos DIC incrementa considerablemente, pudiendo dar como consecuencia resultados erróneos [45]. La precisión de medida de la técnica DIC depende también

de la posición de la cámara y la iluminación, el color de la luz incidente, el tamaño de la región de interés y del tipo de cámara usado en los experimentos.

Este método comienza con la selección de dicha Region of Interest (ROI), donde las comparaciones de imágenes sucesivas se van a realizar. Es indispensable que en toda la ROI aparezca el patrón Speckle previamente presentado. Una vez definida esta región, la imagen se divide en subsets cuadrados que serán comparados directamente entre imágenes para obtener el desplazamiento.

La comparación de dos subsets en imágenes consecutivas, imagen i e $i+1$, empieza por la determinación del centroide de la imagen i . Se emplea un coeficiente de correlación para obtener el subset de la imagen $i+1$ lo más similar posible a la imagen i . Estos coeficientes de correlación pueden ser principalmente calculados a partir de cuatro criterios [46,47]: (i) Cross Correlation Criterion (CC), (ii) Sum of Absolute Differences criterion (SAD), (iii) Sum of Squared Differences (SSD) y (iv) Parametric Sum of Squared Differences (PSSD). A partir de estos criterios, otras modificaciones han ido apareciendo como mejoras tales como Zero-Mean Normalized Cross Correlation (ZNCC), Zero-mean Normalized Sum of Squared Differences (ZNSSD) y Parametric Sum of Squared Differences (PSSD). Durante la presente Tesis Doctoral, el criterio ZNSSD es el que se va a emplear, ya que es el que mejores resultados ha ido devolviendo durante los trabajos, y otros trabajos paralelos siguiendo la misma metodología. En la Figura 8 aparece un esquema sobre como se realiza el cálculo del vector desplazamiento, así como los grados de libertad de este vector. Cabe destacar que estos grados de libertad se refieren a los desplazamientos en píxeles, pudiendo ser lineales, o combinación y giros de estos píxeles en imágenes deformadas.

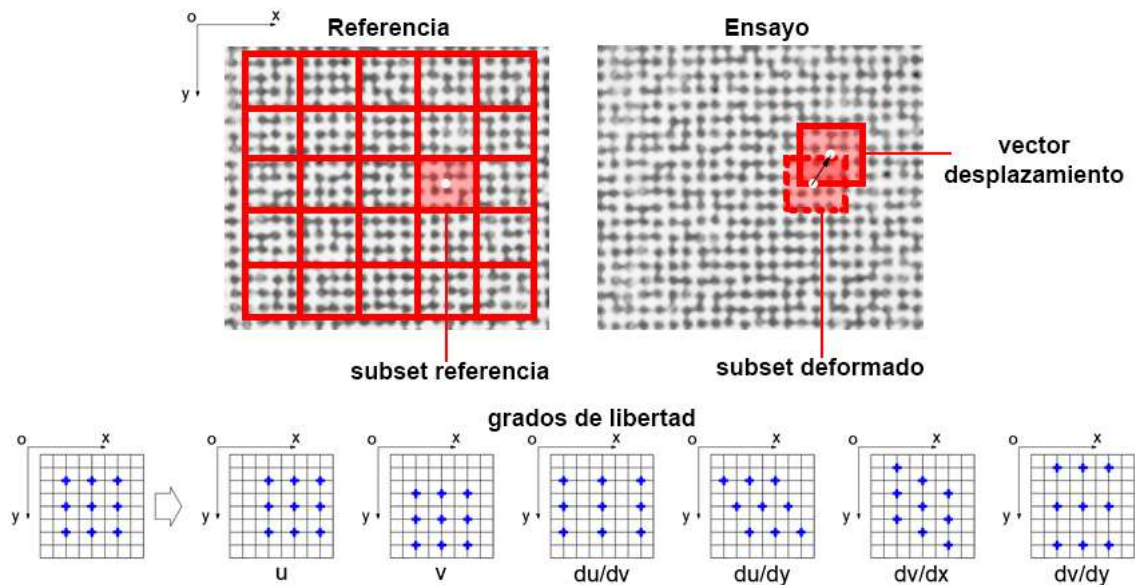


Figura 8. Esquema del cálculo del vector desplazamiento a través de los centroides de los subsets y los grados de libertad de la técnica DIC 2D. Los desplazamientos lineales se denominan u y v para los horizontales y verticales, respectivamente, y los parciales du y dv .

De esta manera, el vector desplazamiento entre dos imágenes consecutivas, i e $i+1$, puede ser determinado con un píxel de precisión. De cara a poder conseguir una precisión subpíxel, se utiliza una interpolación de la escala de grises. El método Quintic B-spline es uno de los que mejores resultados está ofreciendo para ello [44]. Estos algoritmos demandan altas prestaciones en las computadoras, por lo que se debe emplear otro tipo de algoritmos que optimicen el cálculo, tal y como es el Inverse-Compositional Gauss-Newton (IC-GN) [48]. Toda esta estrategia de cálculo se realiza por toda la ROI. De cara a minimizar la propagación de error y optimizar aún

más el coste computacional se ha empleado el algoritmo Reliability-Guided Digital Image Correlation (RG-DIC) [38]. Todos los cálculos correspondientes a esta temática han sido desarrollados con el software open acces Ncorr®, basado en Matlab®.

Correlación Digital de Imágenes 3D

El método DIC 3D es una variación directa de la técnica 2D, donde la principal diferencia radica en el uso de funciones de forma en tres dimensiones que permiten capturar desplazamientos y deformaciones en el espacio tridimensional. Aparte, en esta técnica es necesaria el uso de la triangulación estereoscópica, por lo que debe aparecer un mínimo de dos cámaras (Figura 9) sincronizando la toma de imágenes para que se calcule la superficie 3D y sus cambios bajo distintos estados de carga, garantizando coherencia entre imágenes. Esta coherencia se consigue asegurando una iluminación uniforme, una calibración rigurosa de las cámaras y un enfoque adecuado en toda el área de interés, de forma que se pueda automatizar la correspondencia de puntos entre las imágenes y con ello una reconstrucción 3D de la imagen en forma de nube de puntos. Sobre ella se utilizarán los mismos procesos explicados previamente en la metodología 2D. Por tanto, esta reconstrucción 3D es el punto clave para poder realizar dicha correlación y cálculo de los vectores de desplazamiento. Para materializar el paso del 2D al 3D se recurrirá a modelos matemáticos lineales de la fotogrametría como la Direct Linear Transformation (DLT), que permite resolver, para cada una de las cámaras, las coordenadas de los puntos 3D [40]. Sobre estas coordenadas y el matching generado entre imágenes, se pueden calcular los campos de desplazamiento y deformaciones para cada par de imágenes dentro de la ROI con los algoritmos previamente mencionados.

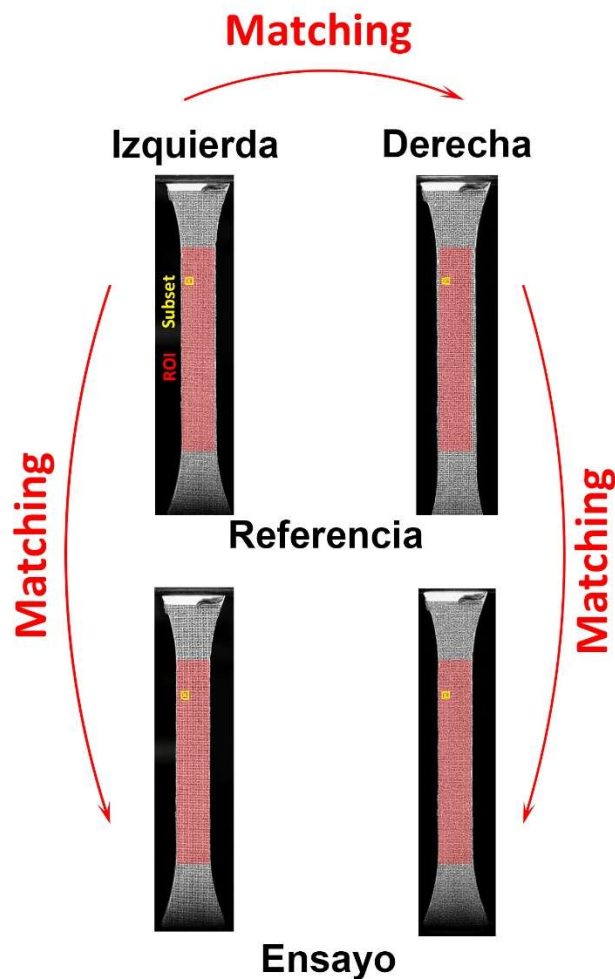


Figura 9. Matching entre imágenes de las diferentes cámaras y estados durante la técnica DIC 3D.

Termografía activa infrarroja

El control de calidad de productos fabricados durante los últimos años ha ido cobrando importancia con su incorporación en el proceso de fabricación. La inspección de la pieza obtenida en cuanto a posibles fracturas o defectos internos es un punto clave en el correcto funcionamiento en los sistemas a emplear. Sin embargo, la inspección visual no es suficiente y es necesario apoyarse en diferentes técnicas que faciliten la detección de estas fallas. En línea con la concienciación medioambiental de la sociedad, para este fin los ensayos no destructivos, Non-Destructive Test, son los más indicados. Ejemplos de estas técnicas son los líquidos penetrantes, los ultrasonidos, rayos X o la termografía activa. Mientras que los líquidos penetrantes generan residuos y las técnicas de ultrasonidos y rayos X son costosas, la termografía activa se destaca como una técnica óptima, ya que es una metodología visual que no precisa de otros agentes más que una cámara termográfica y una fuente térmica de excitación. En este sentido, la inspección por esta técnica para fabricación aditiva muestra una gran sinergia, ya que es una técnica muy escalable y adaptable al tipo de defecto a detectar o el material a estudiar [49–51].

El tipo de fuente de excitación, así como el régimen de activación sobre el target a incidir permite modificar los tipos de técnicas dentro del marco de la termografía activa. Generalmente y para evitar el contacto directo con el material a analizar, las fuentes de excitación son lumínicas, como pueden ser lámparas halógenas, flashes o incluso láser [29,52–56]. Los flashes y láser cuentan con una gran potencia de excitación en un corto periodo de tiempo, por lo que su régimen es un calentamiento muy intenso en un tiempo muy corto, contando además en la variación láser con una excitación muy localizada. Para las lámparas halógenas, el tipo de régimen de iluminación da pie a las técnicas de termografía activa más empleadas como son el step heating [57,58] y el lock-in [59,60]. Todas estas técnicas se encuentran esquematizadas en la Figura 10.

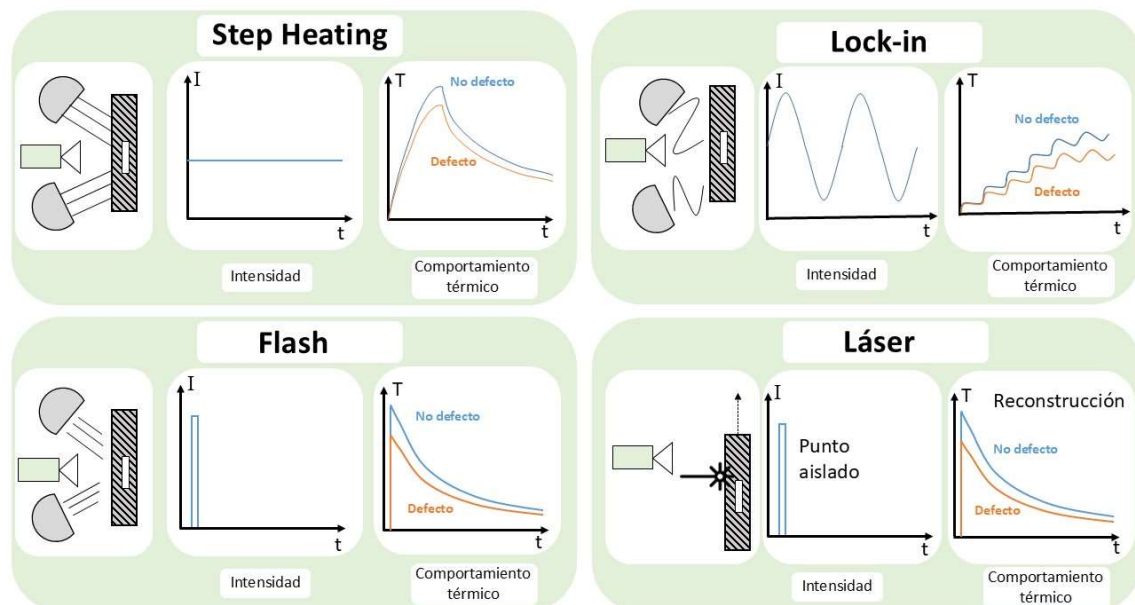


Figura 10. Esquema de funcionamiento de las principales metodologías de Termografía activa, funcionamiento, gráfica de aplicación de calor y gráfica de temperatura por tiempo registrada.

En la metodología Step Heating, el espécimen a estudiar será sometido a una excitación térmica continuada durante un tiempo determinado. Tras ello, también es importante estudiar el enfriamiento del espécimen durante, al menos, el mismo tiempo de calentamiento o incluso tres veces más. De esta manera habrá dos fases diferenciadas donde la diferencia de material o

geometría podrá ser detectada por la cámara termográfica. Si existe defectología interna, se crearán bolsas de aire donde costará más calentar, y donde el enfriamiento también será más costoso.

En la técnica Lockin, la probeta será sometida a una excitación pulsada durante un periodo de tiempo. En esta técnica se suele buscar el punto de estabilización de la temperatura tras la exposición a un número de pulsos. Será en esta estabilización donde la zona de defecto y la zona de no defecto muestre unas diferencias más significativas.

La técnica Flash consiste en una excitación de alta potencia durante un corto periodo de tiempo. Con ello se consigue estudiar la fase de enfriamiento tras la excitación, ya que la diferencia de material o presencia de defectología interna creará una diferencia marcada en la fase, haciendo posible su detección.

Finalmente, la termografía láser es muy similar a la técnica Flash, pero gracias a la naturaleza del láser, la excitación incidirá únicamente sobre un punto muy determinado. Esto hace que existan partes móviles durante el experimento, o bien el láser o bien la probeta para poder hacer un barrido de la muestra a estudiar. Por ello también, será necesaria una reconstrucción posterior de la imagen para poder hacer el procesado pertinente.

Todas estas metodologías se basan en la ley de Stefan-Boltzmann, en la que se enuncia que cualquier cuerpo a una determinada temperatura emite una radiación infrarroja. Las variaciones internas del material, como la aparición de huecos internos, hará que esta radiación sea diferente, máxime si está sufriendo una excitación térmica externa. Por tanto, el registro secuencial de imágenes durante este proceso permitirá realizar una inspección exhaustiva de la probeta íntegra, tanto de manera superficial como interior. En ocasiones, sobre la propia imagen termográfica obtenida se podrá diferenciar y medir el defecto, pero no siempre va a ocurrir. Por este motivo, la Comunidad Científica ha ido desarrollando diferentes algoritmos de imagen que puedan detectar esta defectología interna y poder cuantificarla o medirla.

Al igual que en la técnica DIC, se va a obtener una secuencia de imágenes térmicas, denominados termogramas, ordenadas a lo largo del tiempo (matriz 3D), donde la profundidad es la variable temporal. Pudiendo analizar cada píxel por separado se puede conseguir detectar el defecto interno, aunque a priori no apareciese en la imagen en bruto. Existe una amplia variedad de algoritmos desarrollados como pueden ser: Thermal Signal Reconstruction (TSR) [61]; Signal to Noise Ratio (SNR) [62] o Differentiated Absolute Contrast (DAC) [63], entre otros. La combinación de técnica, procesado, material y tipo de defecto a detectar hace que no exista actualmente una estandarización del proceso. La presente Tesis Doctoral desarrolla un estudio en este ámbito para intentar dar respuesta a esta incógnita de cara a poder optimizar el tipo de proceso a usar sobre diferentes tipos de materiales en el ámbito de la impresión 3D. Todo el proceso queda esquematizado en la Figura 11.

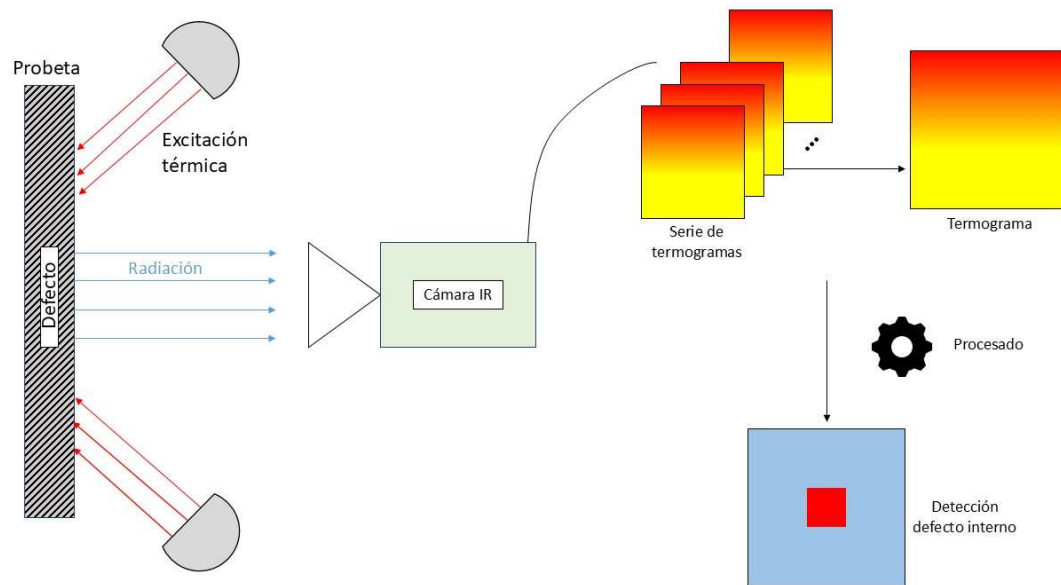


Figura 11. Principio de funcionamiento de la termografía activa infrarroja, con las fuentes de calor y la radiación producida por la probeta, registrada por una cámara termográfica que obtendrá una serie de termogramas, que, con un correcto procesado, detectará el defecto interno de la probeta.

1.1.3 Ingeniería Robusta

Otra de las bases principales de la Industria 4.0 es el campo de las simulaciones. Existe una gran variedad de métodos de simulación, pero una de las técnicas que más fuerza ha ido ganando y más asentada está en la actualidad es el FEM. Este método consiste en una simulación numérica de un sistema físico a partir de la partición de un sistema continuo en unidades finitas denominadas nodos. De esta manera un sistema queda discretizado en una malla de nodos donde se realizarán los cálculos físicos pertinentes, de modo que cada nodo tiene influencia en los demás.

De este modo, el sistema pasa de funciones matemáticas a aproximaciones del valor de la función entre los nodos, por lo que el comportamiento queda definido a partir del comportamiento de los nodos mediante unas funciones matemáticas denominadas funciones de forma. Así se consigue pasar de un sistema continuo a uno reducido con un número determinado de incógnitas, los nodos. El conjunto de relaciones entre nodos con su valor, elementos finitos, se puede escribir en forma de sistema de ecuaciones lineales. La matriz de dicho sistema es la denominada matriz de rigidez.

Las etapas de cálculo se dividen principalmente en tres fases diferenciadas. En primer lugar, se debe realizar un preprocesado para poder configurar correctamente el modelo. Durante esta etapa, se crea la geometría y se define la malla con la configuración de los nodos. Tras ello se configura la función de forma, que va a ser la que ordene que tipo de ecuaciones se van a tener que resolver, construyendo la propia matriz de rigidez y colocando las condiciones de contorno y cargas para esta resolución. Tras ello se realiza el procesado en sí, que consiste en resolver en cada nodo el sistema de ecuaciones que se plantea en el procesado. Finalmente, tras resolverlo, se realiza un postproceso que permite al usuario visualizar los resultados y realizar interpolaciones entre nodos para mejorar la precisión. Cabe destacar el uso de la convergencia para la optimización del número de nodos, lo cual define el coste computacional de la simulación con la aproximación de la solución obtenida. Por la propia naturaleza de cálculo, este modelo es una aproximación de un cálculo teórico, por lo que no siempre va a dar como resultado una predicción perfectamente teórica. Esto depende de múltiples factores, siendo el número de nodos y la configuración del cálculo los más influyentes.

Estos cálculos realizan estas aproximaciones a una solución con un enfoque determinista. Sin embargo, como se ha comentado anteriormente, existen materiales como son los CFRP cuyo comportamiento es heterogéneo y anisotrópico, por lo que este tipo de enfoque no es el óptimo para poder simular el comportamiento del sistema simulado. Por ello, es imprescindible utilizar un enfoque probabilístico o estocástico que tenga en cuenta todas estas variaciones de sus variables discretas expresada a través de la función de densidad de probabilidad, Probability Density Function (PDF) [64–68]. Sin embargo, existen múltiples tipos de PDF, siendo las más comunes la Normal, la Normal-Logarítmica o la Weibull entre otras. Es por ello que es necesario identificar correctamente la función, para ello se aplicará un indicador de la calidad del ajuste, que se realiza a partir de los test de bondad, como puede ser el test Chi cuadrado, el test Kolmogorov-Smirnov o el test Anderson Darling.

De esta manera se conforma lo que se denomina SFEM, que es una evolución teniendo todo lo anterior en cuenta de las aproximaciones deterministas de los modelos basados en FEM. De esta manera, la incertidumbre del modelo está intrínsecamente controlada, considerándose como otro parámetro que el método considera para generar resultados. Estos modelos se basan en modelos subrogados, o metamodelos, que son la modelización matemática de un modelo a través de la imitación de la relación entrada-salida del modelo numérico FEM, pero con una menor complejidad, por lo que el coste computacional disminuye considerablemente. Gracias a ello, se puede automatizar el modelo creado, lo que permite realizar un elevado número de evaluaciones de las variables de entrada para estudiar el resultado final con una pérdida mínima de precisión, lo cual genera una gran sinergia entre este tipo de métodos y los materiales compuestos. Esta

variación de las propiedades de entrada tiene que seguir un comportamiento adecuado a las PDFs generadas.

Tras tener toda esta variación e incertidumbre en cuenta se puede definir una probabilidad de fallo. Este aspecto no es trivial, ya que la normativa imperante es muy restrictiva con respecto a este aspecto, por lo que la correcta caracterización de este valor es de suma importancia a la hora de realizar cualquier proceso industrial. En los materiales compuestos, el criterio aplicado es el criterio de rotura de Tsai Wu, siendo un criterio altamente contrastado por la Comunidad Científica, el cual asume que hay fallo cuando el índice de fallo es mayor que 1 [69]. Gracias a la posibilidad de definir un valor numérico para determinar si existe fallo o no, se puede determinar el comportamiento general del modelo.

Para poder comparar todo el análisis estadístico, se utiliza el análisis Reliability Based-Design Optimization (RBDO) que permite aunar todo lo explicado anteriormente y definir la probabilidad de fallo de un sistema [70,71]. Esta probabilidad de fallo no puede ser resuelta de manera exacta, por lo que se debe abordar desde el punto de vista de la aproximación. Sin embargo, dependiendo del tipo de aproximación que se realice, el coste computacional puede llegar a ser insostenible. En este sentido la combinación de métodos es la que mejores resultados ha ido demostrando. El método de MonteCarlo es un método estadístico que produce situaciones de igual probabilidad a partir de realizar un elevado número de simulaciones, del orden de 10^5 . Dependiendo del tipo de modelo, como puede ser utilizar como base un modelo a partir de FEM, esta estrategia es inviable por su elevado coste computacional. Para abordar este problema, es posible combinar el FEM con técnicas de metamodelización, las cuales generan un modelo matemático simplificado que reduce la varianza y, al mismo tiempo, disminuye significativamente el coste computacional. La metamodelización permite así mantener la precisión del análisis, pero con una carga computacional asumible, haciendo viable el estudio de sistemas complejos en plazos y con recursos razonables. Todo el esquema de cálculo queda registrado en la Figura 12.

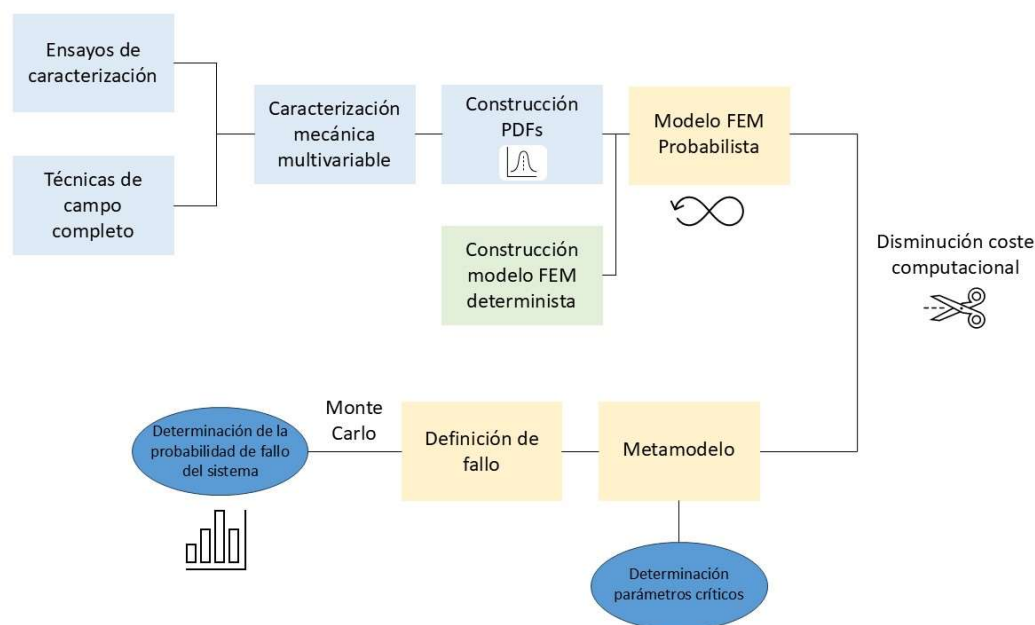


Figura 12. Diagrama de flujo del proceso de cálculo de ingeniería Robusta

En este sentido, el Polynomial Chaos Kriging (PCK), es una opción basada en la combinación de un método de expansión, PCE, y el Kriging, demostrando unos grandes resultados en cuanto a equilibrio entre precisión de los resultados y bajo coste computacional se refiere [72]. El PCK es una estrategia estocástica que aproxima el comportamiento de un sistema a través de la

representación espectral de variables aleatorias, en términos de un set de polinomios multivariantes. Cabe destacar el parámetro de error Leave-One-Error (LOE), que compara esta metamodelización con el primer modelo para obtener la precisión de los cálculos [73]. Gracias a este proceso, se puede conseguir la probabilidad de fallo del sistema, así como un estudio de las variables más influyentes sobre el resultado final.

1.2 Hipótesis de trabajo

Tal y como se ha mostrado anteriormente, la integración de sistemas de imagen, dando un carácter de campo completo, en la cadena de diseño y control de calidad en nuevos ámbitos tanto en materiales como en procesos de fabricación aditiva puede traducirse en un progreso de cara a la optimización de procesos y de resultados en el producto final. Sin embargo, cabe reseñar que este tipo de técnicas se tiene que apoyar en otro tipo de procesos para poder ser útil en estas aplicaciones. En este sentido las simulaciones numéricas aportan un carácter estocástico al proceso de diseño. De la misma manera, procesos de simulación avanzada e inteligencia artificial como Machine Learning pueden servir como base a la detección y medición de defectos durante fabricación aditiva por deposición fundida.

Las técnicas de Correlación Digital de Imágenes y Termografía Activa servirán de base para la determinación en campo completo del comportamiento mecánico y térmico de diferentes materiales fabricados por diversas técnicas de fabricación aditiva. La modelización numérica se llevará a cabo por la técnica de los Elementos Finitos en combinación con metamodelos que reduzcan el coste computacional y permitan dar un carácter estocástico al proceso de diseño.

La presente Tesis Doctoral parte con dos hipótesis de trabajo principales:

HP1: Los materiales compuestos cuentan con una anisotropía y heterogeneidad de comportamiento que dificultan la determinación de sus principales características mecánicas de manera convencional, por lo que se debe emplear una técnica de campo completo que registre todo el comportamiento. De la misma forma, un diseño determinista no es válido para este tipo de material, por lo que se debe afrontar desde un punto de vista estocástico y probabilista.

HP2: En el ámbito de los ensayos no destructivos para el control de calidad de productos contruidos a partir de fabricación aditiva, la termografía activa en sus diferentes variables, en combinación con diferentes postprocesados, es la técnica que mejor se adecúa para la determinación de fallos, tanto externos como internos en este tipo de materiales y productos.

1.3 Objetivos

Esta Tesis Doctoral nace del creciente y continuado interés de las técnicas no destructivas de imagen en procesos de fabricación aditiva, así como en el diagnóstico de nuevos materiales frente a tecnologías convencionales. Además, se enmarca en un contexto geopolítico global que impulsa la relocalización industrial y la sostenibilidad en el ciclo de vida de productos y procesos, alineándose con las tendencias actuales hacia una industria más eficiente y respetuosa con el medio ambiente.

Se plantean por tanto el siguiente **objetivo principal**:

OP: Investigación en el avance y combinación de tecnologías de imagen no destructivas, Correlación Digital de Imágenes y Termografía Activa, en procesos de fabricación aditiva y diagnóstico de nuevos materiales, así como para auditar la calidad en de nuevos productos, sistemas y procesos.

Para alcanzar dicho objetivo principal es necesario cumplir con los siguientes **objetivos específicos**:

OE1: Definición de un procedimiento para la correcta implementación de la Correlación Digital de Imágenes tanto en su modalidad 2D como 3D para optimizar los resultados en ensayos a tracción sobre materiales compuestos.

OE2: Evaluar y comparar la precisión de las técnicas de Correlación Digital de Imágenes 2D y 3D bajo las mismas condiciones experimentales, determinando las ventajas específicas de la modalidad 3D en la medición de desplazamientos y deformaciones tridimensionales.

OE3: Correlacionar y analizar datos obtenidos mediante DIC en ensayos reales con modelos numéricos FEM para comparar el comportamiento teórico y real, optimizando así el modelo numérico para su uso en diseño.

OE4: Establecer un ciclo de diseño que incluya la caracterización de campo completo de materiales compuestos anisotrópicos y heterogéneos, el desarrollo de un modelo numérico y su análisis estocástico para optimizar las prestaciones del diseño.

OE5: Correlación entre modelos numéricos y datos obtenidos por la técnica de termografía activa, definiendo una metodología de predicción de la geometría del defecto de acuerdo con diferentes algoritmos de Machine Learning.

OE6: Estudiar el comportamiento de diferentes materiales con diferentes técnicas de termografía activa, construyendo un set de datos completo que permita dar unas pautas sobre cuál sería la mejor opción según los requerimientos específicos del usuario.

OE7: Estudiar diferentes procesados sobre termogramas con el fin de optimizar la capacidad de detección de defectos en piezas realizadas a partir de fabricación aditiva.

1.4 Estructura de la Tesis Doctoral

Teniendo en cuenta todo lo anteriormente explicado, la presente Tesis Doctoral se ha realizado a partir de un compendio de 6 artículos científicos publicados en revistas indexadas de alto impacto. Estos artículos científicos han permitido avanzar en el estudio de la técnica de Correlación Digital de Imágenes, la simulación y diseño estocástico de productos industriales a partir de materiales compuestos y un avance en la detección de defectología en piezas fabricadas a partir de impresión 3D gracias a la termografía activa.

Esta Tesis Doctoral se articula en el desarrollo de las distintas técnicas presentadas para las diversas aplicaciones estudiadas, de manera que se da un orden coherente a los trabajos e investigación realizados.

En la **Introducción** se presenta el hilo conductor que conecta y relaciona los artículos científicos de la presente Tesis Doctoral, explicando todos los aspectos, técnicas y conceptos que se van a desarrollar. Al aplicar diversas metodologías, este apartado del trabajo realiza una presentación de los diferentes temas a tratar y de las sinergias que aparecen entre ellos. En este sentido, se hace un recorrido sobre las principales técnicas de fabricación aditiva que se van a tratar en la presente Tesis Doctoral. Posteriormente, aparecen las técnicas visuales empleadas, siendo la Correlación Digital de Imágenes como herramienta de medida de campo completo y la Termografía Activa como detector de diversos defectos en la fabricación aditiva por deposición fundida. Finalmente, se introduce al lector la ingeniería robusta y los métodos de modelización numérica desarrollados para conseguir un equilibrio entre precisión y coste computacional.

En la sección **Objetivos** se presentan los objetivos principales que se intentan alcanzar en la presente Tesis Doctoral, así como los objetivos específicos que ayudarán a conseguir la meta final.

Una vez presentada la introducción y los objetivos a conseguir, se presentan los capítulos por separado que estructuran el cuerpo principal de la Tesis Doctoral.

Capítulo II. Caracterización mecánica de materiales compuestos a partir de Correlación Digital de Imágenes y modelos numéricos.

Este capítulo se nutre de tres artículos científicos que dan respuesta a diferentes objetivos específicos que persigue este trabajo, pero que son indispensables para lograr el objetivo principal. En una primera investigación se recoge una comparación entre la técnica de la Correlación Digital de Imágenes en 2D y en 3D en igualdad de condiciones para dar validez a esta técnica, sobre todo en la variante 3D, para ser empleada en requerimientos específicos en trabajos posteriores de esta Tesis Doctoral.

Capítulo III. Detección de defectos en fabricación aditiva por deposición fundida a través de termografía activa.

En este capítulo se muestran los avances en el análisis de defectología mediante la técnica de la termografía activa. Se han probado diferentes técnicas de la metodología que se presentan en la introducción para dar una respuesta a los distintos tipos de materiales y distintos defectos que pueden aparecer sobre ellos. De manera que, se presenta una investigación donde se trata de dar respuesta a una posible estandarización del método para poder optimizar el tipo de defecto a estudiar dependiendo del tipo de material, así como del defecto que se pretende caracterizar.

Capítulo IV. Aplicaciones en industria de las metodologías estudiadas.

En este capítulo se aúna toda la investigación del capítulo anterior en forma de un prototipo funcional de recipiente a presión fabricado a partir de la técnica de Filament Winding que incorpora sensórica avanzada apoyada por el Internet de las Cosas y la red de comunicación

LoraWAN. Todo ello se ha demostrado viable con la prueba validada en un entorno real naval a través de un prototipo de extintor de incendios. Tras ello, se realiza otra validación de la técnica DIC para ser empleada en una aplicación muy concreta, como son sistemas láser de muy alta potencia, a partir de optimizar las herramientas de cálculo. También se aprovecha esta investigación para estudiar y analizar la precisión de la técnica en ámbitos micrométricos. Finalmente, el capítulo acaba con la aplicación de los estudios realizados en un artículo que presenta una metodología de diseño estocástico para recipientes a presión a partir de la caracterización de materiales compuestos realizando ensayos convencionales y avanzados que simulan la aplicación final.

En el apartado **Conclusiones y Trabajos Futuros** se presenta el grado de consecución de los objetivos presentados. Gracias a ello se podrán plantear perspectivas de investigación y aplicación de la investigación presentada en diversas aplicaciones para poder potenciar y mejorar el campo.

Finalmente, se dedica un **Anexo** a exponer el factor de impacto de las revistas donde se han publicado los trabajos científicos.

CAPÍTULO II

CARACTERIZACIÓN MECÁNICA DE MATERIALES COMPUESTOS A PARTIR DE CORRELACIÓN DIGITAL DE IMÁGENES Y MODELOS NUMÉRICOS

2.1 Comparación entre la técnica DIC 2D y 3D

En el primer trabajo se presenta de una manera más detallada la técnica DIC. A igualdad de condiciones y sobre los mismos ensayos se realiza una comparación entre los resultados obtenidos por DIC 2D y 3D. Además, se realiza sobre un material de caracterización compleja como es un composite, concretamente CFRP. Gracias a todo ello se puede validar la técnica como sustituto de otros dispositivos y herramientas como pueden ser las galgas extensiométricas.

A partir de los resultados obtenidos se realizan análisis estadísticos avanzados, que también servirán a posteriori para poder construir los modelos numéricos. Estos análisis construyen las diferentes PDF, de las principales características mecánicas. La correlación entre variables se ha calculado a partir del coeficiente de Spearman y, la comparación entre las dos técnicas se ha llevado a cabo a partir de la prueba de Leven, del T-test, equivalencia de la media, test de Moses y el análisis de igualdad de la distribución a partir de los test U-Mann Whitney, Kruskal Wallis y el test de Kolmogorov-Smirov

Los modelos numéricos se basan en una aplicación común en este tipo de materiales como es la reparación de tuberías a presión. Se aplica el método de ingeniería robusta RBDO, para analizar los resultados obtenidos por DIC. Este análisis comienza con la definición del modelo numérico construido a partir del FEM. Este modelo simula la aplicación previamente comentada, donde se utiliza el material analizado en los test. Como este composite presenta una gran variación en cuanto a propiedades mecánicas, no es posible hacer un análisis determinístico de los resultados. Por ello se utiliza un análisis estocástico donde se investiga la probabilidad de fallo, utilizando como criterio Tsai Wu, una formulación que analiza el fallo en las distintas direcciones y combinación de direcciones de acuerdo con la carga y tensiones sufridas. Si este criterio supera el valor unidad, se entiende que el sistema falla.

Combinando todo ello, se construye un modelo estocástico que tiene en cuenta todas las variaciones del material, modelizadas a partir de las PDF, y se utiliza la metamodelización para aligerar el coste computacional. De lo contrario, el cálculo a partir de simulaciones MonteCarlo para analizar la probabilidad de fallo sería inabordable. Esta simulación MonteCarlo utiliza el metamodelo construido a partir de la técnica PCE, realiza 100,000 simulaciones en un periodo de tiempo muy corto, de en torno a unos 5 segundos, para calcular todas las probabilidades de fallo. Todo esto se realiza por duplicado con los resultados obtenidos por los datos obtenidos por la modalidad 2D y 3D. Todo ello se realiza por la distribución de los resultados obtenidos y por su función de distribución acumulada.

Finalmente, a partir de un análisis de cuartiles, se concluye que los resultados obtenidos por DIC 3D en este tipo de aplicaciones son muy similares a los obtenidos por la técnica más adecuada como es su variante 2D. Aunque esta variante 2D es la técnica óptima para la caracterización de este tipo de materiales en ensayos de tracción, la técnica 3D cuenta con la ventaja de poder registrar movimientos fuera del plano o la capacidad de registrar geometrías más complejas como las planteadas en trabajos futuros.

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A Comparative Study of 2D and 3D Digital Image Correlation Approaches for the Characterization and Numerical Analysis of Composite Materials

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ABSTRACT This article makes a comparison between different Digital Image Correlation methods to determinate the main mechanical characteristics of composite materials. More specifically Carbon Fiber Reinforced Polymers. For this purpose, several tensile tests were carried out using the same camera and lens model. Different statistical methods as well as probabilistic numerical simulations were performed with the aim of evaluating the discrepancies between methods, and between different mechanical parameters. We want to highlight the consistency of the results, enabling the possibility of using 3D methods with non-planar specimen for determining the mechanical properties of Carbon Fiber Reinforced Polymers. In this case, the novelty is focused on the use of different configurations (2D and 3D) to study the differences in terms of results. the objective is not the specific characterization of CFRP, but to analyze the way in which the use of a dataset from DIC3D or, on the contrary, from DIC2D affects the final results. According to this, it is possible to concluded that significative differences arise in the evaluation of the elastic properties that could be assigned to the uncertainties of the methods. However, this significance does not appear in the results of the probabilistic simulation.

INDEX TERMS Carbon fiber reinforced polymer, composite, digital image correlation, finite element method.

I. INTRODUCTION

Composite materials are a real alternative to the traditional steel-based solutions in engineering due to their mechanical properties, environmental resistance (especially in corrosive atmospheres) [1], [2], fatigue performance [3]–[5] and a high weight-resistance ratio [6]. This type of material could be applied to different products such as pressure pipes and vessels [7], [8], most of them made of Carbon Fiber Reinforced Polymer (CFRP) [9], [10] and Glass Fiber Reinforced Polymer (GFRP). From a numerical point of view, composite materials are more complex than metallic materials. This is

due to the wide range of uncertainties during manufacturing and the own complexity of materials [11], [12]. Fiber orientation is one of the main factors, generating an intrinsic heterogeneity to the composite [13]–[15]. Due to this variability of performance, the product design is more complicated than other orthotropic materials, requiring the use of advanced numerical simulations able to represent this heterogeneity. In this context the use of probabilistic approaches based on the use of the Finite Element Method (FEM) could be considered as a feasible solution [16]–[18]. These approaches require the proper definition of the mechanical properties of the composite solution through the application of large experimental campaigns that allow to reproduce their probabilistic density functions (PDFs).

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Different devices can be used for the direct measurement of the material's properties like Linear Displacement Transducer Design (LVDT) [19], sensors as laser transducers, extensometers or strains gauges, with the same precision as the DIC [20]. But the presence of different factors or alterations in these sensors might entail inaccuracies and erroneous data measurements that could vary the inputs of the PDFs. For more details about the different factors the reader is referred to García-Martín *et al.* [21].

In order to avoid these limitations, the Scientific Community has developed different non-contact techniques which can evaluate all the strains over the specimen. Among the main techniques available to determinate the global mechanical characteristics are Moiré Interferometry [22]; Particle Image Velocimetry (PIV) [23]; photoelasticity [24]; multi-camera tracking and the Digital Image Correlation (DIC) [25]–[27].

In this context, DIC supposes a good technique for the characterisation of heterogeneous materials such as wood [28], concrete [29] or composites [25], [30]–[32]. There are two types of DIC strategies: the first one consists of a two-dimensional approach (2D DIC), while the second consists of a three-dimensional approach (3D DIC) [6], [31]. While the 2D DIC approach allows the measurement of displacements and strains in a single study plane, the 3D DIC approach allows the measurement of displacements that take place in different directions out of the main plane [33]. The main advantage of the 2D DIC is the possibility to use a simple setup using a single camera and without the need for external calibration, so the processing time is faster. However, the camera must be positioned completely orthogonally to the study plane and the uncertainties that can occur out of plane can be a disadvantage when this technique is applied [31]. For its part, 3D DIC requires a more complex setup using several cameras, which must be synchronised, in order to solve their relative orientation, requiring longer processing times due to its inner calibration and the high number of images acquired. However, in applications where the geometry is non-planar is the unique approach valid for assessing the mechanical characteristics of the material. This issue is especially relevant in composite designs made of CFRP and using filament winding processes, in which the manufacture of flat specimens for mechanical analysis is not common [34]–[36]. In these specimens the stresses are mainly produced in the plane of the shell (thin shell theory) [37], making use of 3D approaches necessary the strains produced. In this context, it is necessary to make a comparison between the 2D and 3D DIC approaches in order to verify the suitability of the 3D method for determining the mechanical properties of non-planar CFRP specimens for numerical simulations. This comparison has to be exhaustive, not only analyzing the results obtained by the simulations or the results of the test. It is necessary to carry on a statistical comparison.

In this case, the novelty is focused on the use of different configurations (2D and 3D) to study the differences in terms of results. The objective is not the specific characterization

of the CFRP, but to analyze the way in which the use of a dataset from DIC3D or, on the contrary, from DIC2D affects the results. After this introduction, Section 2 describes the materials and methods used for this study, namely 2D DIC, 3D DIC and probabilistic numerical simulations. In Section 3 the experimental results are outlined. Finally, Section 4 shows the conclusions of the research and future projects.

II. MATERIALS & METHODS

A. COMPOSITE SOLUTION AND SPECIMEN PREPARATION

For this work, the composite solution used was a CFRP manufactured with fiber CC 200 T-120, epoxy resin CR82 and complemented by a hardener Biresin CH80-10. The mechanical properties of the different constituents can be consulted in [21].

The manufacturing process of the specimen has been based on ISO 527:1997 [38], [39]. A total of 25 specimens were done, each one with a total of 9 layers with orthogonal orientation among them. The process of manufacturing was the following one: (i) fiber placement with the corresponding orientation; (ii) resin impregnation; and (iii) pressure application to avoid possible resin defects. After placing all the layers, the entire block was introduced in a drying oven at a temperature of 50 °C during 50 minutes. As a result, a CFRP composite with an average thickness of 2 mm apt to the manufacturing of pressure vessels was obtained. When the composite block was completed, it was cut with a Computer Numerical Control (CNC) machine.

B. TEST SET UP AND SPECIMEN PREPARATION

A Servosis ME-405/50/5 test machine was used for performing the tensile test. This machine provides a maximum load of 500 kN, with a TC50Kn REP transducer as the load cell and MTS Model XSA304A Grips as the used in past works [21]. Added to the test machine, it is necessary to use cameras for performing the DIC tests. Specifically, a total of three DSLR Canon 700D cameras, equipped with a 60 mm macro lens and a CMOS APS-C sensor of 22.3×14.9 mm, were used for performing the DIC tests. The image size was of 5184×3456 px with a pixel size of $4.3 \mu\text{m}$. Two cameras were used for 3D DIC and one camera was used for 2D DIC. The 2D DIC camera was placed orthogonal to the plane of the specimen with the aim of minimizing possible uncertainties. The verticality of the specimen has been guaranteed with an inclinometer and with a micrometric ball joint. So, the orthogonality between optic axes of specimen and camera is guaranteed. 3D cameras are placed in both sides and the 2D DIC camera is the one in the middle, orthogonal to the specimen. [40]. Meanwhile, the cameras used for the 3D-DIC were placed forming a stereo angle of 15° (Figure 1) in order to avoid possible depth of field problems [41].

For automating the acquisition process, the cameras were connected to a Programmable Logic Controller (PLC), Siemens Logo. The PLC was programmed to simultaneously send a signal to the cameras and thus capture the

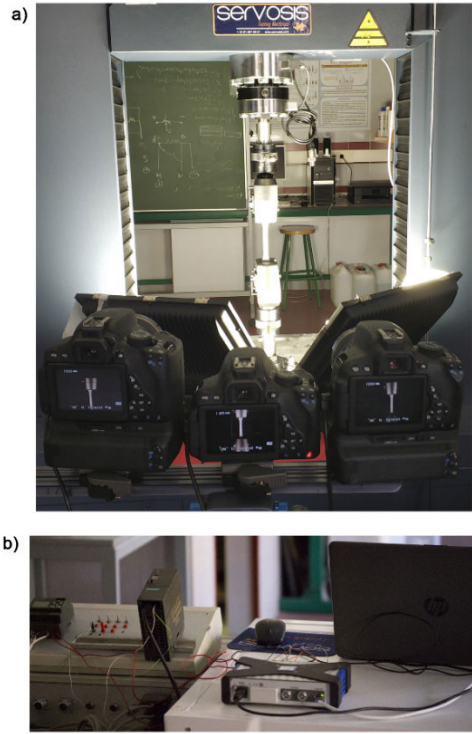


FIGURE 1. General view of the a) image acquisition system and b) data acquisition system. 3D cameras are placed in both sides and the 2D DIC camera is the one in the middle, orthogonal to the specimen.

images. Also, the machine and the PLC were connected to a data acquisition system, QUANTUM, which collects all data. Additionally, two led spotlights were used with the aim of providing a good illumination during the tensile tests (Figure 1).

Finally, the load increment of the test was calculated according with ISO 527-4 [38], [39]. Result to this, the cameras were programmed for capturing one image per second.

For the specimen preparation, first of all is necessary to apply the Speckle pattern. Speckle pattern is one of the most important factors for the final results of the DIC [42]. For this work, a computer speckle pattern was used, since could be considered the most robust and reliable way to create it. To this end, the following considerations were taken into account [43], [46], [46], [47]: i) pattern randomness; ii) circular spots; and iii) covering among 40-70% of the specimen surface, in order to reduce homogeneity. The Mean Intensity Gradient (MIG) was used for assessing the quality of the pattern [48], [49].

Taking into consideration the previous specification, a speckle pattern was designed following the approach proposed by [21]. First of all, a regular mesh with circular specks was created, being the principal parameters for this mesh the diameter, d , of the spots, which is comprised between 3-5 pixels, and the separation (*step*) among centres. The randomness of the pattern was generated applying a Gaussian random factor. The pattern was developed with

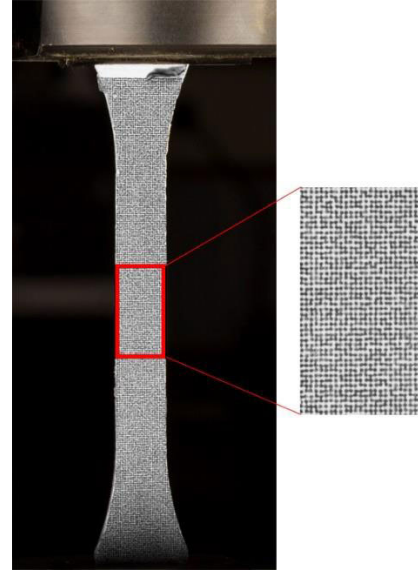


FIGURE 2. Speckle pattern used.

a Matlab®script obtaining a MIG of 56, considering it as acceptable [50]. The defined diameter, d , was 0.324 mm and the step was 0.432 mm. Figure 2 shows the designed speckle impregnate into the specimen.

C. DIGITAL IMAGE CORRELATION APPROACHES

This section describes the different DIC strategies used for estimating the mechanical properties of the composite solution, namely Young Modulus (E), Poisson ratio (ν) and Tensile strength (T). To this end, an ad-hoc set-up was designed to compare the two techniques: on the one hand, the 2D DIC method was applied with the images captured by the central camera. Meanwhile, the 3D DIC method was fed with the images captured by the stereo system (Figure 1). After completion of the test and the data acquisition, the mechanical properties have been defined following the workflow showed in Figure 3.

1) 2D DIGITAL IMAGE CORRELATION

The Bundle Adjustment (BA) approach was applied in order to obtain the inner calibration of the camera. This method needs a set of images – about 20 – of a flat checkerboard calibration target, with variations of position and orientation. The BA algorithm allows to minimise the overall re-projection error of the corners of squares (control points) extracted from the checkerboard calibration target. Then, a Gaussian radial distortion model is applied in order to compensate the distortion of the lens (Eq. 1).

$$\begin{bmatrix} x_d \\ y_d \end{bmatrix} = \left(1 + k_1 r^2 + k_2 r^4 + k_3 r^6 \right) \cdot \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 2p_1 xy + p_2 (r^2 + 2x^2) \\ p_1 (r^2 + 2y^2) + 2p_2 xy \end{bmatrix} \quad (1)$$

where $r^2 = x^2 + y^2$ and represents the radial distance, r , computed from the images' coordinates (x, y) ; (x_d, y_d) are

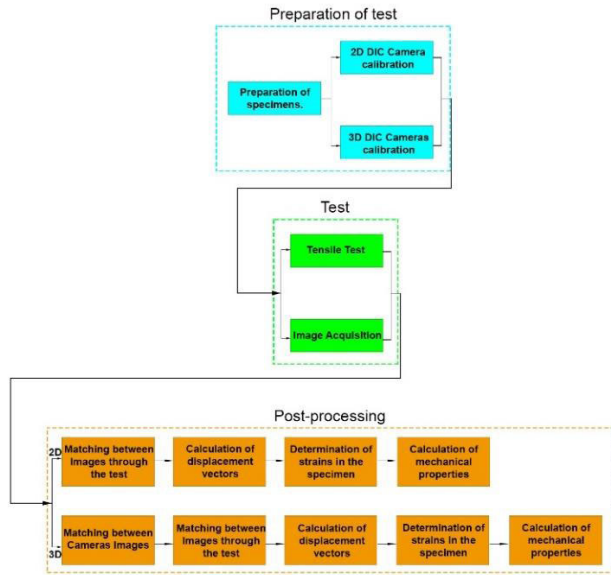


FIGURE 3. Workflow of the 2D and 3D DIC approach process.

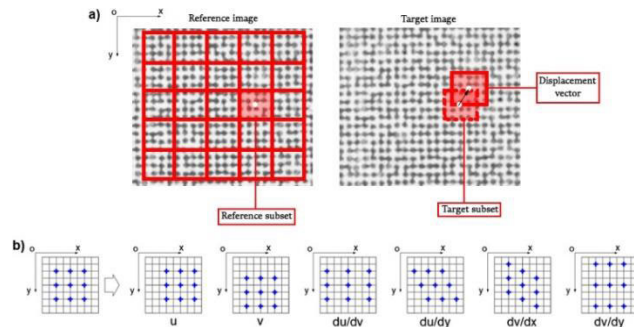


FIGURE 4. 2D DIC: a) calculation of the displacement vector and; b) degree of freedom considered for the strain calculation, u and v are the translation in the x and y direction; du/dy and dv/dx are the shear deformation through x and y directions.

the image coordinates corrected from lens distortion; k_1 , k_2 , k_3 are the radial distortion parameters; and p_1 , p_2 are the decentering distortion parameters.

After calibration, a set of images was processed using a 2D DIC approach (Figure 3) [51]. The DIC method divides the image into square regions, called sub-sets, which are compared between two consecutive images (i and $i + 1$), i being the reference image and $i + 1$ the deformed image. The calculation of displacements and strains of each subset started with the centroid determination in the deformed image ($i + 1$) with the use of [52]. The difference between the subset centroid positions provided the displacement vector, A , between the reference image (i) and the deformed image ($i + 1$) (Figure 4).

To reach sub-pixel precision in DIC, the Quintic B-spline function and a non-linear optimization has been carried out as it was described in past works [21], [53]. It is worth mentioning that the Inverse-Compositional Gauss-Newton

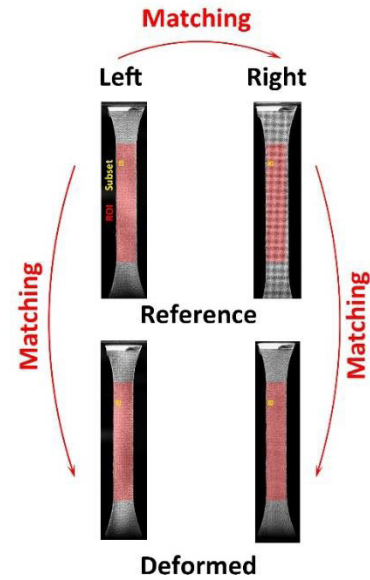


FIGURE 5. Matching between images through 3D DIC.

(IC-GN) algorithm was used for obtaining the solution to the optimisation problem. [54].

The strategy previously shown was applied over the entire Region of Interest (ROI). With the aim of minimizing the error propagation as well as optimizing the computation time, the reliability-guided digital image correlation algorithm (RG-DIC) was used [55].

2) 3D DIGITAL IMAGE CORRELATION

The main difference between 3D DIC and 2D DIC relies on the use of two or more additional cameras to estimate the displacements out of the main plane of the camera. To this end, the cameras need to be positioned in a non-orthogonal position [56]. In line with this, the 3D DIC method requires to solve the inner as well as the relative orientation of the cameras.

On the one hand, the inner calibration of the cameras was carried out using the 2D DIC calibration approach. Then, the relative orientation of the cameras was performed using the Direct Linear Transformation (DLT) [56], [57]. The use of the DLT allows to relate the image coordinates (x_p , y_p) with the object coordinates (X' , Y' , Z') (Eq. 2). With the aim of minimising the uncertainty along the depth-axis, a cylindrical calibration target with control points was used.

$$\begin{aligned} x_p &= \frac{L_1X + L_2Y + L_3Z + L_4}{L_9X + L_{10}Y + L_{11}Z + 1} \\ y_p &= \frac{L_5X + L_6Y + L_7Z + L_9}{L_9X + L_{10}Y + L_{11}Z + 1} \end{aligned} \quad (2)$$

where x_p and y_p are the image point coordinates and $L_1 - L_{11}$ are the mathematical DLT parameters.

The relative orientation of the cameras allows them to obtain the 3D coordinates of homologous points which were determined in the following way (Figure 5): i) matching

between the pair of images (Left-Right); ii) matching between the images captured at the time i and $i + 1$ (Reference-Deformed). This matching was carried out in the same way that the 2D DIC. Then, the DLT transformation was applied in order to obtain the displacements of the subsets using the following least square approach (Eq. 3).

$$M = [A^T A]^{-1} A^T U \quad (3)$$

where A is a design matrix which connects the DLT parameters and the parameters presented in equation (2). M is the displacement matrix for every point. Finally, U is the difference matrix between DLT coordinates and camera parameters.

Thanks to this, it was possible to assess the in-plane displacements (x, y) and the out-of-plane movements (z) depth direction thanks to the use of the DLT. As a result, it was possible to obtain a 3D point cloud of the specimen evaluated which allowed to obtain the full-field displacements and strains using the 2D DIC approach previously defined.

D. STATISTICAL ANALYSIS

Once the process was finished following the 2D DIC and 3D DIC methods, parametric and non-parametric statistical analysis were performed to detect if there were significant differences among the mechanical properties. First, the data obtained for virtual extensometer in each experiment (DIC 2D and DIC 3D) were compared using the Kruskal-Wallis Test for independent samples. This non-parametric test allowed us to demonstrate whether a group of data comes from the same population.

If the existence of a statistically significant difference is not demonstrated, the parameters obtained with all the virtual extensometer for each experiment are compared using different parametric statistics: Levene Test and T-test. In addition, to strengthen the statistical comparison, non-parametric tests were applied: Median test, Kolmogorov-Smirnov, Moose's Test, Mann-Whitney U Test and Kruskal Wallis Test. These tests allowed us to evaluate the existence of statistically significant differences in each test.

E. NUMERICAL ANALYSIS

In order to evaluate how the material uncertainties (input) influence the numerical simulations (output), an advanced numerical strategy was followed. This strategy, which is based on a probabilistic approach, followed two stages: i) the definition of the numerical model and; ii) the reliability analysis.

1) DEFINITION OF THE NUMERICAL MODEL

A FEM model was implemented following the indications established in García-Martín *et al.* [21]. This numerical model consisted in a real case of repaired corroded steel pipe by a composite wrap made of different composite plies. This model required the definition of the following parts (Figure 6): i) the steel pipe; ii) the corroded part and iii) the wrap. The wrap part was meshed as a continuum

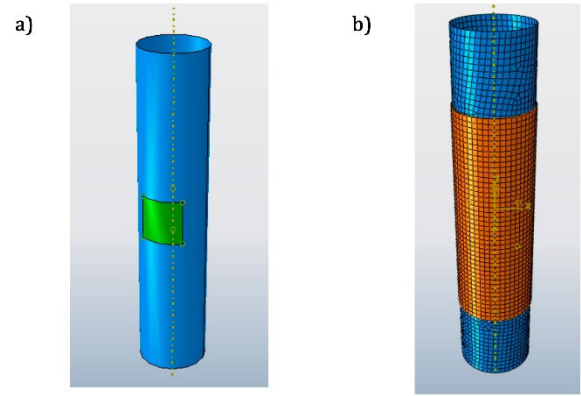


FIGURE 6. Numerical mesh used for evaluating the transmission of uncertainties: a) geometry and; b) numerical mesh. Blue areas correspond with the steel pipe without corrosion. The green area is representing the corrode zone and the orange areas the composite solution.

shell with reduced integration and eight nodes SC8R elements, obtaining a mesh with 5,779 elements. This model will be the start of the construction of the metamodel which will be explained later. And the final results are obtained because of the execution of this model. Also, this is a practical application of the material which is currently used in several simulations [58], [59].

The failure criterion of the models was the Tsai and Wu criterion [60]. This criterion assumes that failure occurs when the failure index (FI) is bigger than 1. FI was calculated by the expression (Eq. 4):

$$FI = F_1\sigma_1 + F_2\sigma_2 + F_3\sigma_3 + F_{11}\sigma_1^2 + F_{22}\sigma_2^2 + F_{33}\sigma_3^2 + 2F_{12}\sigma_1\sigma_2 + 2F_{23}\sigma_2\sigma_3 + 2F_{31}\sigma_3\sigma_1 + F_{44}\sigma_4^2 + F_{55}\sigma_5^2 + F_{66}\sigma_6^2 \leq 1 \quad (4)$$

where:

$$F_1 = \frac{1}{X_T - \frac{1}{X_C}} \quad F_2 = \frac{1}{Y_T - \frac{1}{Y_C}} \quad F_3 = \frac{1}{Z_T - \frac{1}{Z_C}}$$

$$F_{11} = \frac{1}{X_T X_C} \quad F_{22} = \frac{1}{Y_T Y_C} \quad F_{33} = \frac{1}{Z_T Z_C}$$

$$F_{44} = \frac{1}{S_{yz}^2} \quad F_{55} = \frac{1}{S_{zx}^2} \quad F_{66} = \frac{1}{S_{xy}^2}$$

$$F_{12} = \left(-\frac{1}{2}\right) \sqrt{F_{11} F_{22}} \quad F_{23} = \left(-\frac{1}{2}\right) \sqrt{F_{22} F_{33}}$$

$$F_{31} = \left(-\frac{1}{2}\right) \sqrt{F_{33} F_{11}}$$

$\sigma_n \equiv$ Uniaxial tension in the different directions.

$X_T \equiv$ Tensile load

$X_C \equiv$ Compression load

$Y_T \equiv$ Transversal tensile load, in the y direction

$Z_T \equiv$ Transversal tensile load, in the z direction

$Y_C \equiv$ Transversal compression load, in the y direction

$Z_C \equiv$ Transversal compression load, in the z direction

$S_{xy}, S_{yz}, S_{zx} \equiv$ Shear transversal load

2) RELIABILITY ANALYSIS

As it was stated in the introduction, the proper analysis of composite materials requires the use of probabilistic approaches. These approaches allowed us to determine the probability of failure of a system (Eq. 5):

$$P_{fk} = \int_{G_k(d,X) < 0} f_X(X) dX \quad (5)$$

where:

- P_{fk} is the failure probability.
- G_k are the restrictions.
- $f_X(X)$ is the probability density function (PDF) of the random vector $X \in R^m$ and the design vector $d \in R^n$.

However, the solution to this equation is not trivial and requires the use of methods able to approximate this value. For the present case study it was decided to use the Monte Carlo method for approximating this value. This method requires the use of thousands of simulations in order to obtain reliable results, requiring a high computational cost. In order to solve this drawback, a metamodeling strategy was used, in our case the Polynomial Chaos Expansion (PCE) method [61]. This model shows a good performance on those systems with probabilistic inputs. The PCE approximates the behaviour of the numerical simulation using multivariate polynomials, assuming that the real model can be represented as a finite model whose inputs are considered independent variables [62]. In this way, the polynomials were constructed with respect to the PDFs of the independent input parameters by estimating their coefficients through least squares minimisation of the input variables and the real responses. In this case, the adaptive sparse PCE based on the least angle regression [63] was used along with the least angle regression algorithm [64], in order to avoid an over-fitting. In order to evaluate the quality of the metamodel obtained, the modified version of the Leave-one-out error (LOO) [65] was used (Eq. 6-7). This parameter allowed us to perform an estimation of the error with an acceptable computational cost.

$$LOOerror = \frac{1}{N} \sum_{i=1}^N \left(\frac{Y(X^{(i)}) - f^{\sim PCE}(X^{(i)})}{1 - h_i} \right)^2 \quad (6)$$

$$LOOerror^* = LOOerror * \left(1 - \frac{cardA}{N} \right)^{-1} \times \left(1 + tr(\varphi^T \varphi)^{-1} \right) \quad (7)$$

where $Y(X^{(i)})$ is the computational model; $f^{\sim PCE}(X^{(i)})$ is the surrogate model obtained from a specific DoE with N samples; h_i is the i -th diagonal term of the matrix $A(A^T A)^{-1} A^T$; A is the experimental matrix; $cardA$ is the number of terms in the truncate series and; $\varphi = \{\varphi_{ij} = \varphi_j(x^{(i)}), i = 1, \dots, N; j = 1, \dots, cardA\}$.

All the process and simulations were executed using a Intel® XEON E3-1240 v3 processor running at 3,4GHz with 8GB RAM DDRII.

TABLE 1. 2D DIC camera calibration parameters.

Parameters		Initial	Calibrated
Focal length (pixel)	fu	1.5310 x 104	1.5307 x 104
	fv	1.5307 x 104	1.5252 x 104
Principal point (pixel)	u	2.6224 x 103	2.6287 x 103
	v	1.8446 x 103	1.8372 x 103
Radial Distortion parameters	k1	0	-1.465 x 10-3
	k2	0	3.370 x 10-2
	k3	0	-1.450 x 10-5
Decentering distortion parameters	p1	0	1.252 x 10-5
	p2	0	-7.409 x 10-5

III. EXPERIMENTAL RESULTS

A total of 25 composite specimens were manufactured and tested specifically for this research. During each test the 2D and 3D DIC methods were simultaneously applied using the set-up described in the previous section. Thanks to this, it was possible to obtain different mechanical variables such as the Young Modulus (E), the Poisson ratio (ν), and the maximum strength (T).

Previously to perform each test, the specimen was properly prepared according with the suggestion done in Section 2.1. In this case, we started with the specimen preparation applying the speckle pattern. It is worth mentioning that all the images were acquired in RAW format with the aim of enhancing the contrast during the post-processing stage, allowing a better correlation between subsets of different images until the fracture of the specimen. Please note that the cameras were synchronized to always shoot at the same time. The average Ground Sample Distance (GSD) was 0.07 mm/px in all the cases. The test speed was of 2 mm/min and the time among shoots was 2 seconds.

A. DIGITAL IMAGE CORRELATION RESULTS

1) 2D DIC APPROACH

The images acquired by the 2D DIC camera were firstly corrected from lens distortion using the pattern and calibration model defined in Section 2.3.2 (Table 1). To this end, a total of 74 images per specimen were used.

For the 2D DIC post-processing the open-source software Ncorr [66], developed in Matlab®, was used. This software implements the procedures showed in Section 2, allowing to obtain full-field displacements and strains. During this stage a subset size of 20×20 pixels and a step of 7 pixels were used for calculating the full-field displacements. In order to obtain the mechanical properties of each specimen, a total of six virtual extensometers were placed on the surface. Three along the vertical direction and three along the horizontal direction. The first one was placed at the center of the Region of Interest (ROI), the other two were located at 3 mm of distance (Figure 7). Thanks to this, it was possible to obtain for each specimen a total of three Young Modulus (E) and Poisson's ratio (ν) and a maximum strain (T) (Figure 7). Furthermore, the full field of displacements was calculated in order to compare the 2D and 3D approaches (Figure 7B and 7C). Although the angular deviations in 2D-DIC can

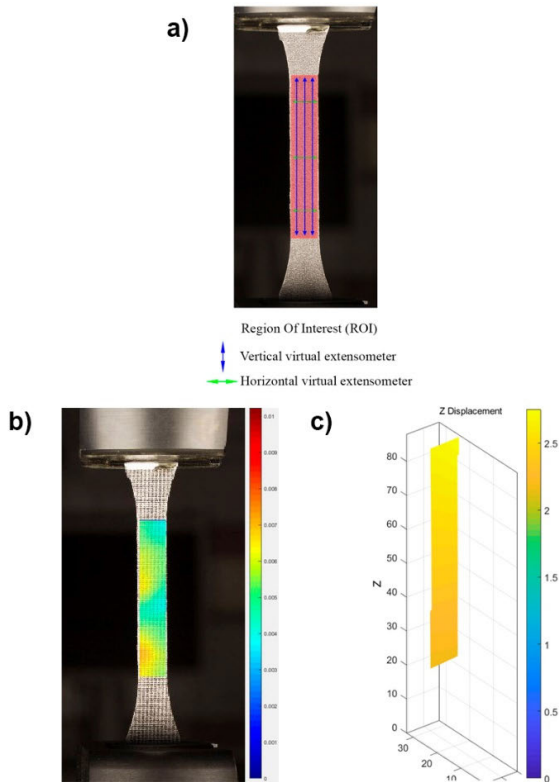


FIGURE 7. Fields of DIC into the specimen; a) Position of the different virtual extensometers used for each specimen; b) Field in the 2D DIC and c) Field in the 3D DIC reconstruction.

cause errors greater than 103μ -strains [67], the procedure used to ensure the orthogonality avoided these errors and differences were not found with respect to the results obtained in 3D. The equality of outcome of both approaches also makes it possible to demonstrate that out-of-plane motions do not occur, something already known in plane tensile tests. Furthermore, a macro lens was used in order to minimize out-of-plane motion and that this does not contribute significantly to in-plane strain measurement error [31].

A non-parametric comparison was performed to analyze the existence of statistical significant differences between the calculated parameters (Young's Modulus (E) and Poisson's ratio (ν)) from each one of the three virtual extensometers within the 2D DIC experiment. For this purpose, a Kruskal Wallis test was applied between the E parameter of each virtual extensometer. This test did not demonstrate the existence of significant differences between extensometers in the variable E (p-value 0.938), nor for the variable ν (p-value 0.694). Also, a parametric T-test was applied for E (p-value 0.950) and ν (lower obtained p-value 0.259). The existence of significant statistical differences among the data provided by each virtual extensometer could not be demonstrated. Therefore, it was possible to work under the hypothesis that the data was homogeneous.

Finally, the PDF of each mechanical variable was computed, allowing to obtain the best PDF model. Then,

TABLE 2. 2D Results obtained from the specimens using 2D DIC approach.

Parameter	Number of data	Mean	Lower Bound	Upper Bound
E-Young's modulus (GPa)	75	51.7322	46.4217	56.9255
ν -Poisson's ratio (-)	75	0.0602	0.0176	0.1692
T-Maximum principal tensile (MPa)	25	484.849	465.107	506.858

TABLE 3. Goodness of fit (GOF) probability of the data obtained by 2D DIC approach; N-Normal, LN-Lognormal, W-Weibull, G-Gamma; 0-Accept and 1-Reject. Chi-Square (Chi), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests of the Young's Modulus (E), Poisson's ratio (ν) and Maximum principal tensile (T).

PD	N			LN			W			G		
F	C	K	A	C	K	A	C	K	A	C	K	A
GO	hi	S	D	hi	S	D	hi	S	D	hi	S	D
E	0	0	0	0	0	0	1	0	0	0	0	0
ν	1	0	0	0	0	0	1	1	1	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 4. Principal parameters of the PDFs.

Parameter	Distribution	μ (Log-Normal)/A (Weibull)	σ (Log-Normal)/B (Weibull)
E	Log-Normal	3.9448	0.0515
ν	Log-Normal	-2.9025	0.4208
T	Weibull	442.0158	10.5146

the different statistics were calculated. Table 3 shows the results of using the Chi-square, Kolmogorov-Smirnov and Anderson-Darling tests.

Based on Table 3, Young Modulus (E) was adapted to a Log-Normal function (LN), Poisson ratio (ν) to a Log-Normal function (LN) and tensile strength (T) to a Weibull function (W). In order to reinforce this Figure 8 shows the graphic representation of the PDFs of each parameter. The principal values of the PDF distributions are shown in Figure 8.

Complementary to the estimation of the different PDF functions, a correlation analysis was carried out. For the present study case it was used the Spearman correlation index [68], [69]. This index varies from 1 (complete positive correlation), 0 (no correlation) and -1 (a complete inverse correlation) according with the following equation (Eq. 8):

$$\rho = \frac{\sum (x - m_x)(y - m_y)}{\sqrt{\sum (x - m_x)^2 \sum (y - m_y)^2}} \quad (8)$$

where x and y are the two vectors of the different parameters and m_x and m_y are the corresponding means.

The correlation between parameters was shown in Table 5. According to this, it was possible to conclude that the Young

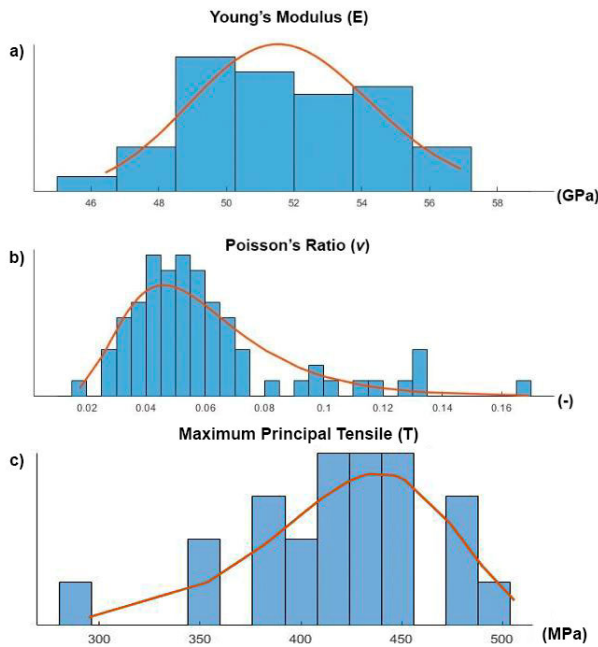


FIGURE 8. Graphical representation of the PDFs obtained by 2D DIC approach. a) Log-Normal distribution of the Young's Modulus (E); b) Log-Normal Distribution of the Poisson's Ratio (ν) and c) Weibull distribution of the Maximum principal tensile (T).

TABLE 5. Correlation matrix between parameters.

Spearman	E	ν	T
E	1	0.096	0.927
ν	0.096	1	0.043
T	0.927	0.043	1

Modulus (E) and the tensile strength (T) of the specimen were highly correlated ($R^2 \cong 0.8527$). Meanwhile the Poisson ratio (ν) did not have correlation with the other two variables.

2) RESULTS FROM THE 3D DIC

For the 3D DIC post-processing the open-source software MultiDIC was used [70]. This software is based on Ncorr [64], using the same algorithms for processing the displacements and strains but including the relative orientation of the cameras.

Firstly, the inner calibration of the cameras was obtained by applying the method used in the previous section, obtaining the following results (Table 6).

Then the relative orientation of the cameras was obtained using the inner calibration parameters as well as the cylindrical calibration target showed in Section 2.3.2 to solve the DLT transformation. These parameters allowed us to reconstruct the position of each subset's centroid in 3D and thus their displacement vector as the difference of the centroid in the pair of images i (reference) and the pair of images $i + 1$ (deformed).

Similarly to the 2D DIC, during the 3D DIC reconstruction a total of six extensometers placed in the same position were

TABLE 6. 3D DIC cameras calibration parameters.

Parameter	Camera 1		Camera 2	
	Initial	Calibrated	Initial	Calibrated
Focal length (pixel)	f_u	1.5247×10^4	1.5256×10^4	1.5345×10^4
	f_v	1.5230×10^4	1.5239×10^4	1.5327×10^4
Principal point (pixel)	u	2.6196×10^3	2.6264×10^3	2.6329×10^3
	v	1.8309×10^3	1.8299×10^3	1.8473×10^3
Radial Distortion	k_1	0	-1.861 $\times 10^{-4}$	0
	k_2	0	3.591×10^{-2}	0
	k_3	0	-1.143	0
Tangential distortion	p_1	0	-2.078 $\times 10^{-5}$	0
	p_2	0	7.772×10^{-5}	-7.245 $\times 10^{-5}$

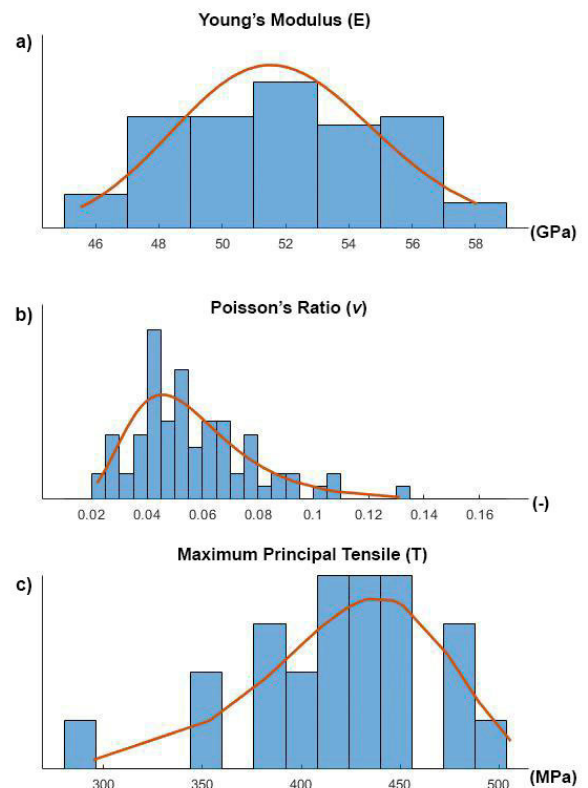


FIGURE 9. Graphical representation of the PDFs obtained by 3D DIC approach. a) Log-Normal distribution of the Young's Modulus (E); b) Log-Normal Distribution of the Poisson's Ratio (ν) and c) Weibull distribution of the Maximum principal tensile (T).

used. Thanks to this it was possible to obtain a set of values of the Young Modulus (E), Poisson ratio (ν) and maximum strain (T) (Table 7). These values were used to calculate the PDF functions following the method used in the previous section (Table 8, Table 9) (Figure 9).

TABLE 7. Results obtained from the specimens using 3D DIC approach.

Parameter	Number of data	Mean	Lower Bound	Upper Bound
E-Young's modulus (GPa)	75	53.9820	48.5101	59.9470
ν -Poisson's ratio (-)	75	0.0626	0.0183	0.1760
T-Maximum principal tensile (MPa)	25	484.849	465.107	506.858

TABLE 8. Goodness of fit (GOF) probability of the data obtained by 3D DIC approach; N-Normal, LN-Lognormal, W-Weibull, G-Gamma; 0-Accept and 1-Reject. Chi-Square (Chi), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests of the Young's Modulus (E), Poisson's ratio (ν) and Maximum principal tensile (T).

PD	N			LN			W			G		
F	Ch	K	A	Ch	K	A	Ch	K	A	Ch	K	A
F	i	S	D	i	S	D	i	S	D	i	S	D
E	0	0	0	0	0	0	1	0	0	0	0	0
ν	1	1	1	0	0	0	1	1	1	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 9. Principal parameters of the PDFs.

Parameter	Distribution	μ (Log-Normal)/A (Weibull)	σ (Log-Normal)/B (Weibull)
E	Log-Normal	3.9871	0.0564
ν	Log-Normal	-2.8616	0.4186
T	Weibull	442.0158	10.5146

TABLE 10. Spearman correlation factor.

Spearman	E	ν	T
E	1	0.036	0.890
ν	0.036	1	0.043
T	0.890	0.043	1

A non-parametric comparison was performed to analyse the existence of statistically significant differences between the calculated parameters (E and T) from each one of the three virtual extensometers within the 3D DIC experiment. For this purpose, a Kruskal Wallis Test was applied first. This test did not demonstrate the existence of significant differences among the extensometers for the variable E (p-value 0.820) nor for the variable ν (p-value 0.693). Also, a parametric T-test was applied for E (p-value 0.805) and ν (p-value 0.277). The existence of statistically significant differences between the data of each virtual extensometer could not be demonstrated. Therefore, it was possible to work under the hypothesis that the data was homogeneous.

As it was done in the previous section, the Spearman correlation factor was calculated (Table 10).

TABLE 11. Comparisons between PDFs of Young's Modulus (E), Poisson's ratio (ν) of the specimens obtained by 2D DIC and 3D DIC.

		DIC 2D	DIC 3D
E, Young's Modulus (GPa)	Mean	51.7322	53.9820
	Median	51.6140	53.4880
	Lower Bound	46.4217	48.5101
	Upper bound	56.9255	59.9470
	PDF	Log-Normal	
ν , Poisson coefficient (-)	μ	3.9448	3.9871
	σ	0.0515	0.0564
	Mean	0.0602	0.0626
	Median	0.0537	0.0555
	Lower Bound	0.0176	0.0183
	Upper Bound	0.1692	0.1760
	PDF	Log-normal	
	μ	-2.9025	-2.8616
	σ	0.4208	0.4186
	Spearman correlation	E-T	0.927
		E- ν	0.096
		ν -T	0.043

The R^2 between E and T was 0.6989 and the RSME was 26.41.

Table 11 shows a comparison between the PDFs obtained by the 2D DIC and the 3D DIC.

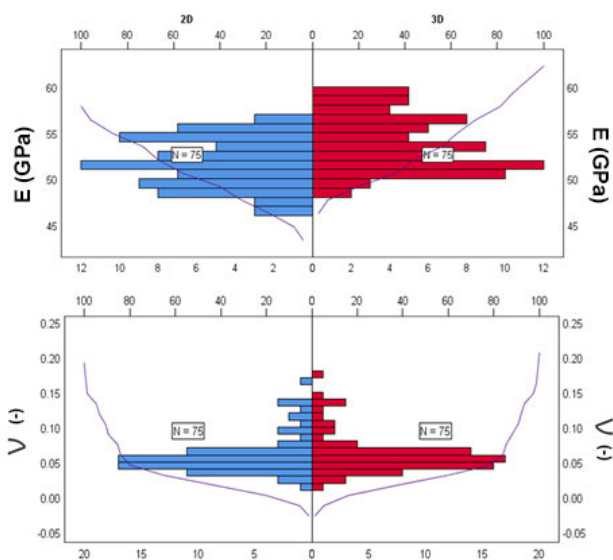
B. STATISTICAL COMPARISON

As it was noted in the previous sections, significant differences were not detected between the data provided by each of the three virtual extensometers (within the same experiment). Therefore, using the results of all virtual extensometer, a general statistical comparison between 2D DIC and 3D DIC, can be made using parametric and non-parametric methods. The parametric statistics applied were Levene Test to study equality of variances, and the T-test to study equality of means. The non-parametric statistics applied were the Median Equality Test and the Moses Test. To analyze the equality of the distribution, the Mann-Whitney U Test, the Kolmogorov-Smirnov Test (K-S) and the Kruskal Wallis Test were used. The results are shown in the Table 12.

For the variable E, both parametric and non-parametric tests indicate that there are statistically significant differences ($p < 0.05$), except in the case of equality of variances. For the variable ν , the existence of significant differences between the two methods cannot be demonstrated. The histogram of both variables can be visualised in Figure 10, observing a significant difference in the central tendency for the

TABLE 12. P-value of the different test applied to compare the two experiments.

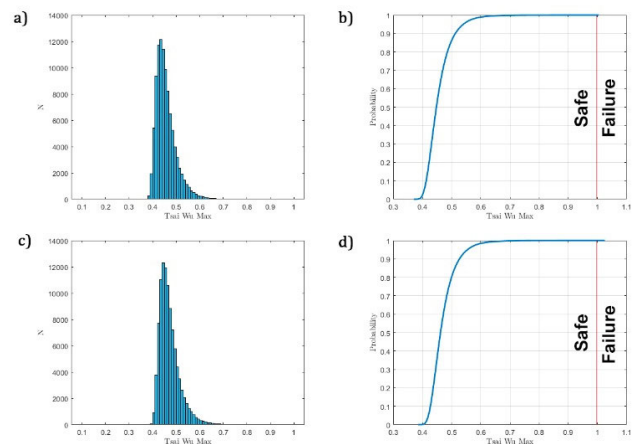
	Parametric test			Non-parametric test		
	Variance equality (Levene)	Means equality T test	Median equality test	Range equality (Moses)	Distribution equality	
					U-Mann-Whitney	K-S Kruskal-Wallis
E	0.104	0.000	0.009	0.000	0.000	0.0003
ν	0.856	0.613	0.514	0.610	0.442	0.97

**FIGURE 10.** Histogram of the variable E (up) and ν (down) obtained for each method DIC 2D and DIC 3D. In blue is represented the histogram obtained by the 2D method and in red the histogram obtained by the 3D strategy. The purple line represents the accumulated.

variable E. These significant differences can be explained from the point of view of the different uncertainties of each of the methods used. While in the 2D approach the main source of uncertainty are out-of-plane strains, in the 3D approach they are mostly related to the calibration of the cameras. This means that although the test procedures are similar, the uncertainties are independent for each technique. In this case, the difference between the strains is approximately 10-4 for values of an order of 20 times greater, so it is acceptable.

C. GLOBAL RELIABILITY ANALYSIS

From the results previously obtained, a global reliability analysis was performed over the deterministic mesh considering the Young Modulus, E, and the Poisson's coefficient, ν , obtained in 2D DIC and 3D DIC as the input variables. As it was described in section 2.5, it was necessary to have a tool to determinate the Tsai Wu maximum in every simulation. So, for this reason a FEM analysis was executed.

**FIGURE 11.** Metamodeling results: a) Tsai-Wu distribution in the 2D DIC metamodel simulations; b) Cumulative distribution function of the 2D-DIC metamodeling simulations; c) Tsai-Wu distribution in the 3D DIC metamodel simulations; b) Cumulative distribution function of the 3D-DIC metamodel simulations.**TABLE 13.** Quartile and percentile Tsai Wu analysis with parameters obtained by 2D DIC and 3D DIC.

	Tsai Wu	
	2D DIC	3D DIC
Quartile 1	0.4269	0.4412
Quartile 2	0.4478	0.4619
Quartile 3	0.4769	0.4908
Quartile 4	1.0046	1.0254
IQR	0.0500	0.0496
IPR80%	0.0977	0.0944
IPR90%	0.1341	0.1339

After that, a metamodel was built. In this way, the computer cost was greatly reduced, and it was possible to carry out a huge number of simulations in less time. As it was commented in section 2.5.2, the LOO error results obtained by the different metamodels were 0.032 in the 2D DIC methodology and 0.0034 in the 3D DIC methodology.

A total of 200 executions to build the metamodel were carried out, and then a total of 100,000 executions of the Reliability analysis were carried out obtaining the probability of failure and the concentration of that as it is shown in Figure 11, where it was compared the probability with the parameters obtained by 2D DIC and 3D DIC.

After the simulations, in the 2D and 3D only one case of 100,000 provided a Tsai Wu higher than 1. Next table (Table 13) outlines the Tsai Wu values at different quartiles.

The inter-quartile (IQR) and inter-percentile (IPR) ranges (Table 13) were extracted from the data generated in the Tsai-Wu analysis. The data show that the distribution for 2D DIC and 3D DIC are similar. This can be corroborated

through the visualization of the histogram and failure plot (Figure 11).

IV. CONCLUSION

This work aims to compare two DIC methods for determining the mechanical properties of CFRP composite solutions. To this end, a total of 25 composite specimens were tested using 3 different cameras at the same time: one for the 2D DIC method and two for the 3D DIC. The mechanical properties of the composite were determined using virtual extensometers in each one of the samples. Then, the Young Modulus, E , and Poisson ratio, ν , were extracted. The Kruskal Wallis test performed on each of these variables reveals that the data captured is homogenous and could be considered as a unique population: one for the Young Modulus, E , and one for the Poisson ratio, ν . According with different parametric and non-parametric tests performed, significant differences for the Young Modulus, E , were detected between the two tests. Specifically, the mean and median of the Young Modulus obtained by 3D-DIC was slightly higher than the one obtained by 2D-DIC. Despite this, the differences obtained were acceptable and may be due to the uncertainties of each test setup.

Finally, a set of probabilistic numerical analysis were carried out with the aim of analysing the discrepancies in the numerical simulations for a real study case, fed by a FEM model, simulating a repaired corroded pipe. To this end it was used the PDF functions of each variable, as well as a metamodeling strategy for reducing the computational costs since it was required to perform a Monte Carlo analysis. The results obtained in both numerical analyses revealed a great similarity between both approaches in terms of interquartile, accumulative histograms and probability of failure. Also, a statistical comparison between the principal mechanical properties shows the same similarity. These results show that the small differences found between 2D and 3D are no longer significant when probabilistic numerical analysis methods are applied. In this way, the uncertainties are blurred and similar valid results are obtained for both methods, since the validity of the 2D-DIC method has been verified in previous works.

In accordance with the results obtained during this work it was possible to conclude that the 3D DIC method was able to provide similar results than the 2D DIC with the advantage of being possible its use in non-planar surfaces. These surfaces were used for the determination of the mechanical properties in CFRP solutions.

Future works will be focused on integrating the 3D approach in all the design chain, starting from the mechanical characterization and ending in the verification of the numerical model using physical specimens.

REFERENCES

- [1] N. Yahaya, N. M. Noor, S. Rabe'ah Ot, L. K. Sing, and M. M. Din, "New technique for studying soil-corrosion of underground pipeline," *J. Appl. Sci.*, vol. 11, no. 9, pp. 1510–1518, Apr. 2011.
- [2] J. L. Alamilla, M. A. Espinosa-Medina, and E. Sosa, "Modelling steel corrosion damage in soil environment," *Corrosion Sci.*, vol. 51, no. 11, pp. 2628–2638, Nov. 2009.
- [3] A. Vedrtam, "Novel method for improving fatigue behavior of carbon fiber reinforced epoxy composite," *Compos. B, Eng.*, vol. 157, pp. 305–321, Jan. 2019.
- [4] P. R. Vieira, E. M. L. Carvalho, J. D. Vieira, and R. D. T. Filho, "Experimental fatigue behavior of pultruded glass fibre reinforced polymer composite materials," *Compos. B, Eng.*, vol. 146, pp. 69–75, Aug. 2018.
- [5] S. S. R. Koloor, M. A. Abdullah, M. N. Tamin, and M. R. Ayatollahi, "Fatigue damage of cohesive interfaces in fiber-reinforced polymer composite laminates," *Compos. Sci. Technol.*, vol. 183, Oct. 2019, Art. no. 107779.
- [6] S. B. Bati and T. Rotunno, "Environmental durability of the bond between the CFRP composite materials and masonry structures," *Hist. Construct.*, vol. 1039, p. 46, Nov. 2001.
- [7] G. B. Sinclair and J. E. Helms, "A review of simple formulae for elastic hoop stresses in cylindrical and spherical pressure vessels: What can be used when," *Int. J. Pressure Vessels Piping*, vol. 128, pp. 1–7, Apr. 2015.
- [8] P. J. I. F. W. P. Laney, "Use of composite pipe materials in the transportation of natural gas," INEEL Field Work Proposal, Tech. Rep. 4340-70, 2002.
- [9] N. D. Hai and H. Mutsuyoshi, "Structural behavior of double-lap joints of steel splice plates bolted/bonded to pultruded hybrid CFRP/GFRP laminates," *Construct. Building Mater.*, vol. 30, pp. 347–359, May 2012.
- [10] M. Mokhtari and A. A. Nia, "The application of CFRP to strengthen buried steel pipelines against subsurface explosion," *Soil Dyn. Earthq. Eng.*, vol. 87, pp. 52–62, Aug. 2016.
- [11] R. Rafiee, "On the mechanical performance of glass-fibre-reinforced thermosetting-resin pipes: A review," *Compos. Struct.*, vol. 143, pp. 151–164, May 2016.
- [12] C. Colombo and L. Vergani, "Optimization of filament winding parameters for the design of a composite pipe," *Compos. B, Eng.*, vol. 148, pp. 207–216, Sep. 2018.
- [13] O. Orell, J. Vuorinen, J. Jokinen, H. Kettunen, P. Hytönen, J. Turunen, and M. Kanerva, "Characterization of elastic constants of anisotropic composites in compression using digital image correlation," *Compos. Struct.*, vol. 185, pp. 176–185, Feb. 2018.
- [14] J. S. Berg and D. F. Adams, "An evaluation of composite material compression test methods," *J. Compos., Technol. Res.*, vol. 11, no. 2, pp. 41–46, 1989.
- [15] C. Barile, C. Casavola, and F. De Cillis, "Mechanical comparison of new composite materials for aerospace applications," *Compos. B, Eng.*, vol. 162, pp. 122–128, Apr. 2019.
- [16] T. He, L. Liu, and A. Makeev, "Uncertainty analysis in composite material properties characterization using digital image correlation and finite element model updating," *Compos. Struct.*, vol. 184, pp. 337–351, Jan. 2018.
- [17] C. T. Sun and R. S. Vaidya, "Prediction of composite properties from a representative volume element," *Compos. Sci. Technol.*, vol. 56, no. 2, pp. 171–179, Jan. 1996.
- [18] M. Nirbhay, A. Dixit, R. Misra, and H. S. Mali, "Tensile test simulation of CFRP test specimen using finite elements," *Proc. Mater. Sci.*, vol. 5, pp. 267–273, Jan. 2014.
- [19] S. Joshi and S. M. Harle, "Linear variable differential transducer (LVDT) & its applications in civil engineering," *Int. J. Transp. Eng. Technol.*, vol. 3, no. 4, pp. 62–66, 2017.
- [20] R. Garcia-Martin, Á. Bautista-De Castro, L. J. Sánchez-Aparicio, J. G. Fueyo, and D. Gonzalez-Aguilera, "Combining digital image correlation and probabilistic approaches for the reliability analysis of composite pressure vessels," *Arch. Civil Mech. Eng.*, vol. 19, no. 1, pp. 224–239, Mar. 2019.
- [21] R. García-Martin, J. López-Rebollo, L. J. Sánchez-Aparicio, J. G. Fueyo, J. Pisonero, and D. González-Aguilera, "Digital image correlation and reliability-based methods for the design and repair of pressure pipes through composite solutions," *Construct. Building Mater.*, vol. 248, Jul. 2020, Art. no. 118625.
- [22] M. A. Seif, U. A. Khashaba, and R. Rojas-Oviedo, "Measuring delamination in carbon/epoxy composites using a shadow moiré laser based imaging technique," *Compos. Struct.*, vol. 79, no. 1, pp. 113–118, Jun. 2007.
- [23] C. Gallage and C. P. G. Jayalath, "Use of particle image velocimetry (PIV) technique to measure strains in geogrids," in *Proc. 7th Int. Symp. Deformation Characteristics Geomaterials (IS-Glasgow)(E3S Web Conf.*, vol. 92. Les Ulis, France: EDP Sciences, 2019, pp. 1–6.

- [24] I. Rullman, M. Patyna, B. Janssen, and B. Willershausen, "Determination of polymerization shrinkage of different composites using a photoelastic method," *Amer. J. Dentistry*, vol. 30, no. 1, pp. 16–22, 2017.
- [25] M. T. Arellano, L. Crouzeix, B. Douchin, F. Collombet, H. H. Moreno, and J. G. Velázquez, "Strain field measurement of filament-wound composites at $\pm 55^\circ$ using digital image correlation: An approach for unit cells employing flat specimens," *Compos. Struct.*, vol. 92, no. 10, pp. 2457–2464, Sep. 2010.
- [26] T. C. Chu, W. F. Ranson, and M. A. Sutton, "Applications of digital-image-correlation techniques to experimental mechanics," *Experim. Mech.*, vol. 25, no. 3, pp. 232–244, Sep. 1985.
- [27] Y. He, A. Makeev, and B. Shonkwiler, "Characterization of nonlinear shear properties for composite materials using digital image correlation and finite element analysis," *Compos. Sci. Technol.*, vol. 73, pp. 64–71, Nov. 2012.
- [28] A. Villarino, J. López-Rebollo, and N. Antón, "Analysis of mechanical behavior through digital image correlation and reliability of *Pinus halepensis* Mill," *Forests*, vol. 11, no. 11, p. 1232, Nov. 2020.
- [29] E. Tejón-López-Zuazo, J. López-Rebollo, L. J. Sánchez-Aparicio, R. García-Martín, and D. González-Aguilera, "Compression and strain predictive models in non-structural recycled concretes made from construction and demolition wastes," *Materials*, vol. 14, no. 12, p. 3177, Jun. 2021.
- [30] A. J. Comer, K. B. Katnam, W. F. Stanley, and T. M. Young, "Characterising the behaviour of composite single lap bonded joints using digital image correlation," *Int. J. Adhes. Adhesives*, vol. 40, pp. 215–223, Jan. 2013.
- [31] M. A. Sutton, J. H. Yan, V. Tiwari, H. W. Schreier, and J. J. Orteu, "The effect of out-of-plane motion on 2D and 3D digital image correlation measurements," *Opt. Lasers Eng.*, vol. 46, no. 10, pp. 746–757, 2008.
- [32] M. A. Caminero, M. Lopez-Pedrosa, C. Pinna, and C. Soutis, "Damage monitoring and analysis of composite laminates with an open hole and adhesively bonded repairs using digital image correlation," *Compos. B, Eng.*, vol. 53, pp. 76–91, Oct. 2013.
- [33] B. Pan, "Digital image correlation for surface deformation measurement: Historical developments, recent advances and future goals," *Meas. Sci. Technol.*, vol. 29, no. 8, Aug. 2018, Art. no. 082001.
- [34] M. Frieß, M. Scheiffele, W. Zankl, and F. J. P. O. H.-C. Hofmann, "Development, manufacture and characterization of C/C-SiC components based on filament winding," in *Proc. HT-CMC*, 2010, pp. 92–97.
- [35] A. F. Hamed, M. M. Hamdan, B. B. Sahari, and S. M. Sapuan, "Experimental characterization of filament wound glass/epoxy and carbon/epoxy composite materials," *ARN J. Eng. Appl. Sci.*, vol. 3, no. 4, pp. 76–87, 2008.
- [36] C. V. Reddy, P. R. Babu, R. Ramnarayanan, and D. Das, "Mechanical characterization of unidirectional carbon and glass/epoxy reinforced composites for high strength applications," *Mater. Today, Proc.*, vol. 4, no. 2, pp. 3166–3172, 2017.
- [37] A. L. Gol'Denveizer, *Theory of Elastic Thin Shells: Solid and Structural Mechanics*. Amsterdam, The Netherlands: Elsevier, 2014.
- [38] *Plastics-Determination of Tensile Properties—Part 4: Test Conditions for Isotropic and Orthotropic Fibre-Reinforced Plastic Composites*, Standard E. ISO, 527-4., International Organization for Standardization (ISO), Geneva, Switzerland, 1997.
- [39] *Determination of Tensile Properties—Part 4: Test Conditions for Isotropic and Orthotropic Fibre-Reinforced Plastic Composites. European Standard*, Standard E. ISO, 527-4, International Organization for Standardization, 1997.
- [40] B. Pan, L. Yu, and D. Wu, "High-accuracy 2D digital image correlation measurements with bilateral telecentric lenses: Error analysis and experimental verification," *Experim. Mech.*, vol. 53, no. 9, pp. 1719–1733, Nov. 2013.
- [41] E. Byrne and M. J. C. S. K. A. H. W. C. S. I. P. Simonsen, "Lens selection and stereo angle," *Correl. Solut. Knowledgebase*, 2016.
- [42] Y. Dong and B. Pan, "A review of speckle pattern fabrication and assessment for digital image correlation," *Exp. Mech.*, vol. 57, no. 8, pp. 1161–1181, Oct. 2017.
- [43] P. Reu, "All about speckles: Aliasing," *Experim. Techn.*, vol. 38, no. 5, pp. 1–3, Sep. 2014.
- [44] P. Reu, "All about speckles: Speckle size measurement," *Experim. Techn.*, vol. 38, no. 6, pp. 1–2, Nov. 2014.
- [45] P. Reu, "All about speckles: Contrast," *Exp. Tech.*, vol. 39, no. 1, pp. 1–2, 2015.
- [46] P. Reu, "All about speckles: Edge sharpness," *Experim. Techn.*, vol. 39, no. 2, pp. 1–2, Mar. 2015.
- [47] D. Lecompte, A. Smits, S. Bossuyt, H. Sol, J. Vantomme, D. Van Hemelrijck, and A. M. Habraken, "Quality assessment of speckle patterns for digital image correlation," *Opt. Lasers Eng.*, vol. 44, no. 11, pp. 1132–1145, Nov. 2006.
- [48] B. Pan, Z. Lu, and H. Xie, "Mean intensity gradient: An effective global parameter for quality assessment of the speckle patterns used in digital image correlation," *Opt. Lasers Eng.*, vol. 48, no. 4, pp. 469–477, Apr. 2010.
- [49] T. Hua, H. Xie, S. Wang, Z. Hu, P. Chen, and Q. Zhang, "Evaluation of the quality of a speckle pattern in the digital image correlation method by mean subset fluctuation," *Opt. Laser Technol.*, vol. 43, no. 1, pp. 9–13, 2011.
- [50] C.-C. Ho, D.-S. Wu, Y.-J. Chang, J.-C. Hsu, C.-L. Kuo, and S.-K. Kuo, "Experimental investigation of speckle pattern by laser scribing for digital image correlation," *J. Laser Micro Nanoeng.*, vol. 12, no. 2, p. 97, 2017.
- [51] H. Lu and P. D. Cary, "Deformation measurements by digital image correlation: Implementation of a second-order displacement gradient," *Exp. Mech.*, vol. 40, no. 4, pp. 393–400, 2000.
- [52] J.-C. Yoo and T. H. Han, "Fast normalized cross-correlation," *Circuits, Syst. Signal Process.*, vol. 28, pp. 819–843, Dec. 2009.
- [53] M. Unser, "Splines: A perfect fit for signal and image processing," *IEEE Signal Process. Mag.*, vol. 16, no. 6, pp. 22–38, Nov. 1999.
- [54] P. Bing, X. Hui-Min, X. Bo-Qin, and D. Fu-Long, "Performance of sub-pixel registration algorithms in digital image correlation," *Meas. Sci. Technol.*, vol. 17, no. 6, p. 1615, 2006.
- [55] B. Pan, W. Dafang, and X. Yong, "Incremental calculation for large deformation measurement using reliability-guided digital image correlation," *Opt. Lasers Eng.*, vol. 50, no. 4, pp. 586–592, Apr. 2012.
- [56] Z. Xiao, J. Liang, D. Yu, Z. Tang, and A. Asundi, "An accurate stereo vision system using cross-shaped target self-calibration method based on photogrammetry," *Opt. Lasers Eng.*, vol. 48, no. 12, pp. 1252–1261, Dec. 2010.
- [57] D. González-Aguilera, L. López-Fernández, P. Rodríguez-González, D. Hernández-López, D. Guerrero, F. Remondino, F. Menna, E. Nocerino, I. Toschi, A. Ballabeni, and M. Gaiani, "GRAPHOS—Open-source software for photogrammetric applications," *Photogramm. Rec.*, vol. 33, no. 161, pp. 11–29, Mar. 2018.
- [58] E. Mahdi and E. Eltai, "Development of cost-effective composite repair system for oil/gas pipelines," *Compos. Struct.*, vol. 202, pp. 802–806, Oct. 2018.
- [59] H. S. D. C. Mattos, J. M. L. Reis, L. M. Paim, M. L. D. Silva, R. L. Junior, and V. A. Perrut, "Failure analysis of corroded pipelines reinforced with composite repair systems," *Eng. Failure Anal.*, vol. 59, pp. 223–236, Jan. 2016.
- [60] S. W. Tsai and E. M. Wu, "A general theory of strength for anisotropic materials," *J. Compos. Mater.*, vol. 5, no. 1, pp. 58–80, Jan. 1971.
- [61] L. Novak and D. Novak, "Polynomial chaos expansion for surrogate modelling: Theory and software," *Beton-Und Stahlbetonbau*, vol. 113, pp. 27–32, Sep. 2018.
- [62] N. Wiener, "The homogeneous chaos," *Amer. J. Math.*, vol. 60, no. 4, pp. 879–936, 1938.
- [63] G. Blatman and B. Sudret, "Adaptive sparse polynomial chaos expansion based on least angle regression," *J. Comput. Phys.*, vol. 230, no. 6, pp. 2345–2367, Mar. 2011.
- [64] B. Efron, T. Hastie, I. Johnstone, and R. Tibshirani, "Least angle regression," *Ann. Statist.*, vol. 32, no. 2, pp. 407–499, 2004.
- [65] G. Deman, K. Konakli, B. Sudret, J. Kerrou, P. Perrochet, and H. Benabderrahmane, "Using sparse polynomial chaos expansions for the global sensitivity analysis of groundwater lifetime expectancy in a multi-layered hydrogeological model," *Rel. Eng. Syst. Saf.*, vol. 147, pp. 156–169, Mar. 2016.
- [66] J. Blaber, B. Adair, and A. Antoniou, "Ncorr: Open-source 2D digital image correlation MATLAB software," *Exp. Mech.*, vol. 55, no. 6, pp. 1105–1122, 2015.
- [67] A. Hijazi, A. Friedl, and C. J. J. Kähler, "Influence of camera's optical axis non-perpendicularity on measurement accuracy of two-dimensional digital image correlation," *JJMIE*, vol. 5, no. 4, pp. 1–10, 2011.
- [68] C. Wissler, "The Spearman correlation formula," *Science*, vol. 22, no. 558, pp. 309–311, Sep. 1905.
- [69] C. Croux and C. Dehon, "Influence functions of the Spearman and Kendall correlation measures," *Stat. Methods Appl.*, vol. 19, no. 4, pp. 497–515, Nov. 2010.
- [70] D. Solav, K. M. Moerman, A. M. Jaeger, K. Genovese, and H. M. Herr, "MultiDIC: An open-source toolbox for multi-view 3D digital image correlation," *IEEE Access*, vol. 6, pp. 30520–30535, 2018.



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mechanical properties of aleppo pine wood (*Pinus halepensis*) from the compression test and the digital image correlation."

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2.3 Correlación entre modelos numéricos y datos adquiridos en ensayos a través de la técnica DIC

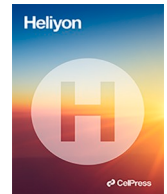
En este trabajo se aprovechan los resultados y conclusiones obtenidas en el primer artículo. Gracias a ello se diseña una metodología que permite realizar un modelo probabilístico de fallo para recipientes a presión fabricados a partir de composites CFRPs construidos a partir de la técnica RW, obteniéndose probetas prácticamente planas y lineales y otras en forma de aro. Sobre las probetas planas se realizan ensayos de tracción longitudinales capaces de caracterizar las propiedades mecánicas del material y volver a construir las PDF que alimentarán los modelos numéricos.

En cuanto a las probetas en forma de aro, se toma el ensayo contemplado en la norma americana ASTM D2290-19a conocido como RHTT. Este ensayo realiza una aproximación del ensayo típico de tracción plano a una geometría no lineal como es un aro. Esto hace que no sea posible el registro del test con DIC 2D, por lo tanto, es necesario el empleo de DIC 3D para poder caracterizar los desplazamientos y deformaciones sufridas por el espécimen durante los esfuerzos. Además, se aprovecha esta situación para poder realizar un ensayo que se asemeje bastante a la aplicación planteada como son los recipientes a presión.

Para realizar este ensayo se realiza un diseño mecánico de los útiles, dando un carácter modular que permita una posible modificación del tipo de ensayo o incluso la capacidad de adaptación a diferentes geometrías de posibles probetas. Todos los ensayos se modelizan a partir de la técnica FEM, permitiendo construir un modelo probabilístico SFEM, capaz de crear un metamodelo avanzado y robusto utilizando los métodos estocásticos ya presentados.

Gracias a ello también se va a poder realizar un matching directo entre los resultados obtenidos por el DIC y el modelo teórico FEM. a su vez se pudo realizar un ajuste en el modelo FEM del ensayo correspondiente al RHTT. Con ello se compara la probabilidad de fallo entre los modelos teóricos y los ensayos realizados, obteniéndose un ajuste que valida los resultados.

Aunando todo lo presentado se presenta una metodología que puede ser una respuesta a la estandarización de ensayos, predicción y diseño de comportamiento mecánico en recipientes a presión de altas prestaciones con un 95% de confianza.



Research article

Surrogate metamodels from digital image correlation for testing high-performance composite vessels

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ABSTRACT

In this work, a workflow has been developed for the generation of surrogate metamodels to predict and evaluate failure with a confidence above 95 % in initial service conditions of high-performance cylindrical vessels manufactured in composites by Roll Wrapping technology. Currently, there is no specific testing standardization for this type of vessel and to fill this gap probabilistic numerical models were developed, performed by the Finite Element Method, fed with the material characteristics obtained experimentally by 2D digital image correlation from flat specimens. From the initial numerical model, a surrogate metamodel was generated by stochastic approximations. Once the metamodels were obtained by robust engineering, an experimental ring-ring tensile test was developed under service conditions and deformations were measured by high-precision 3D digital image correlation. Parametric and robust tests showed that the results of the metamodel did not show statistically significant differences, with errors in the rupture part of less than 2 % with respect to the results obtained in the test, being proposed as a basis for new test procedures.

1. Introduction

Composite materials have become a reality, especially in sectors where the material used must be both lightweight and resistant, such as aerospace, shipbuilding, etc. The most common configuration is Fiber-Reinforced Polymers (FRP) [1,2], which is generated from a matrix, generally, epoxy, reinforced with a fiber whose main characteristic is a high mechanical resistance, such as carbon fiber (CFRP) or glass fiber (GFRP) [3,4]. The final properties of this composite will be a combination of the properties of the fibers and the matrix as a function of their volume fraction, in combination with manufacturing parameters and configurations such as fiber orientation, reinforcement direction, curing time, etc. [5].

There is a problem of uncertainty in defining the properties of composite materials or FRPs [6]. When characterizing them, a great disparity of results appears, due to the high number of parameters and great variability of them. It implies a very wide range of properties, compared to a very specific value as can occur in more conventional materials [7–9]. This is one of the reasons why traditional based-on deterministic simulation design methods are not the most suitable as they do not reflect this uncertainty. Stochastic methods are able to incorporate the uncertainty of the material factor, where they have shown to yield better results [10,11].

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Nomenclature	
DIC	Digital Image Correlation
DLT	Direct Linear Transformation
FEM	Finite Element Method
FI	Failure Index
FRP	Fiber-Reinforced Polymers
GoF	Goodness of Fit
MIG	Mean Intensity Gradient
PCE	Polynomial Chaos Expansion
PDF	Probability Density Functions
LOO	Leave-One-Out
RBDO	Reliability Based-Design Optimization
RHTT	Ring Hoop Tensile Test
ROI	Region Of Interest
RW	Roll Wrapping

The precise definition of the material requires a large number of characterization tests whose objective is to define the behavior of the material through the Probability Density Functions (PDF) of the studied variable, which will be used to feed the numerical methods using the Finite Element Method (FEM) [12–16]. This method consists of discretization by means of nodes of a continuous medium allowing the simulation of the physical behaviors of different models. The application of numerical methods in combination with the different PDF will allow to obtain the failure probability of the system, thus achieving more reliable designs and avoiding the use of such a wide range of properties, hence the importance of a correct adjustment of the distribution. The FEM is a very useful tool that allows the integration of the probabilistic distribution of the variables of this type of material with more advanced engineering design tools such as robust engineering [14,17,18], the most suitable for design for materials being the one known as Reliability Based-Design Optimization (RBDO) [19–21]. This integration makes it possible to move from a deterministic FEM to stochastic FEM [22–24], which is a numerical model that allows the calculation of mechanical stresses and strains under real stresses, providing a complete study of results and considering the uncertainty that affects the input variables [25]. The problem is the high computational cost required for this operation. This problem can be solved with the use of the so-called surrogate models, where a high number of executions can be performed with a much lower computational cost without loss of accuracy [26,27]. In turn, surrogate methods, by making it possible to run multiple variations within the PDF of each feature, allow to evaluate the incidence/influence of each variable, selecting the variables that most influence the design in order to reduce the computational burden [24,28].

On the other hand, composite materials based on a polymeric matrix in combination with fibers are anisotropic materials, which do not have the same characteristics in all directions; therefore, local measurement techniques are not always valid and full-field techniques are required. The Digital Image Correlation (DIC) technique is well established in this regard, both in its 2D and 3D modes [29–39].

One of the most common manufacturing methods to obtain tubular geometries with composite materials is the manufacturing technique known as Roll Wrapping (RW) [40]. The testing and characterization methods for this manufacturing process have not been as widely developed compared to other types of composites and there are not global quality standards for the commissioning and failure prediction of this type of geometry [41–43].

The RW depends on several parameters which affect the final behavior of the product, such as winding pressure, curing time, number of layers, etc. A test protocol, Ring Hoop Tensile Test (RHTT), will be used based on digital image correlation that has been designed for this purpose as a validation and testing method. In addition, all characterization will be performed on pseudo-flat specimens cut from an RW shaped tube. The results will be statistically analyzed with a probabilistic approach oriented to the study of advanced materials and manufacturing methods.

Due to the very specific behavior of high-performance composite tanks, it is necessary to use advanced testing protocols such as RHTT [44,45]. This test is designed/oriented to calculate geometrically the mechanical behavior of pipes and tubes [46] and can also be applied to cylindrical vessels, since in this type of vessels the most critical load is usually radial, as in pipes. Taking all this into account, this work has employed a combination of DIC and stochastic simulation to improve predictive models of failure in high performance composite tanks.

Based on the indicated subjects, the authors want to know if it is possible to find a test that obtains a result closer to the in-service reliability of roll-wrapped tanks by combining digital image correlation and metamodels generated using probabilistic FEM. For this purpose, this work proposes a methodology that integrates various cutting-edge techniques in modern design. It begins with a comprehensive characterization of materials based on DIC, correlates this technique with numerical models for validation and refinement, and proceeds to develop a probabilistic model using stochastic methods to analyze the behavior of pressure tanks made of composite materials.

2. Materials and methods

2.1. Materials

The material used in this work is a Carbon Fiber Reinforce Polymer (CFRP) with epoxy resin matrix CR82® and 3 K carbon fiber 200 gr/m² Twill weave 2 × 2 (twill) made by fiber Toray® T300. The used composite material has a total of 10 layers with $\pm 45^\circ$ orientations. The properties of the matrix and the fiber are outlined in Table 1, according to manufacturers datasheets.

The cameras used for image acquisition are two identical bodies model Canon 700D DSLR cameras equipped with a 60 mm macro-lens. These cameras have a 22.3 mm × 14.9 mm APS-C CMOS sensor (pixel size of 4.3 μ m). The image obtained is 5184 px x 3456 px.

All tests were carried out on a Servosis ME-405/50/5 tensile testing machine with a maximum load of 500 kN, with a TC50 Kn REP transducer as load cell.

2.2. Methods

The process has been specifically designed to evaluate the results of the surrogated metamodels and to compare them with the experimental results with the experimental results where the 3D DIC was implemented (Fig. 2). In order to include an accurate characterization of the final metamodels and to take into account the repeatability of the tests, different tensile tests on flat specimens have been performed by applying 2D DIC to generate probabilistic distributions of the measured variable. The main objective is to determine the main mechanical properties of the material by combining the different techniques. With DIC, Young's modulus (E) and Poisson's coefficient (ν) will be obtained. In a direct way, the Tensile Strength (T) will be obtained, which is necessary to determine the failure criterion, and, finally, the transversal elastic modulus (S) will also be obtained. With these initial data and their corresponding distributions, an initial numerical model will be fed through FEM. Taking into account the probability distribution functions PDFs of each property, multiple runs will be reiteratively performed by applying metamodeling and in this way a failure probability of this model will be obtained. The model will simulate the RHTT test on rings. This test has also been experimentally performed in laboratory and 3D DIC has been applied on it in order to have a complete field analysis of displacements and deformations, which will be directly compared with the FEM model. In this way, it will be possible to observe and analyze the probability of failure of the real specimens versus the numerical models, always supported with DIC methodology to be able to observe the theoretical-practical differences that appear (Fig. 1).

2.3. Tests set up

The specimens used for tensile tests are flat rectangular specimens with dimensions of 200 mm × 20 mm and a thickness of 1 mm. 20 specimens have been produced for this purpose. These specimens (Fig. 2) have been obtained by cutting them longitudinally from a 98 mm inner diameter tube. Due to the width/diameter ratio obtained, being 10–49 mm, it is considered that the curvature is practically negligible. The hoops have been obtained from transversal cuts on the same previous tube, 98 mm outside diameter and 1 mm thickness. The width of the hoops is 20 mm (Fig. 2).

For DIC analysis, as the reader can see in Fig. 2, a Speckle pattern has been placed on all specimens [47,48]. The main considerations to be taken into account are: i) randomness of the pattern; ii) circular dots and iii) coverage of about 40–70 % of the specimen surface to reduce the homogeneity of the specimen. The Mean Intensity Gradient (MIG) is the parameter used to ensure the quality of the pattern. Prior to applying the Speckle pattern, the specimen was coated with white matte spray paint to prevent glare that could distort the measurement. To ensure uniformity of illumination, two LED spotlights were placed so that they shine directly on the specimen. Both tests were performed with a specimen-to-camera distance of 1 m. In the case of DIC 3D the cameras are 260 mm apart.

Taking into account these specifications, a pattern based on circles with a diameter, d , between 3 and 5 pixels and a step between points has been designed. By applying a Gaussian random factor, the pattern is able to achieve a MIG of 56. The defined diameter is 0.324 mm and the step is 0.432 mm (Fig. 2).

The tensile test was carried out in accordance with ISO 527–4:2021 [49]. For the synchronization of the cameras with the measuring equipment, a Programmable Logic Controller (PLC) was used. This microcontroller will send a signal so that every second an image will be taken. Previous experiences testing CFRP allows to obtain 30 images per test using this trigger [50,51]. 2D DIC test

Table 1
Mechanical properties of Toray ® T300 fiber and CR82® resin.

Resin	Viscosity	18,000–25,000 cps
	Glass Transition	130–140 °C
	Tensile Strength	50–70 MPa
	Elongation	4–5 %
Fiber	Density	1.78–1.82 g/cm ³
	Tensile Strength	≥4000 MPa
	Elongation at break	≥1.5 %
	Young's Modulus	230–260 GPa

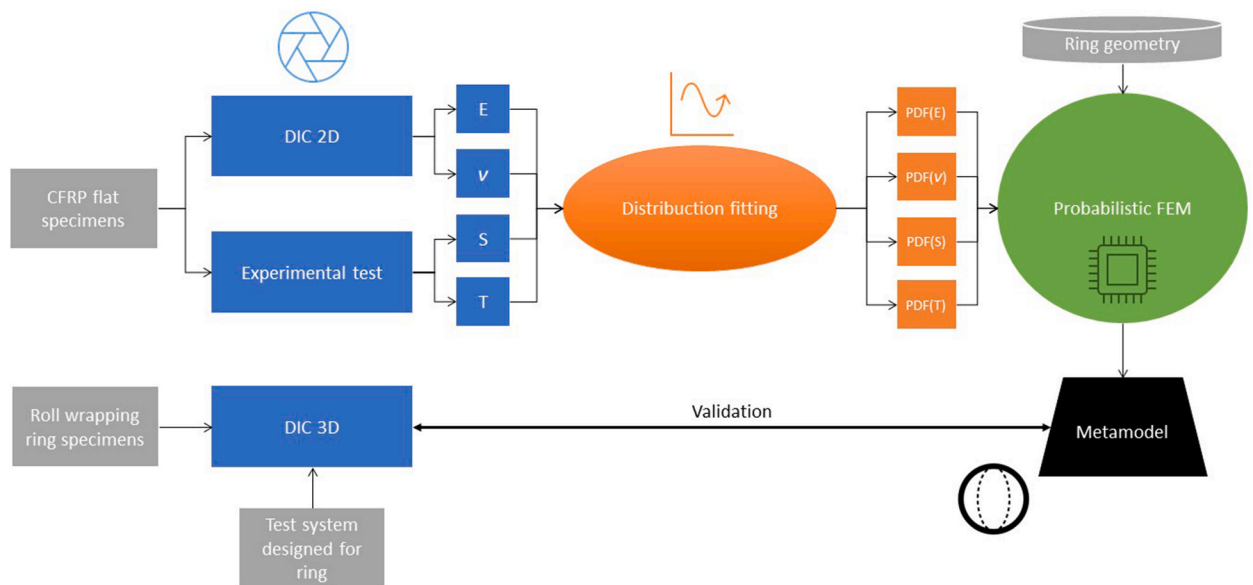


Fig. 1. Workflow followed in the methodology applied.

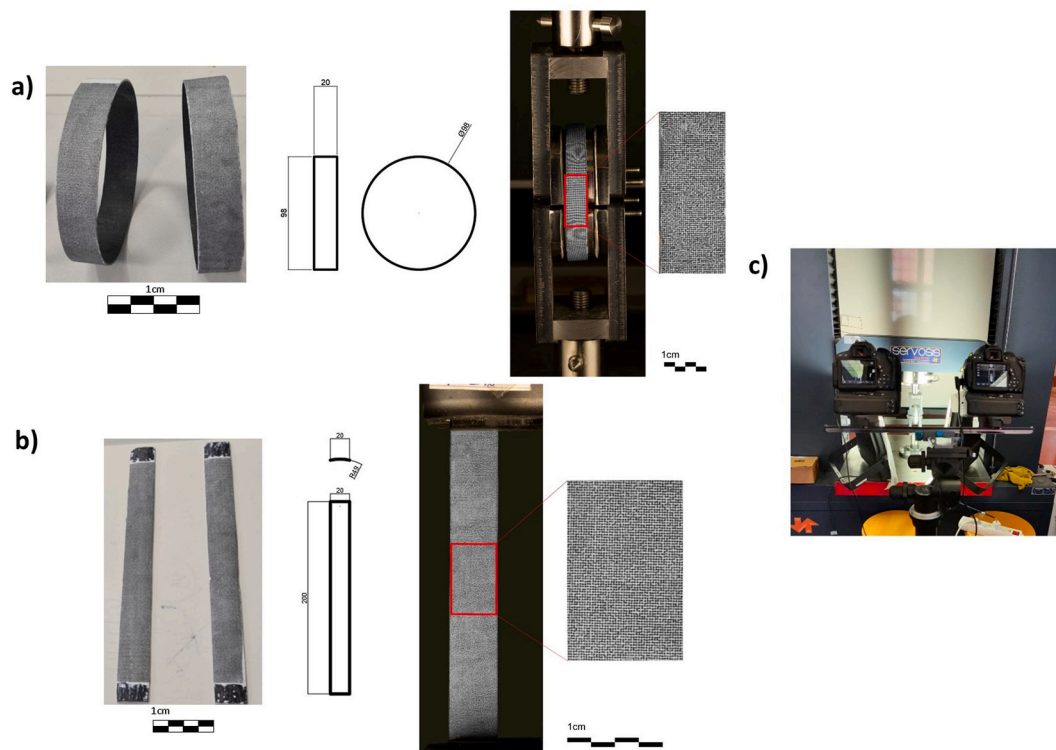


Fig. 2. Dimensions and Speckle pattern: a) longitudinal specimen and b) ring specimen and c) Test setup.

allows obtaining the main mechanical properties of the material, such as Young's modulus, Poisson's ratio and failure strain.

For the 3D DIC test, according to ASTM D 2290–12 [52], tests can be performed on rings specimens in a similar way to a plane tensile test. Due to the manufacturing method, it is more consistent to perform tests on formed specimens than on a sheet material. This is partly due to the possible occurrence of prestresses and stresses due to the manufacturing process. For this reason, it is intended to carry out a campaign of tests on circular specimens, due to their similarity to the final product [53,54]. 36 ring specimens have been analyzed.

In order to carry out these tests and in view of the lack of standardization in this respect, an ad hoc system has been designed to hold the specimens (rings). The system has a modular character to facilitate the assembly of the specimens, as well as their fastening. It has a semicircular piece (or main crescent) where the inside of the ring will be placed (Brown part in Fig. 3). Two half-moon-shaped plates are placed on both sides of the specimen to ensure a correct seating and centering of the specimen and it avoids possible lateral displacements (yellow and blue part in Fig. 3). Finally, on the outside of the assembly, two flat plates will be placed to connect the specimen seat to the testing machine. These pieces work by shearing and in turn have housings for the screws and pins that ensure the stability of the assembly during the whole test (Brown and maroon parts in Fig. 3). The side end plate is threaded to reinforce the system and avoid possible openings due to stress. In the upper part there is a plate where the side plates will be screwed and serves as a connection to the machine by a threaded system. All the parts are solid, except for the holes made to guarantee the non-existence of movements, they are made by stainless steel. This guarantees that the efforts transmitted will be supported without any problem by the machine.

2.3.1. DIC processing

The 2D DIC technique will be used to make displacement and strain measurements in order to obtain the mechanical properties of the material. This is a non-contact technique that permits full field measurements unlike a strain gauge.

The method has already been described in previous works where this technique has been applied [50,51]. The DIC method compares subsets, square region divisions of the image, in consecutive images. The displacements are defined by the difference of image centroids, resulting in a displacement vector A .

Sub-pixel accuracy is achieved thanks to Quintic B Spline function [55]. It is noteworthy to mention that the Inverse-Compositional Gauss-Newton (IC-GN) algorithm has been used for the solution to find the optimization of the problem. The Ncorr tool has been used, which is a free software in Matlab® [56].

All this is applied on a Region Of Interest (ROI). The Reliability-Guided Digital Image Correlation algorithm has been employed to minimize error propagation.

Once the deformations, ϵ , have been calculated, knowing at all times the force applied by the machine, and therefore the stress, σ , the Young's modulus, E , can be obtained. These calculations have been performed on the elastic range of the material. For this purpose,

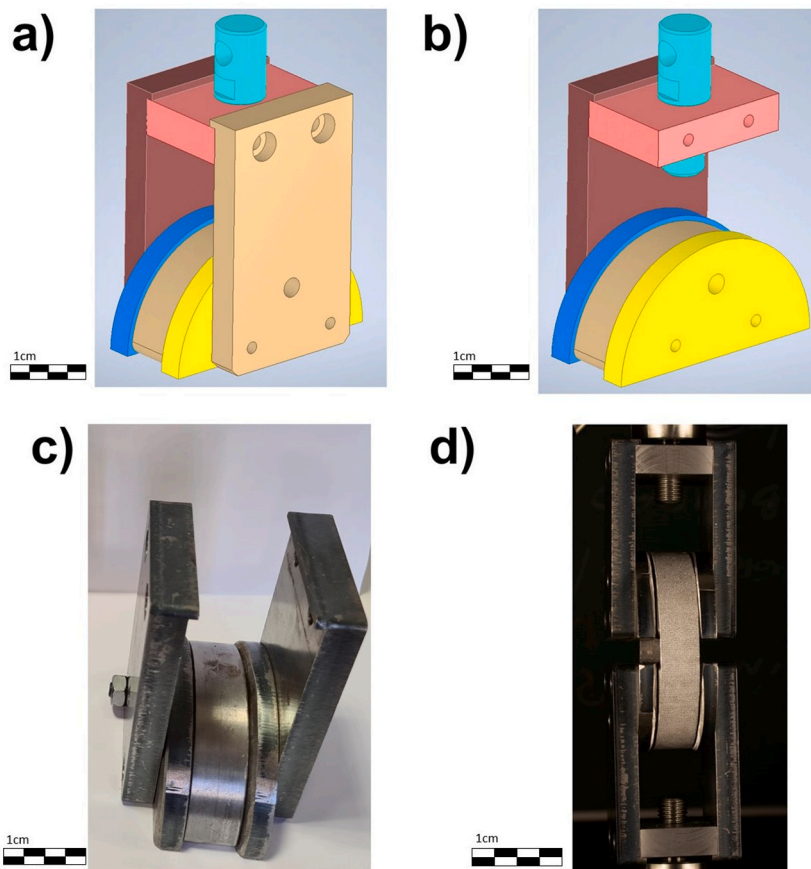


Fig. 3. Ad hoc system to hold the 3D specimens: a) design of the system in Autodesk® Inventor; b) design of the system opened in Autodesk® Inventor; c) real system manufactured and d) complete System.

Hooke's law is applied (Equation (1)).

$$E = \frac{\sigma}{\varepsilon} \quad (1)$$

To use 3D DIC, the principle of stereo view is required, so a minimum of 2 cameras is needed. In contrast to 2D, since the cameras are not perpendicular to the data acquisition, it is necessary to calculate the internal parameters of the camera as well as an orientation.

The relative orientation of the cameras was carried out using the Direct Linear Transformation (DLT). The use of DLT allows the image coordinates (x_p, y_p) to be related to the object coordinates (X', Y', Z'). In order to minimize the uncertainty in the depth axis, a cylindrical calibration target with points was used [50,51].

Where x_p and y_p are the coordinates of each point in the image and $L_1 - L_{11}$ are the mathematical parameters of the DLT.

Once the internal parameters of the camera were solved, the relative orientation of the cameras is performed using a cylinder pattern and a calibration plate [51]. For this, the following steps are followed: i) matching between the simultaneous images taken by the different cameras; ii) matching between successive stereo images, being the same as the one used in 2D DIC. After that, the DLT transformation has been applied to obtain the displacements of the subsets using the least squares approximation.

Thanks to the use of DLT it is possible to detect movements in depth, out-of-plane (Z). As a result, a full-field 3D point cloud of the specimen is obtained by calculating displacements and deformations using 2D DIC approximations.

2.3.2. Numerical model

Two FEM models have been developed in order to make a direct comparison with respect to the results obtained with DIC 3D. These numerical models consist of the recreation of the same tests introducing all the uncertainties of the material.

- A 2D FEM model based on the plane tensile test.
- A 3D FEM model based on the RHTT test.

The plane tensile test consists of a single model corresponding to the specimen, with a total of 1350 nodes with SC8R element type distributed in such a way that the geometry of the specimen is similar to the real one with a total of 10 layers. Each layer has its corresponding mechanical properties. In order to simulate the tensile test, an encastre has been placed on the lower face, preventing any movement and rotation as it occurs with the lower jaw of the machine. To simulate the tensile test, a displacement type boundary condition has been placed on the upper face, this being the mean rupture displacement obtained from the tests.

The RHTT test consists of 3 parts. Two rigid crescents, creating only the surface since the rest of the piece is not necessary and does not affect the model, achieving a significant reduction in computational cost. These pieces are equal, with a total of 675 nodes of type R3D4. The ring has been made with the same dimensions as the specimens to be tested. In this part there are 1368 nodes of type SC8R, distributed in 10 layers as in the previous model. In the same way as in the 2D model, an attempt has been made to simulate the RHTT test as accurately as possible. In this way, a Penalty type contact between the tools and the specimen has been configured. The movement system of the fixtures is exactly the same as for the 2D tests, so the lower fixture has been left fixed with an embedded type

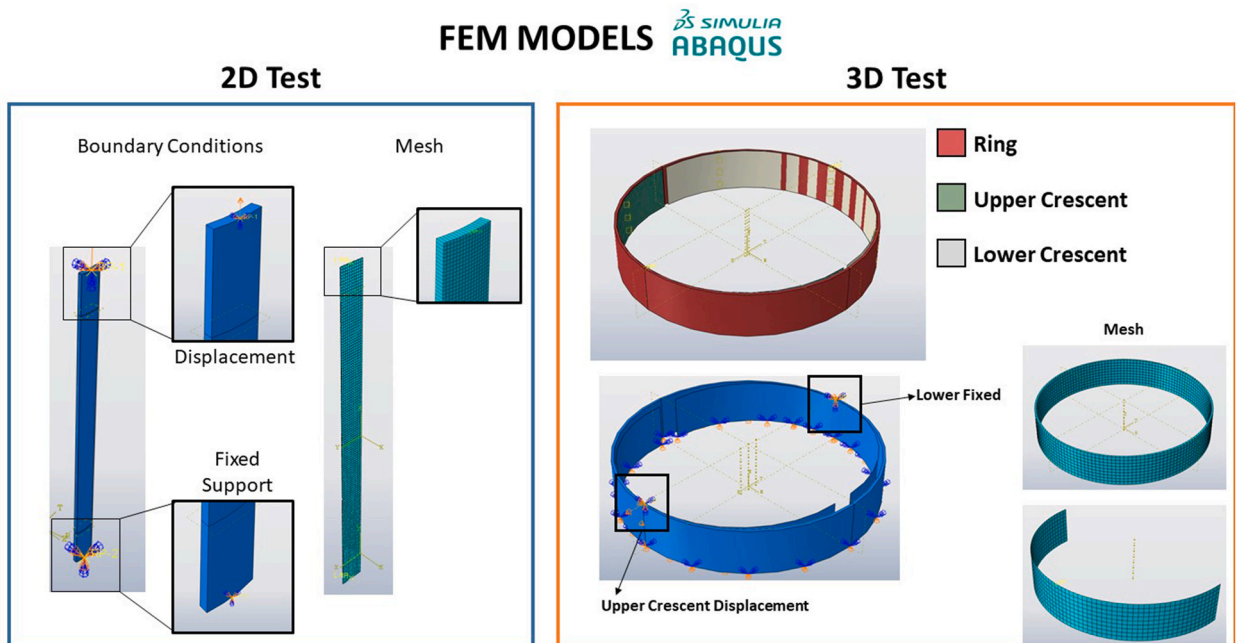


Fig. 4. Different FEM models developed in 2D and 3D.

boundary condition, and the upper fixture has been configured to have a vertical displacement equal to the mean hoop breakage displacement. The models configuration are shown in Fig. 4. All models were made in Abaqus®, after that, metamodels were carried out in Matlab® using the free library UQLab®.

The convergence study that has been carried out has taken into account the following aspects: i) size and complexity of the models studied, ii) the repetitiveness of the calculations for the preparation of metamodels and iii) the power of the available computers. Taking this into account, absolute convergence was not achieved, but the mesh size chosen does not significantly affect the results obtained, obtaining a feasible balance between the results obtained and the computational cost required.

2.3.3. Surrogate metamodels

The uncertainty of the model is intrinsically controlled, being considered as another parameter within the method to generate the final results, which have been compared with the experimental results of the calibrated DIC.

The surrogate models allow an analysis to be made from multiple variations in properties to subsequently study the final performance without a significant loss of accuracy, which is why there is a great synergy between these methods and the composite materials [50,51].

To evaluate the PDF distribution that best fits the results obtained for each variable, three different tests will be used: Chi-Square (Chi), Kolmogorov-Smirnov (KS) and the Anderson-Darling test (AD) [57]. These tests will allow to estimate the PDF distribution that best fits the data. In addition, probability plots will be used to confirm adequate fit.

Once the mechanical properties have been statistically defined, a comparison criterion must be defined. For this purpose, the Tsai-Wu failure criterion is used (equation (2)) [58]. This criterion assumes that failure occurs when the Failure Index (FI) is greater than 1.

$$FI = F_1\sigma_1 + F_2\sigma_2 + F_3\sigma_3 + F_{11}\sigma_1^2 + F_{22}\sigma_2^2 + F_{33}\sigma_3^2 + 2F_{12}\sigma_1\sigma_2 + 2F_{23}\sigma_2\sigma_3 + 2F_{31}\sigma_3\sigma_1 + F_{44}\sigma_4^2 + F_{55}\sigma_5^2 + F_{66}\sigma_6^2 \leq 1 \quad (2)$$

Where:

$$\begin{aligned} F_1 &= \frac{1}{X_T - \frac{1}{X_C}} \quad F_2 = \frac{1}{Y_T - \frac{1}{Y_C}} \quad F_3 = \frac{1}{Z_T - \frac{1}{Z_C}} \\ F_{11} &= \frac{1}{X_T X_C} \quad F_{22} = \frac{1}{Y_T Y_C} \quad F_{33} = \frac{1}{Z_T Z_C} \\ F_{44} &= \frac{1}{S_{yz}^2} \quad F_{55} = \frac{1}{S_{zx}^2} \quad F_{66} = \frac{1}{S_{xy}^2} \\ F_{12} &= \left(-\frac{1}{2}\right) \sqrt{F_{11} F_{22}} \quad F_{23} = \left(-\frac{1}{2}\right) \sqrt{F_{22} F_{33}} \quad F_{31} = \left(-\frac{1}{2}\right) \sqrt{F_{33} F_{11}} \end{aligned}$$

Where:

σ_n $\equiv$ Uniaxial tension in the different directions.

X_T $\equiv$ Tensile load.

X_C $\equiv$ Compression load.

Y_T $\equiv$ Transversal tensile load, in the Y direction.

Z_T $\equiv$ Transversal tensile load, in the Z direction.

Y_C $\equiv$ Transversal compression load, in the Y direction.

Z_C $\equiv$ Transversal compression load, in the Z direction.

S_{xy} ; S_{yz} ; S_{zx} $\equiv$ Shear transversal load.

Thus, the mean failure displacement in the tested specimens was taken and the Tsai Wu criterion [58] was implemented to define whether it has reached failure or not. This parameter has been determined because in the initial FEM model is the one that determines all the behavior. Thus, the rupture criterion is 1 with the final displacement. In order to compare all the statistical analysis, RBDO Analysis has been used (Equation (3)) [59]. This makes it possible to determine the probability of failure of the system:

$$P_{fk} = \int_{G_k(d,X) < 0} f_X(X) dX \quad (3)$$

Where.

- P_{fk} is the failure probability.
- G_k are the constrictions.
- $f_X(X)$ is the probability density function (PDF) of the random vector $X \in R^m$ and the design vector $d \in R^n$.

However, the solution to this equation is not trivial and requires the use of approximation methods to calculate this value. For this work, it has been decided to use the Monte Carlo method for approximating this value [60,61]. This method requires the use of thousands of simulations to obtain results with confidence, demanding high computational costs [41,62,63]. In order to solve this

problem, a metamodeling strategy has been used, in this case the Polynomial Chaos Expansion (PCE) method [64–66].

This method is a stochastic approximation of a system behavior through the spectral representation of random variables using a set of multivariate polynomials. The numerical simulation is assumed to represent a finite variance model, $f(x)$ whose input x is a random vector of independence and constrained variables $X \in R^m$. This independence of inputs allows the definition of polynomials as the tensorization of univariate polynomials with respect to the marginal PDFs via equation (4):

$$Y \approx f(x) = \sum_{a \in A} \gamma_a + \varphi_a(x) \quad (4)$$

Where.

- α is the multi-index $\alpha = \{\alpha_1, \dots, \alpha_M\}$.
- $A \subset N^M$ is the index set for the multivariate orthonormal polynomial.
- γ_a are the deterministic coefficients to be computed.
- $\varphi_a(x)$ are the multivariate orthonormal polynomials.

For the estimation of coefficients (equation (5)) the least squares approximation has been used, posing a minimization problem between the vector of random inputs (X) and the response model (Y):.

$$\varphi_a = \underset{N}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^N \left[\gamma^{(i)} - \sum_{a \in A} \gamma_a \varphi_a(x^{(i)}) \right]^2 \quad (5)$$

To reach an overfitting situation with a large number of input dimensions, the adaptive sparse PCE based on minimum angle regression is used [67]. This type of procedure allows the resolution of engineering problems with a high number of dimensions. To guarantee the quality of the surrogated model, a version of the Leave-One-Out error (LOO) has been used (equation (6)) [68]. This error offers a good compromise between fair error estimation and affordable computational cost.

$$LOO_{error} = \frac{1}{N} \sum_{i=1}^N \left(\frac{Y(X^{(i)}) - f^{PCE}(X^{(i)})}{1 - h_i} \right)^2 \quad LOO_{error}^* = LOO_{error} \cdot \left(1 - \frac{cardA}{N} \right)^{-1} \left(1 + \operatorname{tr}(\varphi^T \varphi)^{-1} \right) \quad (6)$$

Where:

$Y(X^{(i)})$ is the computational model.

$f^{PCE}(X^{(i)})$ is the surrogated model of the specific Design of Experiment (DoE) with N samples.

h_i is the i th diagonal term of the matrix $A(A^T A)^{-1}$, where A is the experimental matrix.

$cardA$ is the number of terms in the truncate series and φ is shown in equation (7).

$$\varphi = \{\varphi_{ij} = \varphi_j(X^{(i)}), i = 1, \dots, N; j = 1, \dots, cardA\} \quad (7)$$

2.4. Comparison between FEM and DIC

In order to validate the order of scale of these methodologies, a parametric and non-parametric statistic tests will be applied to compare the surrogated metamodel with respect the initial FEM model and also with respect the results of the experimental 3D DIC test. For this purpose, the nodes and points of the ROI in both 2D and 3D have been selected. A rotation and displacement have been performed, so that both models are located on the same axis with the same coordinate system. Thanks to this rotation and adjustment of axes, the difference between each node and point can be calculated in true magnitude. In this way, the displacements and deformations of both models can be directly compared.

3. Results

3.1. Mechanical properties of the material

First, mechanical properties were calculated from tensile tests and 2D DIC. In order to avoid perspective distortions, the camera has been placed orthogonal to the specimen, ensuring this perpendicularity with an inclinometer and a micrometric ball joint. To calculate both transverse and longitudinal displacements and deformations, virtual strain gauges have been placed on the processed specimens.

Table 2

Statistical values of the mechanical properties obtained from the tests.

Variable	Mean	SE Mean	St.Dev.	Coef. Var.	Median	IQR	Skewness	Kurtosis
<i>E</i>	71.603	596	4766	6.66	71655	5007	0.21	2.22
<i>T</i>	810.732	9.35	74.79	9.23	817.30	73.02	−0.62	0.21
<i>ν</i>	0.01731	0.0196	0.1567	90.53	0.1240	0.1436	2.58	8.80
<i>G</i>	30.992	2.11	9.20	29.68	34.12	16.11	−0.45	−1.07

Specifically, a ROI as large as possible has been selected avoiding conflicting points or shadows; 4 longitudinal extensometers with a uniform spacing of 10 mm and 4 transverse extensometers with a uniform spacing of 30 mm were used. It should be noted that, for both 2D and 3D DIC, an accuracy of $0.7 \mu\text{m}$ was achieved. This accuracy was achieved thanks to the fact that the preprocessing is the same for both techniques.

A total of 20 longitudinal planar specimens have been analyzed, with their corresponding values of Tensile Strength (T). Taking on account the extensometers, a total of 80 available results of Young's modulus (E) and Poisson's Coefficient (ν). The results of the transversal elastic modulus (G) tests have also been analyzed (Table 2).

A correlation study has been carried out between the variables obtained from the 2D DIC, which are the Young's Modulus (E), Poisson's Coefficient (ν) and Tensile Strength (T). A direct comparison has been made and the calculation of the correlation comes through a Pearson coefficient [69,70]. The aim of this comparison is to validate the necessity of surrogated models and the independence of study of the different variables. Results are shown in Fig. 5.

Given the variability of the results and to integrate the uncertainty within the process avoiding a classical deterministic approach, the study of Probabilistic Density Functions has been used. The probability of applying a Normal (N), Log-Normal (LN), Weibull (W) and Gamma (G) functions was studied. Subsequently, different Goodness of Fit (GoF) tests were used to validate the selection of these functions. Specifically, the Chi-Square (Chi), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests were used (Table 3). The results obtained show that E follows Log-Normal distributions while ν , T and G Weibull distributions. The mean of the distributions and its standard error is also used as a criterion to assess the differences between the fitted distributions (Table 4). The best fit plotted over the histogram and the probability plot for the distribution is shown in Fig. 6, Figs. 7 and 8. As can be seen, all the tests done allows to consider that there is the best fit in the PDF distributions. This reduces the risk of a-priori error conditioning the final simulation results.

3.2. Surrogate model and correlation results

A comparison was made between the failure probability of the specimens tested with the mean rupture displacement. Subsequently, the independent probability of each specimen with this mean displacement was calculated. If it breaks, it will have a value Tsai-Wu ≥ 1 . As explained in section 2, a numerical FEM model was used to simulate the test performed. In a first instance, 100,000 runs have been performed obtaining the distributions of the Tsai-Wu value shown in Fig. 11. However, there is a very significant difference between the surrogated model and the experimentally obtained values.

To determine the origin of the deviation, a comparison was made between the data obtained by 3D DIC with respect the data obtained by initial based-on FEM numerical model and also with respect the surrogated metamodel using parametric and non-parametric tests. The results have been compared in such a way that the difference between each node of the FEM model and the closest point to it in DIC has been recorded. In this way, the distribution of differences between DIC and FEM is observed in Fig. 9.

As can be seen, the largest errors occur at the ends. This is due to the fact that the designed grips show a slight movement during the test because there is a large number of parts connected by pins and bolts and these can move along the application of the load. These large errors show that the comparison between methodologies is not valid, for this reason, a displacement measurement of these grips has been made, especially in the lower one through the different images during the test. Thanks to the data obtained by DIC 3D it has

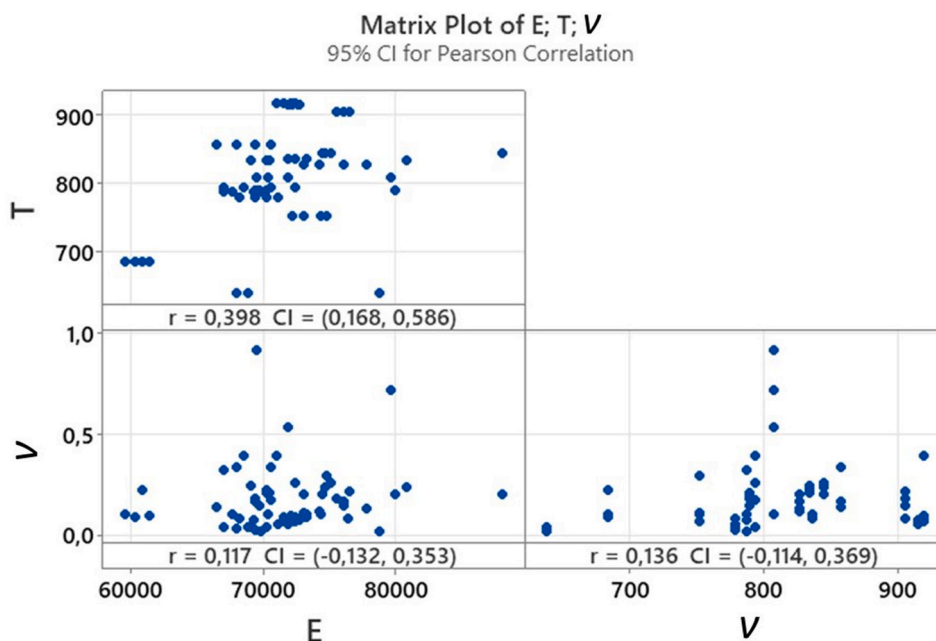


Fig. 5. Matrix plot and R-Pearson correlation coefficient for E , T and ν .

Table 3

Goodness of Fit (GoF) of the parameters obtained. A value of 0 indicates that the PDF is acceptable and 1 that it should be rejected.

Parameter	N			LN			W			G		
	Chi	KS	AD	Chi	KS	AD	Chi	KS	AD	Chi	KS	AD
<i>E</i>	0	0	0	0	0	0	1	0	0	0	0	0
ν	1	0	1	1	0	0	0	0	0	0	0	0
<i>T</i>	1	0	0	1	1	0	1	0	0	1	0	0
<i>S</i>	0	0	0	0	0	0	0	0	0	0	0	0

Table 4

Mean and standard error for each fitted distribution.

Distribution	Mean	Standard Error	95 % Normal CI	
			Lower	Upper
<i>E</i>				
Normal	71602.7	591.063	70444.3	72761.2
Lognormal ^a	71603.2	593.179	70450.0	72775.3
Weibull	71151.8	760.284	69677.1	72657.6
Gamma	71602.7	591.350	70443.7	72761.7
ν				
Normal	0.173112	0.0194353	0.135019	0.211204
Lognormal ^a	0.175621	0.0207471	0.139322	0.221378
Weibull	0.174483	0.0173623	0.143566	0.212057
Gamma	0.173111	0.0165515	0.140670	0.205550
<i>T</i>				
Normal	810.732	9.27586	792.551	828.912
Lognormal	810.830	9.66633	792.104	829.999
Weibull ^a	810.822	9.30871	792.781	829.274
Gamma	810.732	9.50710	792.098	829.366
<i>G</i>				
Normal	30.9915	2.05363	26.9665	35.0166
Lognormal	31.1325	2.40881	26.7518	36.2304
Weibull ^a	31.1298	1.93140	27.5655	35.1551
Gamma	30.9915	2.21000	26.6599	35.3231

^a The best fit based on Anderson-Darling.

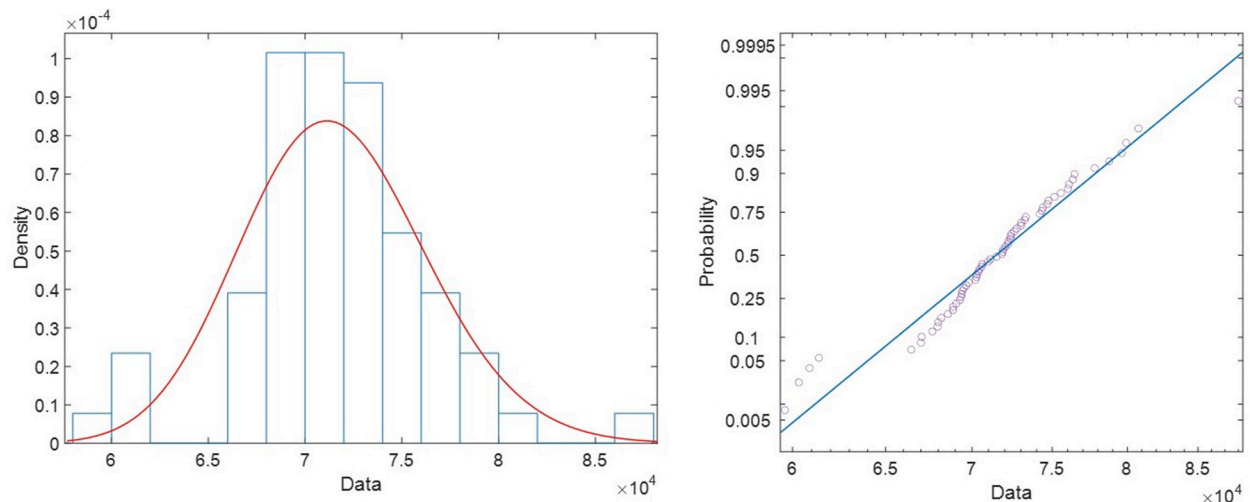


Fig. 6. Best fit (lognormal) for *E* (left) and probability plot for lognormal distribution (right).

been possible to identify this problem, so that the verification of the FEM model using this technique has been possible. In this way, the result has been significantly adjusted. As validation, the same procedure has been carried out on the model and the 2D DIC, obtaining satisfactory results with errors lower than 3 % as shown in Fig. 10.

Once the adjustment has been made, the metamodel has been run again adjusting these displacements detected in the DIC-FEM comparison. 100,000 runs have been performed again and the result obtained in this case is observed in Fig. 11.

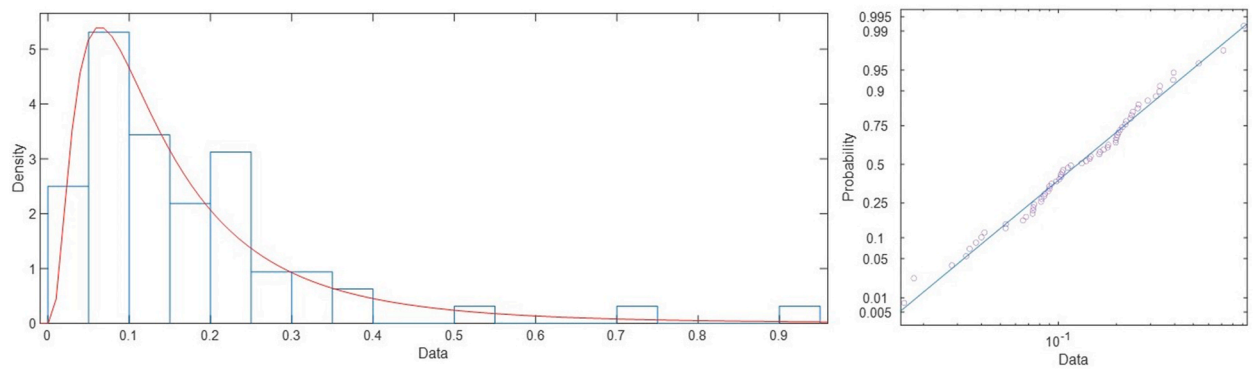


Fig. 7. Best fit (lognormal) for ν (left) and probability plot for lognormal distribution (right).

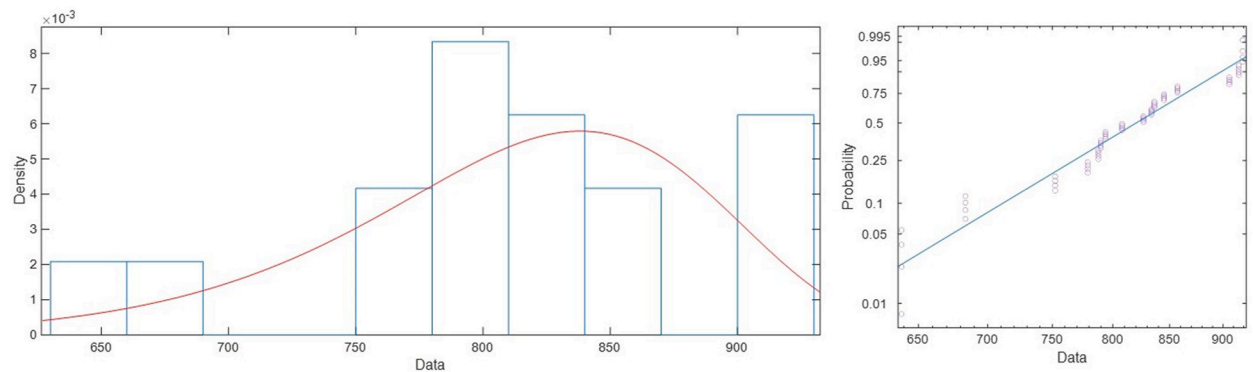


Fig. 8. Best fit (Weibull) for T (left) and probability plot for Weibull distribution (right).

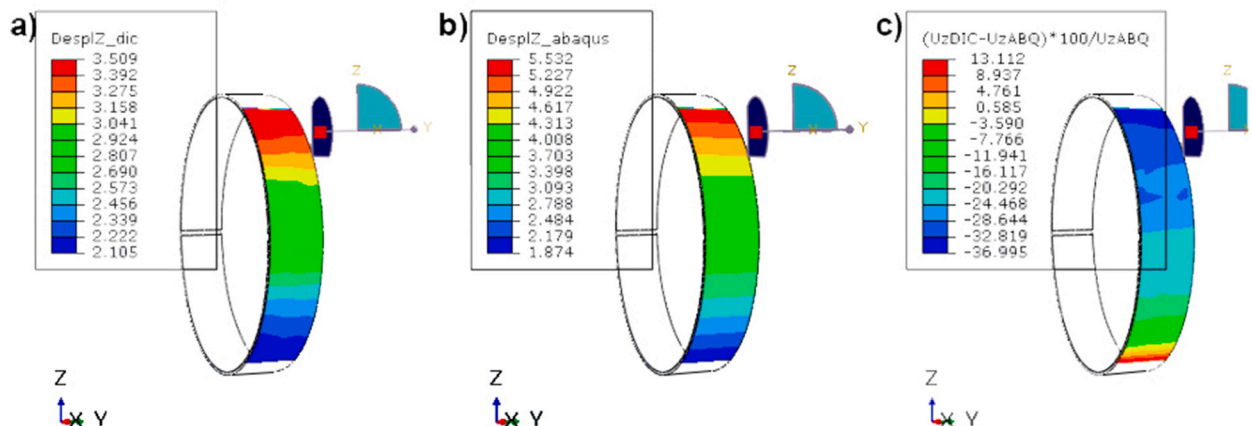


Fig. 9. Results obtained by FEM and DIC and differences between methods: a) displacements obtained by DIC in mm; b) displacements obtained from FEM in mm and c) calculated error between FEM and DIC in %.

The Cumulative Density Function (CDF) was calculated for both the optimized Tsai-Wu model. Using the experimental data, a non-parametric probability distribution was fitted, and the 95 % confidence bands were calculated. As the reader can see (Fig. 12), the function of the optimized method falls within the bands starting at approximately 0.9. The corrected results are already remarkably similar to those of the optimized method (Table 4) to the values obtained directly to those of the real specimens.

Taking into account the non-normality of the data distributions evaluated using Kolmogorov-Smirnov and Anderson-Darling (Table 5), the nonparametric U-Man White test was conducted. Statistically significant differences were found between the experimental results with respect the first model ($p = 0.000$), also between the first metamodel and the corrected metamodel ($p = 0.000$), and

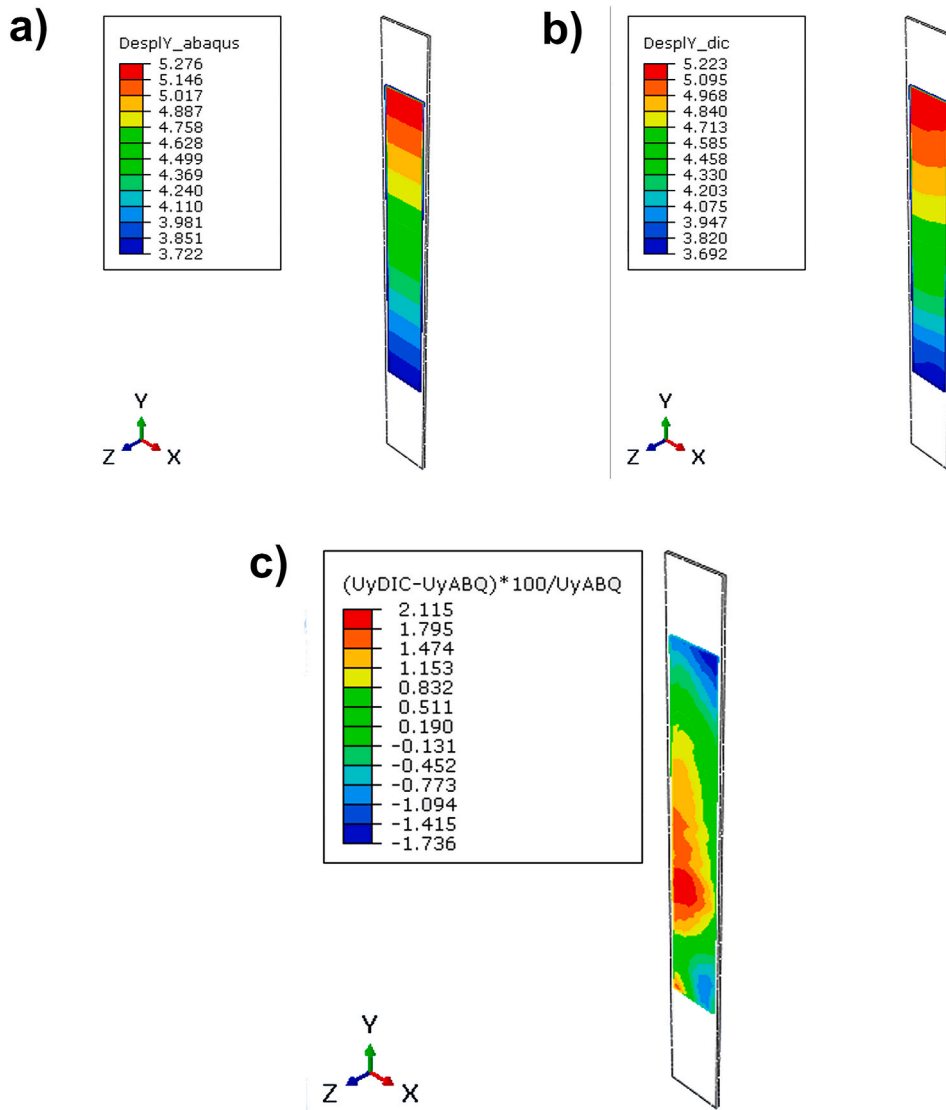


Fig. 10. Differences between FEM and DIC: a) displacement result in FEM; b) displacement in DIC; and c) error between FEM and DIC.

between the real and optimized metamodel ($p = 0.000$). This shows that there are statistically significant differences in the medians (robust test) between the first model respect to the corrected model and relate to the experimental values.

However, when this test is applied to evaluate the difference between the medians of the test and the corrected metamodel, no statistically significant differences were detected in the median ($p = .113$). Nevertheless, the analysis of quartiles does show critical differences in the variability of the process but the experimental results present a greater variability than those provided by the corrected model (Table 5). The calculated error is the relative error with respect to the data obtained by the cumulative experimental data shown in Fig. 12.

3.2.1. 3D DIC calibration

To ensure the robustness of the results, it is important to clarify the calibration parameters obtained from the cameras and their calibration according to the 3D DIC technique, as shown in the following Table 6.

4. Discussion

As it has been observed, the system is very sensitive to inaccuracies and any failure is very important when it comes to correctly defining this type of material. In this sense, the literature shows that stochastic approaches are the best solutions [71,72]. For this reason, the DIC is not only a powerful tool for the determination of the mechanical properties of these, but it is also a very useful tool to observe and check what is happening, during the data collection and in a full field of the specimen [29,73], and what solutions can be

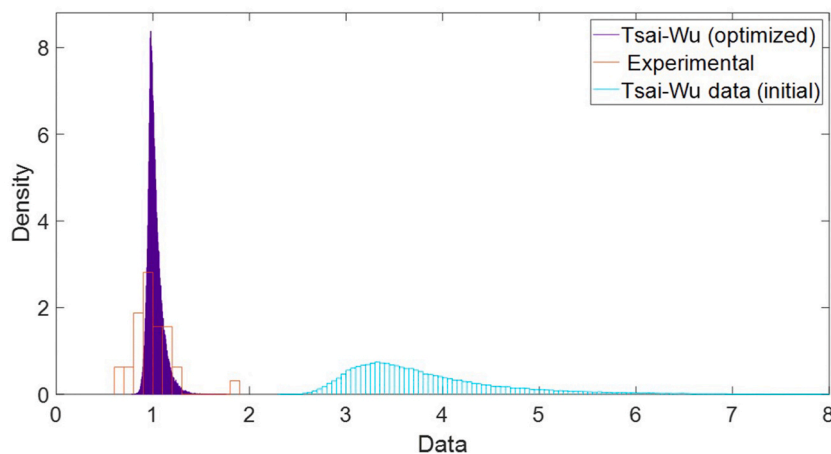


Fig. 11. Histograms of the Tsai-Wu distributions (initial and optimized) with respect to the histogram of the experimental data obtained with DIC 3D.

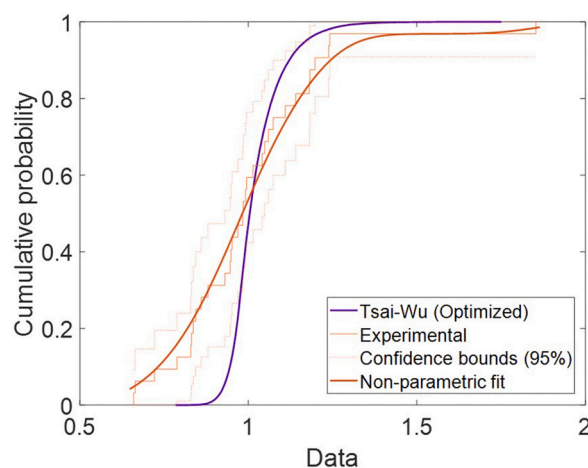


Fig. 12. Cumulative distribution function (CDF) representation of Tsai Wu.

Table 5

Comparison of quartiles on the data obtained by the tests, the first metamodel and the adjusted metamodel.

	Tests	1st Model	Error (%)	Corrected Model	Error (%)
Quartile 1	0.6596	2.3172	251.30	0.7836	18.80
Quartile 2	0.8437	3.2484	285.02	0.9718	15.18
Quartile 3	0.9835	3.6106	267.12	1.0042	2.10
Quartile 4	1.0739	4.1543	286.00	1.0554	1.72
IQR	0.3239	1.2989	401.01	0.2206	31.89
K-S	<0.000	<0.000	0	<0.000	0
A-D	0.032	0.001	96.88	0.001	96.88

provided.

The main discrepancies between tests and simulations are usually given by the anisotropic character of the material, in traditional materials, the results are very similar between the different techniques, focusing on the subset of the DIC technique [74,75]. The behavior of the material has a large variation depending on the direction of the stress, therefore, characterizing and replicating this behavior accurately is not always possible. Comparing the deformation map in both 2D and 3D, it is observed that with the DIC this large variation of deformations is recorded without any clear pattern, as shown in Fig. 13. The reached results are in agreement with the conclusions reached in other studies [76]. Due to the large variation of properties in anisotropic materials in different directions, applying a global DIC leads to a loss of accuracy in obtaining results. This causes differences between the theoretical model and the results obtained by the DIC, so it is necessary to adjust the model in order to obtain the true behavior.

Table 6
3D DIC cameras calibration parameters.

Parameter		Camera 1		Camera 2	
		Initial	Calibrated	Initial	Calibrated
Principal Point (pixel)	x_p	2.6196 E3	2.6264 E3	2.6329 E3	2.6294 E3
	y_p	1.8309 E3	1.8299 E3	1.8473 E3	1.8473 E3
Radial Distortion	k_1	0	-1.861E-4	0	7.944 E-5
	k_2	0	3.591 E-2	0	-3.763 E-3
	k_3	0	-1.143	0	1.687 E-1
Tangential Distortion	p_1	0	-2.078 E-5	0	-5.237 E-7
	p_2	0	7.772 E-5	0	-7.245 E-5

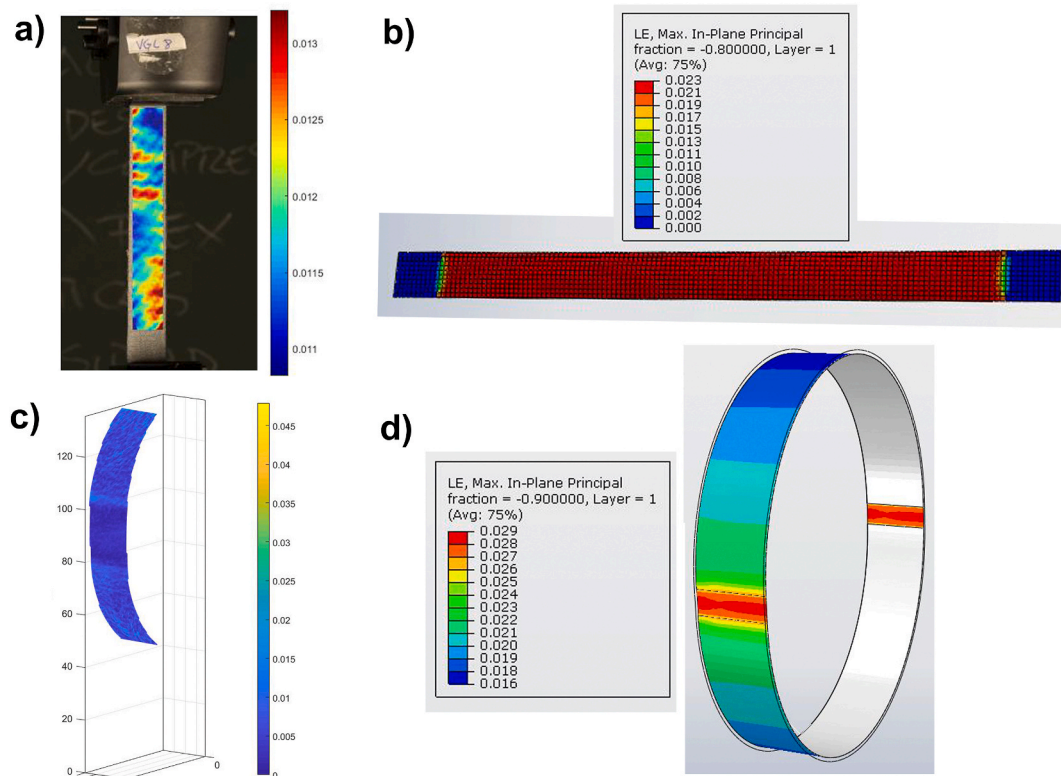


Fig. 13. Comparison of the distribution of the deformations between real model measured by DIC and theoretical FEM model: a) deformations recorded by DIC 2D; b) deformations on the 2D FEM model; c) deformations recorded by DIC 3D and d) deformations on the 3D FEM model.

For this reason, the use of direct geometric relationships applied on conventional materials on the RHTT are not feasible when the material is anisotropic and has a high rate of variation as in the case of high-performance deposits made of composite materials. The optimization of the metamodel allows generating a failure model that resembles the one extracted by testing. The centering of both distributions is similar but the surrogated model has a lower variability than the one obtained by physical testing. This fact may be due to the variability that occurs in the physical tests and to the anisotropy of the physical properties of the composite and possibly also to the error in the adjustments of distributions of E , ν and T parameters, obtained experimentally.

The application of destructive physical tests provides greater reliability, but the increase in costs and time is significant, making it impossible to use them more extensively. For this reason, metamodels make testing processes more efficient, saving costs, both economic and computational, and time. If it is possible to extend the number of destructive tests, metamodels can be complementary and can serve as a basis for the application of Industry 4.0 technologies, such as digital twins, or be compatible with learning algorithms oriented to artificial intelligence.

In the current literature there is no direct comparison between nodes simulated in FEM and results obtained by DIC directly and in full field. However, what is found is the comparison of properties obtained and simulated global behavior with a very small error [74, 76]. In this work, it has been possible to obtain a full field comparison, being able to observe where these concrete differences between the theoretical FEM model and the experimental results obtained by the DIC are found since having anisotropic materials, making a global comparison would have an intrinsically high error.

5. Conclusions

Testing protocols of high-performance tanks built in composite materials require powerful tools capable of giving an accurate and full-field response of displacements and deformations. Therefore, it has been demonstrated that the DIC technique is a useful and adequate technology to record these behaviors, obtaining errors, especially in flat behaviors, lower than 2 % between the real model and the theoretical model of behavior.

The theoretical behavior of this type of materials is difficult to predict due to the anisotropic characteristics of composite materials. In this sense, the feeding of subrogated models with the mechanical characterization of the materials with 2D DIC, performing a stochastic simulation, offers differences between the theoretical values and the real approximate values in the rupture zone, where it is more relevant. In this case, thanks to the DIC technique, it has been possible to obtain a more realistic theoretical simulation, so that the errors in the results are less than 2 % once the model has been corrected, compared to about 300 % for the first theoretical model. It has therefore been corroborated by a solid comparison with the experimental results, in which no statistically significant differences were found between the results based on metamodels and the experimental results. Thus, it is possible to establish models that serve as a basis for predicting failures with more than 95 % confidence when composite tanks are put into service. This would save costly and complex tank tests that would require high working pressures, long test times and the generation of waste and contamination.

Therefore, the workflow created in this work combines complete techniques such as 2D and 3D DIC with advanced stochastic numerical models, offering a possible answer to the demand for standardization of testing and prediction of mechanical behavior in high performance cylindrical vessels, giving predictions above 95 % reliability in terms of breakage.

Additional information

No additional information is available for this paper.

Data availability statement

Data included in article/supp. material/referenced in article.

CRediT authorship contribution statement

Javier Pisonero: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Manuel Rodríguez-Martín:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Jose G. Fueyo:** Writing – review & editing, Validation, Formal analysis. **Diego González-Aguilera:** Writing – review & editing, Visualization, Supervision. **Roberto García-Martín:** Writing – review & editing, Visualization, Supervision, Resources, Funding acquisition.

Declaration of competing interest

Authors declares no conflicts of interest

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References

- [1] P.E. Irving, C. Soutis, *Polymer Composites in the Aerospace Industry*, Woodhead Publishing, 2019.
- [2] H. Hariz, S. Sapuan, and R. Ilyas, "Advanced composite in aerospace application: a review on future aspect of fiber-reinforced polymer (FRP) in aerospace industry," Presented at the Seminar on Advanced Bio- and Mineral Based Natural Fibre Composites (SBMC2021),.
- [3] D.K. Rajak, D.D. Pagar, P.L. Menezes, E. Linul, Fiber-reinforced polymer composites: manufacturing, properties, and applications, *Polymers* 11 (10) (2019) 1667.
- [4] R. Scaffaro, A. Di Bartolo, N.T. Dintcheva, Matrix and filler recycling of carbon and glass fiber-reinforced polymer composites: a review, *Polymers* 13 (21) (2021) 3817.
- [5] P. Laborde-Lahoz, et al., Mechanical characterization of carbon nanotube composite materials, *Mech. Adv. Mater. Struct.* 12 (1) (2005) 13–19.
- [6] Q.T. Shubhra, A.M. Alam, M.A. Quaiyum, Mechanical properties of polypropylene composites: a review, *J. Thermoplast. Compos. Mater.* 26 (3) (2013) 362–391.
- [7] M. Heidari-Rarani, M. Rafiee-Afarani, A. Zahedi, Mechanical characterization of FDM 3D printing of continuous carbon fiber reinforced PLA composites, *Compos. B Eng.* 175 (2019) 107147.
- [8] H. Singh, T. Singh, Effect of fillers of various sizes on mechanical characterization of natural fiber polymer hybrid composites: a review, *Mater. Today: Proc.* 18 (2019) 5345–5350.
- [9] X. Xiao, X. Shanyong, F. Bin, The strength recovery effect of scarf bonding on the CFRP laminates with impact damage, *Heliyon* 9 (8) (2023) e19143.
- [10] M. Thapa, S.B. Mulani, R.W. Walters, Stochastic multi-scale modeling of carbon fiber reinforced composites with polynomial chaos, *Compos. Struct.* 213 (2019) 82–97.
- [11] N.H. Pham, L.M. Nguyen, D.T. Phan, Q. Tran-Dinh, ProxSARAH: an efficient algorithmic framework for stochastic composite Nonconvex optimization, *J. Mach. Learn. Res.* 21 (110) (2020) 1–48.
- [12] V. Babak, V. Eremenko, A. Zaporozhets, Research of diagnostic parameters of composite materials using Johnson distribution, *International Journal of Computing* 18 (4) (2019) 483–494.

- [13] S. Naskar, T. Mukhopadhyay, S. Sriramula, Probabilistic micromechanical spatial variability quantification in laminated composites, *Compos. B Eng.* 151 (2018) 291–325.
- [14] E. Öztürk, FEM and statistical-based assessment of AISI-4140 dry hard turning using micro-textured insert, *J. Manuf. Process.* 81 (2022) 290–300.
- [15] S.K. Sahu, P.R. Sreekanth, Evaluation of tensile properties of spherical shaped SiC inclusions inside recycled HDPE matrix using FEM based representative volume element approach, *Heliyon* 9 (3) (2023) e14034.
- [16] A. Mutafti, N. Yidris, M. Ishak, R. Zahari, An investigation on longitudinal residual strains distribution of thin-walled press-braked cold formed steel sections using 3D FEM technique, *Heliyon* 4 (11) (2018) e00937.
- [17] B. Wang, Y. Cai, Z. Li, C. Ding, T. Yang, X. Cui, Stochastic stable node-based smoothed finite element method for uncertainty and reliability analysis of thermo-mechanical problems, *Eng. Anal. Bound. Elem.* 114 (2020) 23–44.
- [18] J. Peeters, C. Ibarra-Castaneda, S. Sfarra, X. Maldague, J. Dirckx, G. Steenackers, Robust quantitative depth estimation on CFRP samples using active thermography inspection and numerical simulation updating, *NDT E Int.* 87 (2017) 119–123.
- [19] K. Choi, B. Youn, On probabilistic approaches for reliability-based design optimization (RBDO), in: 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 2002, p. 5472.
- [20] S. Slesongsom, S. Kumar, S. Bureerat, Multi-objective reliability-based partial topology optimization of a composite aircraft wing, *Symmetry* 15 (2) (2023) 305.
- [21] D. Hozic, C.-J. Thore, C. Cameron, M. Loukil, Deterministic-based robust design optimization of composite structures under material uncertainty, *Compos. Struct.* 322 (2023) 117336.
- [22] Z. Zheng, H. Dai, M. Beer, Efficient structural reliability analysis via a weak-intrusive stochastic finite element method, *Probabilist. Eng. Mech.* 71 (2023) 103414.
- [23] C. Nastos, P. Komninos, D. Zarouchas, Non-destructive strength prediction of composite laminates utilizing deep learning and the stochastic finite element methods, *Compos. Struct.* 311 (2023) 116815.
- [24] V. Papadopoulos, D.G. Giovanis, *Stochastic Finite Element Methods an Introduction*, 2018.
- [25] E. Madenci, Y.O. Özkılıç, L. Gemi, Experimental and theoretical investigation on flexure performance of pultruded GFRP composite beams with damage analyses, *Compos. Struct.* 242 (2020) 112162.
- [26] S. Yan, X. Zou, M. Ilkhani, A. Jones, An efficient multiscale surrogate modelling framework for composite materials considering progressive damage based on artificial neural networks, *Compos. B Eng.* 194 (2020) 108014.
- [27] D. Gunasegaram, et al., "Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal, *Addit. Manuf.* 46 (2021) 102089.
- [28] M.A. Gutiérrez, S. Krenk, Stochastic finite element methods. *Encyclopedia of Computational Mechanics*, second ed., 2018, pp. 1–25.
- [29] E. del Rey Castillo, T. Allen, R. Henry, M. Griffith, J. Ingham, Digital image correlation (DIC) for measurement of strains and displacements in coarse, low volume-fraction FRP composites used in civil infrastructure, *Compos. Struct.* 212 (2019) 43–57.
- [30] Y. Wang, Q. Luo, H. Xie, Q. Li, G. Sun, Digital image correlation (DIC) based damage detection for CFRP laminates by using machine learning based image semantic segmentation, *Int. J. Mech. Sci.* 230 (2022) 107529.
- [31] M. Pinto, S. Gupta, A. Shukla, Study of implosion of carbon/epoxy composite hollow cylinders using 3-D Digital Image Correlation, *Compos. Struct.* 119 (2015) 272–286.
- [32] G. Rebergue, B. Blaysat, H. Chanal, E. Duc, Advanced DIC for accurate part deflection measurement in a machining environment, *J. Manuf. Process.* 33 (2018) 10–23.
- [33] H. Suthar, A. Bhattacharya, S.K. Paul, Characterizing the anisotropic response of similar and dissimilar FSW joints by DIC-based simultaneous strain measurements on two orthogonal surfaces, *J. Manuf. Process.* 84 (2022) 697–712.
- [34] D. Rahmatabadi, A. Shahmirzaloo, R. Hashemi, M. Farahani, Using digital image correlation for characterizing the elastic and plastic parameters of ultrafine-grained Al 1050 strips fabricated via accumulative roll bonding process, *Mater. Res. Express* 6 (8) (2019) 086542.
- [35] D. Rahmatabadi, A. Shahmirzaloo, M. Farahani, M. Tayyebi, R. Hashemi, Characterizing the elastic and plastic properties of the multilayered Al/Brass composite produced by ARB using DIC, *Mater. Sci. Eng.* 753 (2019) 70–78.
- [36] J. Holmes, S. Sommacal, R. Das, Z. Stachurski, P. Compston, Digital image and volume correlation for deformation and damage characterisation of fibre-reinforced composites: a review, *Compos. Struct.* (2023) 116994.
- [37] H. Hosseini-Toudeshky, A. Navaei, Characterization of elastic modulus at glass/fiber interphase using single fiber composite tensile tests and utilizing DIC and FEM, *Mech. Adv. Mater. Struct.* (2023) 1–13.
- [38] M. Jerabek, Z. Major, R.W. Lang, Strain determination of polymeric materials using digital image correlation, *Polym. Test.* 29 (3) (2010) 407–416.
- [39] R. Janeliukstis, X. Chen, Review of digital image correlation application to large-scale composite structure testing, *Compos. Struct.* 271 (2021) 114143.
- [40] S. Gowid, E. Mahdi, S.S. Youssef, E. Moustafa, A. Moseh, A. Shokry, Experimental investigation of the dynamic characteristics of wrapped and wound fiber and metal/fiber reinforced composite pipes, *Compos. Struct.* 276 (2021) 114569.
- [41] R. Rafiee, M.A. Torabi, Stochastic prediction of burst pressure in composite pressure vessels, *Compos. Struct.* 185 (2018) 573–583.
- [42] A. Air, M. Shamsuddoha, B.G. Prusty, A review of Type V composite pressure vessels and automated fibre placement based manufacturing, *Compos. B Eng.* 253 (2023) 110573.
- [43] R. Rafiee, A. Salehi, Estimating the burst pressure of a filament wound composite pressure vessel using two-scale and multi-scale analyses, *Mech. Adv. Mater. Struct.* 30 (13) (2023) 2668–2683.
- [44] J. Calaf-Chica, J. Martínez-Peña, P.M.B. Díez, M.P. Calzada, Ring Hoop Tension Test for yield strength estimation: numerical analysis for a novel correlation method and applicability for mechanical testing of tubes and pipes, *Mech. Mater.* 169 (2022) 104295.
- [45] R. Rafiee, F. Abbasi, Numerical and experimental analyses of the hoop tensile strength of filament-wound composite tubes, *Mech. Compos. Mater.* 56 (4) (2020) 423–436.
- [46] Z. Ktari, C. Leita, P.A. Prates, A. Khalfallah, Mechanical design of ring tensile specimen via surrogate modelling for inverse material parameter identification, *Mech. Mater.* 153 (2021) 103673.
- [47] Y. Dong, B. Pan, A review of speckle pattern fabrication and assessment for digital image correlation, *Exp. Mech.* 57 (8) (2017) 1161–1181.
- [48] D. Lecompte, et al., Quality assessment of speckle patterns for digital image correlation, *Opt. Laser. Eng.* 44 (11) (2006) 1132–1145.
- [49] 527-4, *Plastics: Determination of Tensile Properties: Part 4: Test Conditions for Isotropic and Orthotropic Fibre-Reinforced Plastic Composites*, 2021. *ISO 527-4: 1997*.
- [50] R. García-Martin, J. López-Rebollo, L.J. Sánchez-Aparicio, J.G. Fuego, J. Pisonero, D. González-Aguilera, Digital image correlation and reliability-based methods for the design and repair of pressure pipes through composite solutions, *Construct. Build. Mater.* 248 (2020) 118625.
- [51] J. Pisonero, et al., A comparative study of 2D and 3D Digital Image Correlation approaches for the characterization and numerical analysis of composite materials, *IEEE Access* (2021).
- [52] Standard Test Method for Apparent Hoop Tensile Strength of Plastic or Reinforced Plastic Pipe, 2012.
- [53] T.M. El-Bagory, T.A. Alkanhal, M.Y. Younan, Effect of specimen geometry on the predicted mechanical behavior of polyethylene pipe material, *J. Pressure Vessel Technol.* 137 (6) (2015).
- [54] A. Gunoz, Y. Kepir, M. Kara, Tensile strength alteration of GFRP composite pipes under seawater-dominated conditions, *J. Fail. Anal. Prev.* 20 (4) (2020) 1426–1430.
- [55] P. Bing, X. Hui-Min, X. Bo-Qin, D. Fu-Long, Performance of sub-pixel registration algorithms in digital image correlation, *Meas. Sci. Technol.* 17 (6) (2006) 1615.
- [56] J. Blaber, B. Adair, A. Antoniou, Ncorr: open-source 2D digital image correlation matlab software, *Exp. Mech.* 55 (6) (2015) 1105–1122.
- [57] R. D'Agostino, *Goodness-of-fit-techniques*, Routledge, 2017.
- [58] S.W. Tsai, E.M. Wu, A general theory of strength for anisotropic materials, *J. Compos. Mater.* 5 (1) (1971) 58–80.
- [59] R. Rackwitz, Reliability analysis—a review and some perspectives, *Struct. Saf.* 23 (4) (2001) 365–395.

- [60] K. Goda, S.L. Phoenix, Reliability approach to the tensile strength of unidirectional CFRP composites by Monte-Carlo simulation in a shear-lag model, *Compos. Sci. Technol.* 50 (4) (1994) 457–468.
- [61] M.Y. Chiang, X. Wang, C.R. Schultheisz, J. He, Prediction and three-dimensional Monte-Carlo simulation for tensile properties of unidirectional hybrid composites, *Compos. Sci. Technol.* 65 (11–12) (2005) 1719–1727.
- [62] R. Rafiee, F. Reshadi, S. Eidi, Stochastic analysis of functional failure pressures in glass fiber reinforced polyester pipes, *Mater. Des.* 67 (2015) 422–427.
- [63] S.S. Tomar, S. Zafar, M. Talha, W. Gao, D. Hui, State of the art of composite structures in non-deterministic framework: a review, *Thin-Walled Struct.* 132 (2018) 700–716.
- [64] L. Novak, D. Novak, Polynomial chaos expansion for surrogate modelling: theory and software, *Beton-und Stahlbetonbau* 113 (2018) 27–32.
- [65] G. Deman, K. Konakli, B. Sudret, J. Kerrou, P. Perrochet, H. Benabderrahmane, Using sparse polynomial chaos expansions for the global sensitivity analysis of groundwater lifetime expectancy in a multi-layered hydrogeological model, *Reliab. Eng. Syst. Saf.* 147 (2016) 156–169.
- [66] M. Ehre, I. Papaioannou, D. Straub, Global sensitivity analysis in high dimensions with PLS-PCE, *Reliab. Eng. Syst. Saf.* 198 (2020) 106861.
- [67] G. Blatman, B. Sudret, Adaptive sparse polynomial chaos expansion based on least angle regression, *J. Comput. Phys.* 230 (6) (2011) 2345–2367.
- [68] K. Fukunaga, D.M. Hummels, Leave-one-out procedures for nonparametric error estimates, *IEEE Trans. Pattern Anal. Mach. Intell.* 11 (4) (1989) 421–423.
- [69] C. Wissler, The Spearman correlation formula, *Science* 22 (558) (1905) 309–311.
- [70] C. Croux, C. Dehon, Influence functions of the Spearman and Kendall correlation measures, *Stat. Methods Appl.* 19 (4) (2010) 497–515.
- [71] A. Behera, M.M. Thawre, A. Ballal, Failure analysis of CFRP multidirectional laminates using the probabilistic Weibull distribution model under static loading, *Fibers Polym.* 20 (2019) 2390–2399.
- [72] S. Gomes, et al., Probabilistic-based characterisation of the mechanical properties of CFRP laminates, *Construct. Build. Mater.* 169 (2018) 132–141.
- [73] M. Kashfuddoja, M. Ramji, Whole-field strain analysis and damage assessment of adhesively bonded patch repair of CFRP laminates using 3D-DIC and FEA, *Compos. B Eng.* 53 (2013) 46–61.
- [74] G.G. Gonz  les, F. Antunes, E. S  rgio, J. Vasco-Olmo, F. D  az, D. Neto, A comparison between FEM predictions and DIC results of crack tip displacement field in CT specimens made of titanium, *Theor. Appl. Fract. Mech.* 127 (2023) 104055.
- [75] B. Pan, B. Wang, G. Lubineau, A. Moussawi, Comparison of subset-based local and finite element-based global digital image correlation, *Exp. Mech.* 55 (2015) 887–901.
- [76] B. Wang, B. Pan, "Subset-based local vs. finite element-based global digital image correlation: a comparison study, *Theor Appl Mech Lett* 6 (5) (2016) 200–208.

CAPÍTULO III

**DETECCIÓN DE DEFECTOS EN
FABRICACIÓN ADITIVA POR DEPOSICIÓN
FUNDIDA A TRAVÉS DE TERMOGRAFÍA
ACTIVA**

3.1 Detección de defectología interna en impresión 3D a partir de termografía activa aplicando la técnica step heating

En este capítulo se aborda la implementación de la técnica de termografía activa para el control de calidad de piezas fabricadas a partir de métodos de impresión 3D. En este primer trabajo correspondiente al capítulo se realiza una comparativa entre modelos teóricos construidos a partir del FEM y los resultados obtenidos sobre ensayos en probetas fabricadas en PLA y Nylon. Estas probetas se dotan de un hueco interno que simula una falla interna como las que se pueden producir durante la impresión de la pieza. Teniendo todas las geometrías perfectamente registradas, se utiliza la técnica Step Heating para calentar la pieza mientras se van registrando imágenes termográficas a lo largo del ensayo. Este mismo proceso se simula a partir del FEM, de modo que se puede hacer una comparativa directa entre resultados experimentales y modelos teóricos de comportamiento.

Gracias a contar con un modelo teórico y resultados experimentales similares, se puede construir una metodología que permita predecir la longitud del defecto interno con precisión a partir de los termogramas obtenidos. Esto se realiza a partir de la construcción de modelos reiterativos que alimentan los algoritmos de machine learning. Tras entrenar a los algoritmos y a partir de una optimización bayesiana se consigue la validación de esta predicción. Estos algoritmos se alimentan en las características físicas de los ensayos, por lo que no es necesario utilizar algoritmos muy avanzados, simplificando el proceso de computación a partir de una buena toma de datos.

Con todo ello, se consigue predecir las dimensiones del defecto interno utilizando únicamente las características del material., los resultados más precisos se consiguen en los defectos más pequeños. Por otro lado, se encuentra una tendencia a sobredimensionar los defectos más grandes. El error intrínseco de los algoritmos es de en torno a un milímetro. Cabe destacar que, empleando un algoritmo entrenado, la desviación de la predicción de resultados para el tamaño de defecto varía entre el 13% y el 37% para PLA y entre el 13% y el 36% para Nylon. La metodología presentada puede ser extrapolable a otros tipos de variantes de la termografía activa para estimar la profundidad de los defectos.



Step heating thermography supported by machine learning and simulation for internal defect size measurement in additive manufacturing

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ABSTRACT

A methodology based on step-heating thermography for predicting the length dimension of small defects in additive manufacturing from temperature data measured on thermal images is proposed. Regression learners were applied with different configurations to predict the length of the defects. These algorithms were trained using large datasets generated with Finite Element Method simulations. The different predictive methods obtained were optimized using Bayesian inference. Using predictive methods generated and based on intrinsic performance results, knowing the material characteristics, the defect length can be predicted from single temperature data in defect and non-defect zone. Thus, the developed algorithms were implemented in a laboratory set-up carried out on ad-hoc manufactured parts of Nylon and polylactic acid which include induced defects with different sizes and thicknesses. Using the trained algorithm, the deviation of the predicted results for the defect size varied between 13% and 37% for PLA and between 13% and 36% for Nylon.

1. Introduction

Additive manufacturing (AM) is integrated within the industry to increase the perceived value in any of the following three areas: profit, risk, and time [1]. Furthermore, AM is one of the cornerstones of the 4.0 Industry which seeks to define a methodology to induce a transformation from machine dominant manufacturing to digital manufacturing, [2]. Non-destructive testing (NDT) is a core technology for quality and safety assurance of critical engineering equipment and product manufacturing, and is an effective means of ensuring the quality of both materials and control [3]. Since quality control and inspection are one of the main steps of additive manufacturing, NDT techniques are applied in different manufacturing processes, especially in those related to critical sectors (e.g. nuclear reactors [4]). However, the complexity of the geometry, together with the difficulty of finding the optimum parameters to achieve the desired end result and problems arising from poor process repeatability, makes it difficult to manufacture quality-assured parts, with implications for certification [5] and, finally, the absence of inspection international standards for NDT on additive manufactured pieces can induce important inspection limitations like

inaccessible surfaces or specific defects generated in the layers not easily detectable.

The active thermography is based on the effect that any type of discontinuity in the structure of materials can alter thermal diffusivity and cause alterations in heat flow [6]. This principle allows the detection of internal defects in materials [7], and for dimensional evaluation of these [8]. Also for intermediate elements in materials or construction elements [9].

So active thermography is really an NDT that can be applied for material evaluation and defect detection, even in AM materials [10,11], or polymers and/or carbon fiber reinforced plastics (CFRP) [12–18] in the latter case, even with portable devices [19,20] or new approaches like pulse-compression thermography nondestructive evaluation [21] which improves the defect capability with respect pulsed thermography. Also, thermography can be applied to extract information about the welding zones during the extrusion [22], and for AM metallic materials, for example, to detect defects for lack of fusion in selective laser melting processes [23], to detect corrosion [24] or for evaluating welded unions [25], to characterize the fatigue of the material [26] or in combination with other optical non-destructive techniques like shearography [27].

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The detectability of defects in flash thermography in low diffusivity materials such as additive manufacturing has been extensively studied [16,28] but this is not the case in easier application modalities such as the applied for this research: step heating [28]. This modality requires less equipment, is lower cost, and causes less thermal stress to the objects compared to the flash mode [28].

In AM, the Finite Element Method (FEM) has been used as a tool to predict various parameters and outcomes, such as the mechanical properties of the parts generated, the shape of the melting bath, the microstructure, and dimensions [29]. FEM methods are also useful to complement and optimize the cost and efficiency of the active thermography processes [10,11]. In [10], numerical simulations for Step-heating thermography were experimentally validated.

Different studies have addressed the application of the Finite Element Method (FEM) in active thermography for testing CFRP, [12], for thermal predictions in the manufacturing process [29], for composites and metals using pulse thermography [30,31], for glass-epoxy composites using step phase thermography [32], in robotized devices [33] and for simulation of eddy current thermography in composites. Some of them have used well-known FEM solutions like Ansys® [34,35] or Abaqus® [11]. The thermal conductivity equations can be numerically solved using sophisticated simulation tools [36], which can be both deterministic and probabilistic. Therefore, FEM models can be useful for estimating the physical parameters in active thermography tests. Additionally, these FEM models can also be used to extract a massive set of data that allows to feed predictive models based on artificial intelligence as a starting point.

Machine Learning/Deep Learning (ML/DL) techniques are currently applied in many industrial fields and these techniques have been also used to optimize the processes and parameters in AM [37]. In fact, it is trending that researchers in the field of AM are paying more and more attention to taking advantage of the important benefits of Artificial Intelligence (AI) for the optimization of design tasks for process control [29].

In [38], ML/DL was applied for detecting cracks, in [4,39] to reduce the thermographic noise for defect detection on metallic pieces, and, in

[29], ML was applied for the study of the evolution of the thermal field during direct energy deposition in stainless steels. In [40], DL was applied to characterize defects in composites, also using step-heating thermography. In [41] a DL model was applied to classify defects in fiberglass.

Within the most recent state of the art, thermography has been combined with ML strategies in the context of AM, for example, in [11] a theoretical different predictive algorithm feed from simulation data was proposed. This study analyzed the predictive performance of some algorithms for Nylon parts based on different measures of error and variability of the outputs without optimizing or applying experimental validation. That work [11] has served as the basis for this work because it allowed the selection of the predictive algorithms that would potentially be most effective (Support Vector Machine and Gaussian Process Regression methods).

The main research objectives of the work are: I) Generate a based-on active thermography method to measure the size of an internal defect of small thickness like layer defects in additively manufactured materials (materials with a clear lack of standardization at the quality testing level). II) Feed the method only with easy-to-extract temperature data with a simplified and well-known modality of active thermography: step-heating thermography. III) Validate the method under laboratory conditions and analyze the differences in error data as a function of flaw size and thickness. The presented research seeks to cover the research objectives and in this, a specific method (Fig. 1) for predicting the defect length dimension from thermal imagery was designed and validated using experimental data based on a simplified Step-Heating (S-H) thermography modality. Thus, a Mean Square Error (MSE) optimization algorithm is applied to optimize the predictive model and obtain the most appropriate hyperparameters and this predictive model is experimentally validated. Different processes are carried out which finally converge towards obtaining the results of deviations and predictive performance (Fig. 1). The reiterated FEM simulations generated many datasets that allowed us to train different predictive models. These datasets were independently generated for PLA and for Nylon, taking into account the physical properties and characteristics of each of them.

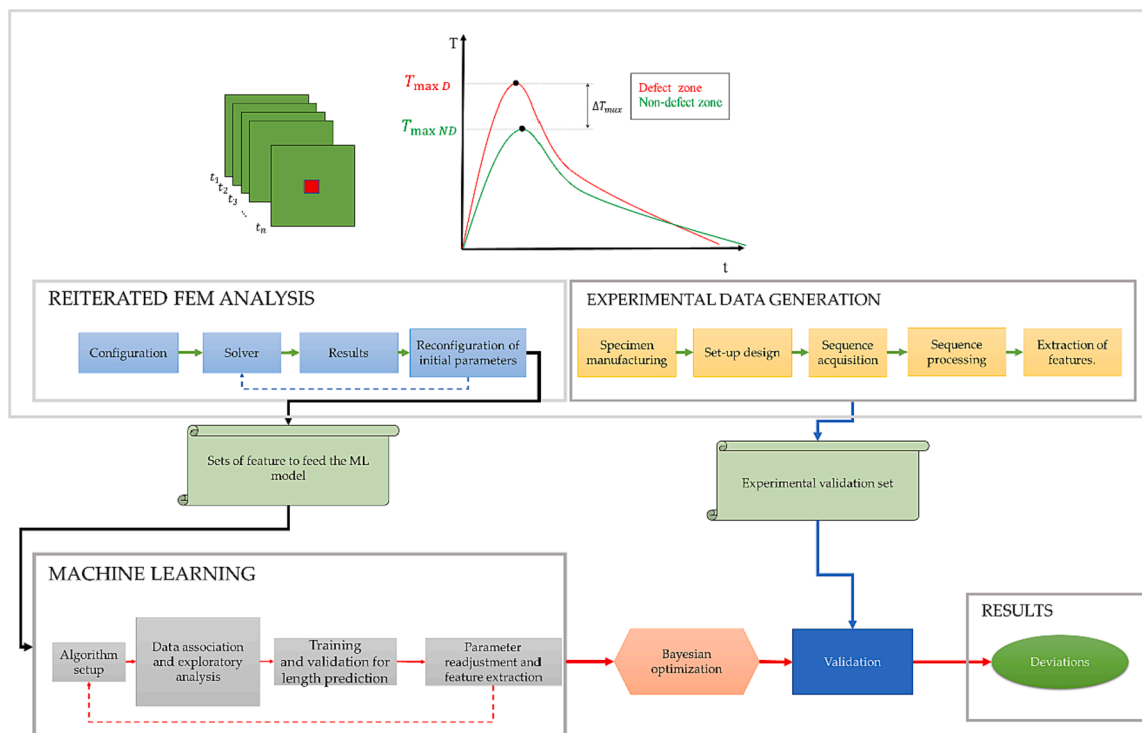


Fig. 1. Methodological workflow to predict the length of the defect from the thermal data.

Finally, the results of the experiment were used for the validation of the method. This process was repeated for both Nylon and PLA to compare the responses of predictive methods in the two types of materials. All this flow work will be explained in detail in the following sections.

2. Simulation

In [10], the usefulness of FEM simulation for active thermography processes in additive manufacturing materials was demonstrated and validated. For that reason, in this work, a specific approach is designed based on FEM simulation iteration with a probabilistic component that serves as a basis to feed ML models.

To simulate the thermal behavior of the additive material specimens, Abaqus2019® program was used and different analyses were automated using python. Firstly, the simulation setup and the boundary conditions established for the FEM analysis will be exposed. Secondly, the methodology to generate the datasets from the reiterative simulation procedure will be detailed.

2.1. Boundary conditions and simulation setup

A solid model with the shape of a rectangular cube was prepared with the same dimensions as the physical specimens (Fig. 2) that will be experimentally tested. A tetrahedral-shaped internal defect was generated in the model with a length and width in the interval indicated in Table 1 which also shows the input and output variables that have been considered for the FEM analysis. Regarding the input variables, Table 1 shows their baseline values, as well as the range of variation (in percentage) that have been studied both for the thermal properties of the two materials and for the dimensions of the tested specimens. In this way, 5,020 elements and 6,534 nodes were used to build the model. The

type of element used was the one called in Abaqus DC3D8, which is an 8-node linear isoparametric transfer brick, an element capable of simulating the thermal behavior of a material. A biased type of mesh was used that varied the size of the element used: from a resolution of 10 mm in the areas far from the defect, which are therefore of less interest, to a resolution of 1 mm in the closest ones. The size and number of elements with the biased mesh were established after performing a convergence analysis, observing that, the finer meshes did not yield better results. Fewer elements in the model allow for more interactions without increasing processing time.

To define the thermal behavior of the material, the thermal variables of conductivity and specific heat, and density must be specified as baseline values (Table 1). To characterize the heat exchange by radiation and by convection between the surface and the surrounding air, the baseline for emissivity (ϵ), and film coefficient (h) parameters also had to be defined, respectively. Please note that ϵ depends not only on the type of material but also on the surface finish. Furthermore, a predefined field was specified for all the surfaces of the solid, both internals and externals, to specify the ambient temperature surrounding the solid, which was considered to be 20 °C. Next, in the so-called Step-Heating (S-H) configuration, the upper surface of the solid was heated by means of an external heat energy source applied for 180 s trying to obtain the maximum contrast between the defect zone and the non-defect zone. Once this temperature is reached, the supposed external heat source is removed, and the solid is cooled to ambient temperature.

The temperature distribution that appears on the surface of the solid during the heating and cooling steps is not theoretically uniform due to the presence of the defect. The lack of material in this position causes the area close to the defect is heated faster and the same happens during the cooling step. The key is to compare the surface temperature (on the side to which the heat source is applied) in the position over the defect, with

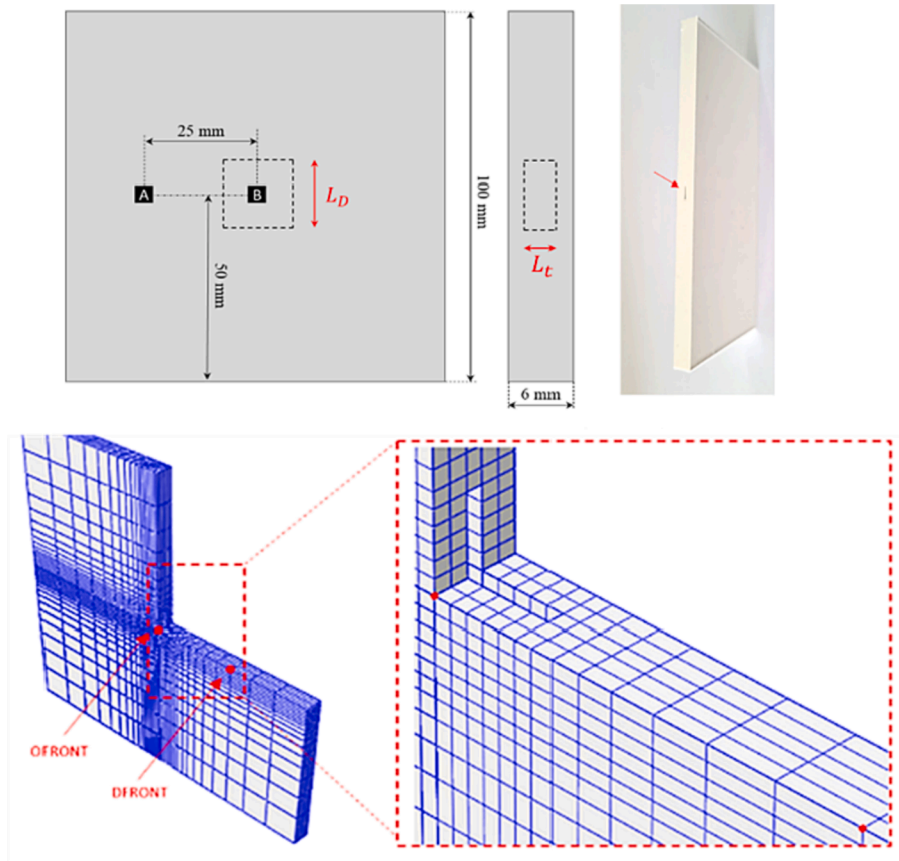


Fig. 2. Geometry and measures of the specimen. A and B are 4x4 px regions of interest where the temperature is monitored (up, left). Cut specimen to visualize the defect (thickness of the defect 0.9 mm, defect length L_D , 10 mm) (up, right) Mesh of the FEM model with the defect in its center (down).

Table 1

Different considered features for each task, SC is the “Specimen Characteristics”, I is the “input” and O is the “output”. The feature “Defect Length” (LD) is the length of the quadrangular side of the defect and the feature “Defect thickness” (L_T) is the thickness of the defect. R is the “Response” and F is the “Feature”.

Feature			FEM				Prediction	Experimental
			Baseline value PLA	FEM Baseline value Nylon	Lower range (%)	Upper range (%)		
Defect length	L_D (mm)	I	10	10	5	15	R	SC
Defect thickness*	L_T (mm)	I	0.6	0.6	0.3	0.9	**	SC
Specific heat	c (J/kg·K)	I	1800	1590	−25 %	+25 %	F	SC
Conductivity	k (W/m ² ·K)	I	0.13	0.22	−25 %	+25 %	F	SC
Density	ρ (kg/m ³)	I	1300	1100	−25 %	+25 %	F	SC
Emissivity	ε	I	0.95	0.95	−5 %	+5 %	F	SC
Film coef.	h (W/m ² ·°C)	I	10.5	10.5	−25 %	+25 %	F	SC
Max. temp.	T_M (°C)***	O					F	O
Contrast Front Max.	ΔT_{max} (°C)	O					F	O

*Defect depth can be calculated from defect thickness as $D_d = \frac{6}{2} - \frac{L_T}{2}$. The minimum value is 2.55 mm. and the maximum value is 2.85 mm.

**Defect thickness is not considered for the prediction model generations because is considered an unknown parameter.

*** T_M is the maximum temperature raised in the non-defect zone for the highest contrast thermogram.

another one far from it (B and A regions respectively in Fig. 2) at the moment of higher thermal contrast between the temperature of the two points. It allows to see how the defect affects the heating and cooling processes, trying to establish a relationship between the difference in temperatures in these surface positions (A and B) to corroborate the presence of the defect and also its possible size. To this end, the maximum contrast (ΔT_{max}) variable was defined as the maximum difference in temperatures between the point over the defect and another one far from it during the studied period. This variable was measured throughout the whole thermal process, determining its maximum value and recording the time in which it occurs. The maximum temperature reached on the surface of the test piece, just above the defect, was also determined. Although this maximum temperature occurs just at the end of the heating stage, due to thermal inertia, the maximum (ΔT_{max}) value does not always occur at the final moment of the application of the heat source, being this last data considered since it is the moment of better visualization of the defect.

2.2. Reiterative FEM analysis

Once the model was defined according to all previous indications, the script generated by Abaqus in Python programming language was

programmed to include the input variables (Table 1) and to obtain the output variables listed. An example of a visual result for the simulation is shown in Fig. 3. In this figure, the reader can see how the heat is distributed on the surface and inside the material, which justifies the need for additional methods to obtain measurements of the defect since no clear reflection of the defect on the surface is obtained.

From the baseline values of the seven input variables (Table 1) that have been considered in the study and considering their ranges of variation, different combinations of their values based on Design of Experiments (DoE) were performed. With this technique, it is possible to approximate the space of results, whose dimension is equal to the number of input variables and which is also continuous and therefore infinite, from the results obtained from a discrete number of iterations and therefore from a finite number of combinations of the input variables.

When using this methodology, it is of paramount importance to define adequately both, the number of iterations to be done and the methodology to define the combinations, hence, with the least number of iterations, the best possible approximation of the output fields can be obtained. In this study, the so-called Optimal Latin Hypercube (OLH) methodology was used, employing a total of 1,000 combinations. The advantage of this methodology is that the chosen combinations are

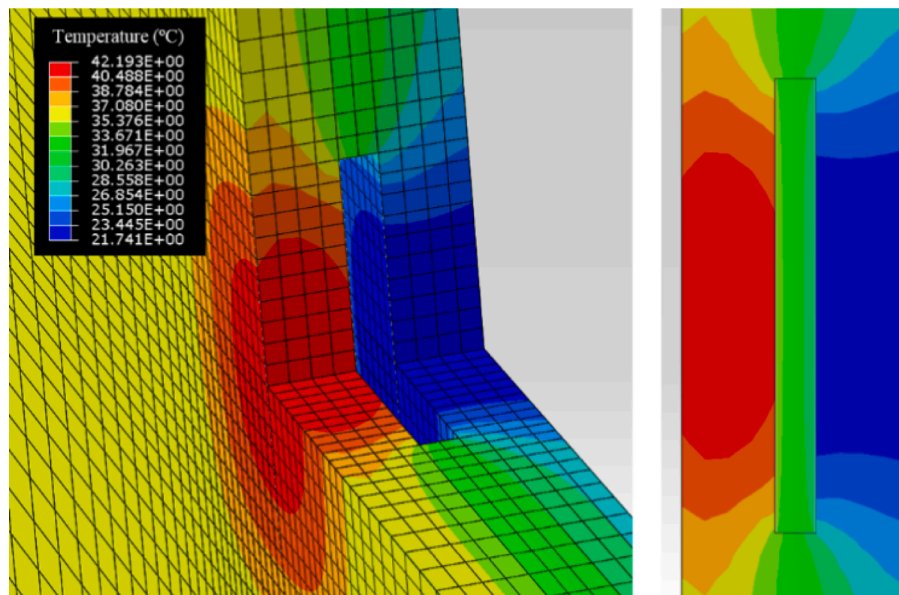


Fig. 3. Results of FEM simulation for a defect where the different temperature area are shown.

spread evenly, allowing a higher order effect to be captured, having the disadvantage that it increases the time required to obtain the optimal combinations, especially when the number of combinations and the number of input variables is large.

With the 1,000 combinations of output variables obtained, it is possible, using extrapolation and approximation techniques, to generate the mathematical equations that define the continuous results space for the ranges of the input variables studied.

The model was simulated 1000 times, modifying, within previously proposed ranges of values, the input variables within the established ranges (Table 1). Thank to this, a database of values of the input and output variables was obtained, which in this study, it is used to feed the ML methods.

Being a dataset generated by random inputs (within the bounds of Table 1), a subset of that data can still be also considered random. Therefore, to analyze the sensitivity of the model to different training data set sizes, alternative experiments can be done with a subset of 100 or 500 data. The error parameters based on RMSE and MAE remained in the same order of magnitude although a larger dataset (1000) was used because it was considered that a larger training set size would make the model more reliable.

3. ML algorithms

With the simulation, the thermal contrast is calculated for a multitude of defects of different dimensions and with different thermal properties. The data to feed the models are numerical, of dimension 1. These are obtained from the reiterative FEM simulation described in the last section and are used to train the predictive algorithms which allow predicting the defect length dimension from the thermal data (Fig. 1).

For the generation of the prediction models, different regression learning algorithms were used and tested. These algorithms are fed with the datasets generated by reiterative FEM simulation. Different typologies of learning regression models were tested to this aim: (i) linear regression, (ii) Support Vector Machine (SVM), and (iii) Gaussian regression. These models are configured with different hyperparameters and characteristics which allow to raise a better result and they have been used for the classification of defects in materials [3].

On the one hand, there exist various regression learner models: linear regression using a constant and linear term, linear interaction regression considering intercept, linear and interaction terms that applies the interaction between predictors, and, finally, stepwise linear regression, which applies a method to analyze the importance and weight of each variable. Please note that this last model is not as fast as the other two. Based on [11], linear interaction regression since was the best because it provided adequate performance (similar to the stepwise regression and better than linear regression) while consuming much less computational resources.

On the other hand, SVM are flexible and customizable models with different kernel functions (Radial Base Function (RBF), Quadratic, Cubic, or Linear). However, the SVM are really non-parametric methods that sometimes are highly affected by outliers [42]. In this research, the four kernel functions were tested. Specifically, for the RBF kernel, three different kernel scales were included: fine, medium, and coarse. Those prediction errors that were less than the threshold (ϵ) were ignored and treated as equal to zero.

Finally, the Gaussian Processes Regression (GPR) methods are based on the application of non-parametric kernel functions based on probabilistic models (Bayesian inference) [43]. They are non-parametric methods that are usually more suitable for complex problems than the previously described standard regression methods, especially for the treatment of complex and noisy nonlinear functions [44] and for their cross-validation. Different kernel functions and basic functions can be used for the GPR mode: while the firsts determine the form of the prior mean function, the seconds determine the correlation in the response as a function of the distance between the predictor values.

The evaluation of the models has been traditionally implemented by computing the difference between the observed values and the predicted value. The goodness of the regression learning models can be evaluated using classical statistical performance results (e.g. [11,45]) which are calculated from the observed and predicted values. In this research, three statistical error types were obtained for each model: correlation coefficient (R2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

The training time is also considered a reportable parameter. Since all the experiments were implemented using the same workstation, the training time was measured for each model in order to compare the training speed of each algorithm. This information is useful to study the operability of the method, mainly its integration into industrial software. Additionally, the distribution and morphology of the residuals were considered for each model.

Once the different regression learners were applied to the data, the optimization of the models was implemented to obtain the maximum performance that each method can provide. MSE optimization based on Bayesian Optimization was applied to find the optimum hyperparameters. The optimization was applied for each studied model to obtain the hyperparameters and performance of each optimized model.

4. Experimental validation

For the experimental validation of the method, 18 ad-hoc designed specimens with the same shape (Fig. 2) were manufactured by 3D printing. Nine of them were manufactured in Polylactic Acid (PLA) and the other nine in Nylon (PA-12). Each specimen has the same size as the model generated for the FEM simulation: the thickness of 6 mm and a size of 100×100 mm.

Different square defects were generated in the specimens with an empty volume in the center to simulate a lack of material in one or various layers. The defect is completely covered by the AM material both above and below.

The sizes of the defect (L_D) were within the range established in Table 1 (5, 10, and 15 mm). For each size, three specimens were manufactured with thicknesses (L_T) of 0.3, 0.6, and 0.9 mm (Table 2). That is, the depth of the defect is sited at the same depth from the front or back of faces, 2.85, 2.7, and 2.55 mm, respectively. Please note that a thickness of 0.3 mm is almost the minimum layer height that many 3D printers allow. These measures were the same for the Nylon and the PLA specimens.

The specimen depth was not directly considered since the objective is to be able to predict different defect sizes with different thicknesses in a specimen of the same characteristics, simulating a layer defect during additive manufacturing. However, since the specimen width is constant

Table 2
Different manufactured specimens for this research.

Specimen	$L_D(mm)$	$L_T(mm)$	Depth from surface (mm)	Material
1	5	0.30	2.85	PA-12
2	5	0.60	2.70	PA-12
3	5	0.90	2.55	PA-12
4	10	0.30	2.85	PA-12
5	10	0.60	2.70	PA-12
6	10	0.90	2.55	PA-12
7	15	0.30	2.85	PA-12
8	15	0.60	2.70	PA-12
9	15	0.90	2.55	PA-12
10	5	0.30	2.85	PLA
11	5	0.60	2.70	PLA
12	5	0.90	2.55	PLA
13	10	0.30	2.85	PLA
14	10	0.60	2.70	PLA
15	10	0.90	2.55	PLA
16	15	0.30	2.85	PLA
17	15	0.60	2.70	PLA
18	15	0.90	2.55	PLA

(6 mm), the defect depth is directly proportional to the thickness.

All the specimens were manufactured using a 100 % filler to fit the thermal properties with respect to the simulations performed, which consider solid material. Fig. 2 shows the generic location of the defects in the sample and a physical realization of them. On the specimen, two temperature measurement 4x4 pixel regions for defect and non-defect area (B and A in Fig. 2 respectively) have been established, both are separated at 25 mm (as in the FEM simulation) which is considered sufficient based on the dimension of the specimen, dimension of the defect, thermal diffusivity of the material and also on heat conduction previous FEM analysis. Each defect was generated in a specimen (one single defect by specimen) to avoid alterations in the heat flow.

A validation setup is an ad-hoc experiment to obtain results that allow us to know the level of fitting of the predictions using ML models. To do this, the S-H thermography in reflection modality was applied using a ring of flash lamps (6 lamps of 600 W) arranged in convergent orientation toward the object (Fig. 4). The distance from the camera to the object was established at 50 cm to cover the complete target in the frame view and to guarantee the minima focal distance of the camera. The configuration of the set-up was kept constant for all experiments to ensure the same optical conditions and also to keep the radiated energy on the object constant.

The set-up characteristics were set to reply to the thermal conditions of the FEM simulation. A heating sequence of 180 s was applied to all specimens and subsequently, a cooling sequence of 540 s was recorded (the same parameters that were used for the simulation). This cooling-heating time was applied based on trial-and-error seeking a balance between the efficiency of the method and its effectiveness. The frequency was established at 3 fps, being sufficient for the used low-thermal conductivity materials [46]. The 18 specimens described in the materials section (9 of PLA and 9 of Nylon) were tested for the internal defect using this set-up. Environmental parameters measured in the laboratory using Testo probes (temperature and humidity) were considered in the data acquisition. Data were collected based on two little Regions of Interest (ROI's) of 4x4 px, one for the defect area and the other for the non-defect area (Fig. 2). The mean of the pixels values was calculated to do the procedure more robust.

Once the data collection was implemented, each sequence was processed using Thermographic Signal Reconstruction (TSR) [47] in the heating phase and in the cooling phase, independently. As a result, the noise was reduced and the maximum contrast values between the defect area (center of the specimen) and the non-defect area were extracted.

5. Results

The results section will be divided into 4 subsections. The results of the FEM method are first exposed. Next, the predictive performance results for each of the regression learning methods applied are

presented. Subsequently, the results of the optimization carried out to the previous methods are indicated. Finally, the experimental validation of the method is properly considered.

5.1. Reiterative FEM results and Pareto analysis

From the FEM prepared in Abaqus, the temperature-time curves were obtained for the measurement positions just above the defect (B region in Fig. 2) and far from it (A region in Fig. 2), for the two materials (PLA and Nylon) when heating of 180 s to achieve a thermal contrast of 15 °C in the surface of materials [48]. This heating time will be also applied for the experimental validation.

The maximum contrast and the times in which they appear in these curves are automatically extracted by means of the modified Python script of the model. A total of 1,000 iterations were carried out giving 1,000 combinations of results with which the mathematical equations of order n that approximate the results are adjusted, where n is the number of input variables. From the results obtained, it is possible to carry out various types of analysis, such as the Pareto analysis (Fig. 4), which makes it possible to determine the input variables that have the greatest effect on the output variables. Specifically, Fig. 5 shows, from the highest to the lowest, the percentage of effect that the seven input variables considered have on the maximum value of the Contrast Front curve. It can be observed that the Pareto diagram shows that the length of the defect causes the biggest effect over the Contrast Front maximum value ΔT_{max} . These results justify the generation of the models for the defect length prediction based on thermal contrast.

5.2. Predictive performance and optimization results

The different models were trained considering all the predictor variables (Table 3) and using 10-fold cross-validation. The preprocessing using Principal Components Analysis (PCA) was applied but gave notably worse results. For this reason, it was not used. Please note that other thermal variables such as the time required to reach the maximum contrast between defect and non-defect zones or the average temperature during the experiment were tested (including within the features set for training). As the predictive performance worsened in general terms, they were rejected and those that added value to the model were not finally considered.

The results for each ML algorithm that provided a better predictive performance are reported for the PLA (Table 4), being these similar to the two materials studied (Nylon and PLA). For each model, three datasets were generated using FEM, one of 100, one of 500, and one of 1,000, in order to feed the predictive models.

The regression learner algorithms were trained with the three data sets (100, 500, and 1,000) to evaluate the evolution of performance while the amount of data for training increases. The results obtained

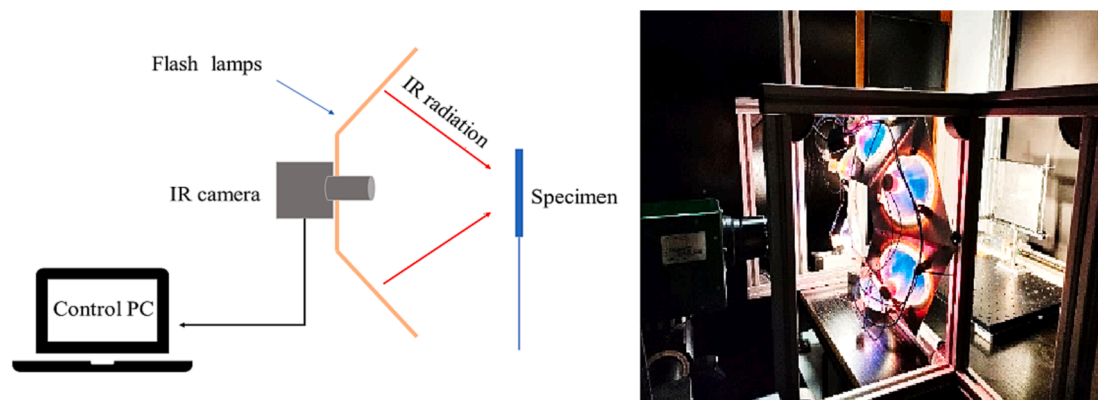


Fig. 4. Thermographic set-up for the validation of the method (left). Converged halogen lamps (600 W) used for the experiment (right).

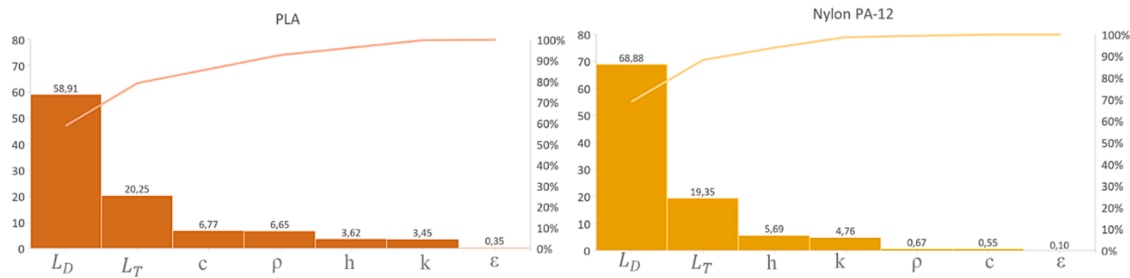


Fig. 5. Pareto diagram to visualize the weight of the different features in the maximum value of the variable ContrastFront ($\Delta T_{\max}$), Nylon (left), and PLA (right).

Table 3

ML Algorithms which raised an adequate predictive performance.

Algorithm	Description
LRi	Linear interaction regression (considering intercept, linear and interaction terms) that applies the interaction between predictions
SVMc	Support Vector Machine configured with Cubic kernel
GPRs	Gaussian process regression configured with a Square Exponential Kernel Function
GPRr	Gaussian process regression configured with a Rational Kernel Function
GPRm	Gaussian process regression configured with a Mattern 5/2 Kernel Function
GPROtm	Gaussian process regression ad-hoc optimized for the dataset following a MSE optimization process

Table 4

Intrinsically performance evaluation of the trained algorithms for the 1,000 sets of data.

Algorithm	RMSE	Rsquare	MAE	Training time (s)*
LRi	0.001850	0.79	0.001488	0.9810
GPRs	0.001642	0.84	0.001292	34.265
GPRr	0.001642	0.84	0.001292	89.183
GPRm	0.001965	0.76	0.001367	39.740
SVMc	0.001790	0.80	0.001410	9.6480

*Intel Core i7-5700HQ, 2.7 GHz CPU without parallel computing.

were based on 1,000 datasets generated models with higher performance (Table 4). The predictive model of defects in Nylon follows a similar trend. Training the algorithms with the 100 and 500 datasets allowed verifying the convergence of the model because the error results were slightly higher for little datasets (100 and 500) than for bigger datasets (1,000). This can be a favorable indicator because it corresponds to the expected behavior and implies that the number of training data favors the effectiveness and learning capability of the model.

MAE is in the scale of the response (defect length). Therefore, it can be said that the mean error is of the order of mm for all algorithms trained. Specifically, GPR model is the one that gives the best predictive performance, even for small data training sets. However, training times are significantly longer (in the order of tens of seconds) than SVM models and linear regression models (in the order of a second). This trend is repeated in the predictive model for Nylon. In GPR models it was detected a slight non-linear trend between predicted and real values. This trend is repeated in the predictive model for Nylon. In GPR models it was detected a slight non-linear trend between predicted and real values. It is also possible to check how the variability of the prediction response is higher for large defect lengths. This could indicate the less favorable suitability of the method for such extreme values. Additionally, in the predicted vs real data, a higher error is observed for the higher values of defect length for all the trained models, being this compatible with [11].

5.3. Optimization

In the predictive model for PLA, when the SVM was optimized using

20 iterations, better results are not really achieved (RMSE 0.0018532, R2 0.79, and MAE 0.001425). However, the optimization of the GPR, once the optimization method has applied all the iterations, does slightly improve the results. The hyperparameters obtained are shown in Table 5.

In the predictive model for Nylon, when the SVM was also optimized using 20 iterations, better results are not achieved (RMSE 0.001317, R2 0.89, and MAE 0.0010517). However, the optimization of the GPR does slightly improve the results (RMSE 0.0011785, R2 0.92, MAE 0.000949). The hyperparameters obtained are shown in Table 5. The models also show less favorable performance for the higher values of dimension length.

5.4. Validation results

The experimental methodology described in section 4 was applied. The different defects were shown in the image (an example of a PLA specimen is shown in Fig. 6, being the results for the other specimens very similar). As the reader can see, the defect is better visualized for the higher length defects, but although the defect when well visualized can be measured on the image (once it is scaled), the token measure is really ambiguous (due to the heat flux diffusion and limitations image resolution) so the actual geometry of the defect may not be well-shown (Fig. 3). The average heating time to reach the maximum thermal contrast was 179.72 s.

The results obtained by simulation for the fabricated specimens (ad-hoc manufactured for this research as the reader can see in Fig. 2-right) were compared with the results of the experimental test described in Section 2 in order to evaluate the consistency of the methods and to detect possible a priori errors. In Fig. 7, the reader can observe the similarity between the results, which is proof that the simulation approach is consistent prior with the physical phenomenon evaluated. This trend was similar to the rest of the specimens evaluated.

Once this check had been carried out, we conducted an experimental study based on S-H thermography in reflection modality applied to real

Table 5

Hyperparameters obtained from the MSE optimization of the algorithms developed for the PLA and Nylon.

Hyperparameter	Optimized model for PLA	Optimized model for Nylon
Regression learner applied	GPR	GPR
Basis function	linear	Zero
Kernel function:	Isotropic Rational	Non-isotropic mattern
	Quadratic	5/2
Kernel scale	184.5	5.461
Sigma	0.0123	0.000126
Acquisition function	Expected improvement per second plus (Matlab®)	
RMSE	0.0016812	0.001179
RSquare	0.83	0.92
MSE	2.826×10^{-6}	1.389×10^{-6}
MAE	0.001335	0.00094944
Training / optimization time (s)	1324.9	1028.7

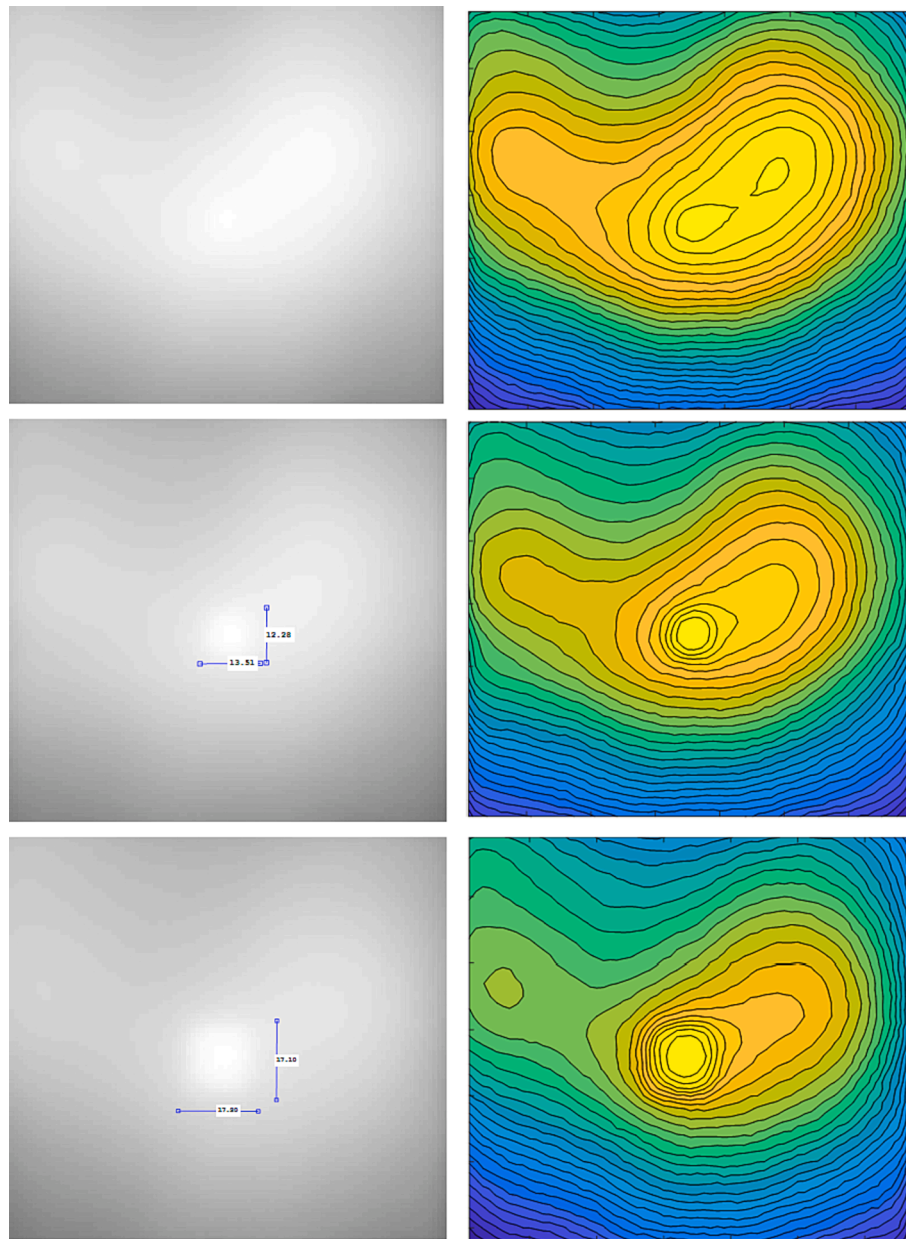


Fig. 6. Left: Thermogram at the instant of the greatest contrast between the defect zone and the non-defect zone for PLA specimen of 0.6 mm thickness and 5 mm of defect length (up), 10 mm of defect length (center), and 15 mm (down). Right, contour map (30 levels) generated from each thermogram.

physics specimens with known size defects (Fig. 2) and thermal properties (Table 1), to record the thermal contrast and introduce it to the predictive models to estimate the defect length.

In this way, once predictive algorithms were trained from the parameters generated by FEM ($c, k, \rho, \epsilon, h, T_M, \Delta T_{max}$) following the steps indicated in the last sections, the algorithms allowed to predict the length dimension of the defect (L_D) as a response from the maximum thermal contrast data (ΔT_{max}): $f(c, k, \rho, \epsilon, h, T_M, \Delta T_{max}) \rightarrow L_D$. Since the first four parameters are really physical properties that can be known, the predictive method should allow the prediction of defect length from the measurement of two thermal parameters that can be easily measured with thermography: T_M and ΔT_{max} .

The defect length, in this experimental phase, is known for each physical specimen (it was a manufacturing parameter), so we were able to calculate the deviations between the real dimension and the ones provided by the predictive models based on the thermal maximum contrast moment.

The deviation between the length dimension predicted by the algorithm and the real length dimension (experimentally obtained) is shown in Table 6 and Table 7 for both Nylon and PLA materials. As can be seen, this deviation is greater when the thickness of the defect is smaller. In addition, as can be seen, the optimized model does not necessarily give better values, hypothetically due to the uncertainty of the experimental process and the anisotropy performance of the additive materials.

6. Discussion

The predictive algorithms have been designed to predict the length dimension of the square defect using only the physical characteristics of the material and the maximum thermal contrast from the temperature measures in two points when applying a step heating approach. The S-H thermography modality is simple and ML algorithms help to obtain a defect prediction without the need to use sophisticated and expensive techniques. So, in this research, we have on purpose simplified the

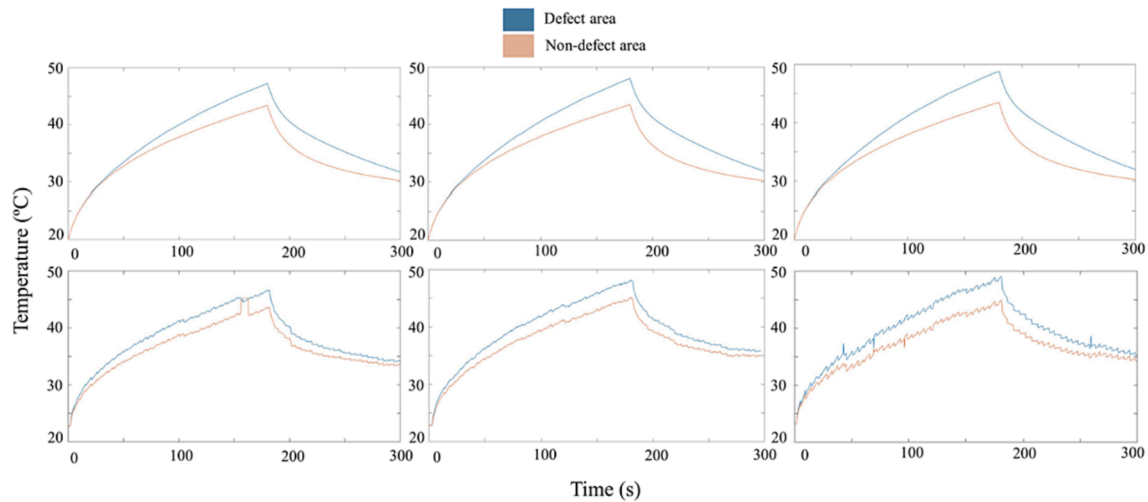


Fig. 7. Differences in the heating and cooling curves between the defect (blue) and non-defect (brown) zone for 10 mm defect length and PLA: results from FEM simulation (up) and from the experimental test (in raw) (down). The X-axis represents the time and the Y-axis the temperature for all plots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6

Error results from the comparison between the experimental value and the predicted value for PLA. Average Error (In absolute value) for the different thickness (t) and length (l). AV mean average for all the tested specimens for the same defect length (AVd) and defect thickness (AVt).

L_T	L_D	LRI	SVMc	GPRs	GPRr	GPRm	GPRopt
0.9	15	-22.4 %	-26.9 %	-21.3 %	-19.5 %	-21.2 %	-21.4 %
0.9	10	0.8 %	-7.4 %	1.3 %	1.2 %	1.5 %	2.2 %
0.9	5	45.1 %	29.9 %	43.0 %	33.8 %	43.5 %	47.4 %
0.6	15	-37.3 %	-41.2 %	-36.2 %	-37.3 %	-36.1 %	-36.6 %
0.6	10	-19.3 %	-27.6 %	-19.9 %	-23.6 %	-19.7 %	-18.1 %
0.6	5	22.1 %	8.6 %	17.8 %	8.8 %	18.5 %	24.4 %
0.3	15	-53.6 %	-59.2 %	-54.9 %	-57.7 %	-54.6 %	-52.7 %
0.3	10	-20.1 %	-25.7 %	-19.2 %	-23.6 %	-19.1 %	-19.2 %
0.3	5	15.2 %	1.8 %	9.6 %	1.7 %	10.5 %	17.7 %
AVd 0.9		22.74 %	21.40 %	21.85 %	18.17 %	22.07 %	23.65 %
AVd 0.6		26.23 %	25.77 %	24.63 %	23.23 %	24.76 %	26.36 %
AVd 0.3		29.60 %	28.90 %	27.89 %	27.68 %	28.05 %	29.85 %
AVt 0.015		37.74 %	42.41 %	37.43 %	38.16 %	37.30 %	36.89 %
AVt 0.010		13.40 %	20.24 %	13.47 %	16.16 %	13.41 %	13.17 %
AVt 0.005		27.43 %	20.24 %	13.47 %	16.16 %	13.41 %	13.17 %

Table 7

Error results from the comparison between the experimental value and the predicted value for Nylon. Average Error (In absolute value) for the different thickness (t) and length (l). AV mean average for all the tested specimens for the same defect length (AVd) and defect thickness (AVt).

L_T	L_D	LRI	SVMc	GPRs	GPRr	GPRm	GPRopt
0.9	15	-33.76 %	-19.01 %	-20.72 %	-20.72 %	-20.56 %	-21.93 %
0.9	10	-20.24 %	1.45 %	1.25 %	1.25 %	1.38 %	-3.64 %
0.9	5	-48.81 %	-10.07 %	-12.96 %	-12.96 %	-12.59 %	-20.96 %
0.6	15	-54.32 %	-37.62 %	-38.46 %	-38.46 %	-38.36 %	-42.30 %
0.6	10	-35.03 %	-4.44 %	-8.55 %	-8.55 %	-8.36 %	-14.44 %
0.6	5	-53.69 %	-12.58 %	-16.73 %	-16.73 %	-16.33 %	-24.85 %
0.3	15	-71.64 %	-52.16 %	-53.93 %	-53.93 %	-53.82 %	-57.60 %
0.3	10	-63.53 %	-44.69 %	-44.42 %	-44.42 %	-44.29 %	-48.71 %
0.3	5	-55.85 %	-17.30 %	-21.51 %	-21.51 %	-21.10 %	-29.26 %
AVd 0.9		34.27 %	10.18 %	11.64 %	11.64 %	11.51 %	15.51 %
AVd 0.6		47.68 %	18.21 %	21.25 %	21.25 %	21.02 %	27.20 %
AVd 0.3		63.67 %	38.05 %	39.95 %	39.95 %	39.74 %	45.19 %
AVt 0.015		53.24 %	36.27 %	37.70 %	37.70 %	37.58 %	40.61 %
AVt 0.01		39.60 %	16.86 %	18.07 %	18.07 %	18.01 %	22.26 %
AVt 0.005		52.78 %	13.31 %	17.06 %	17.06 %	16.68 %	25.02 %

number of thermal parameters as possible and we have used the simplest thermographic methodology. The methods have been trained with different thermal parameters (applying a variability in the training data), which would make it robust to material characteristics.

As a result, it is possible to predict the length dimension of the defects

using only this data and the features of the material. For this purpose, we have used data from FEM simulation that adequately reproduce the results of the test, being the results compatible with the literature [10,11].

On the other hand, it has been shown that the results of the

prediction of the length dimension are more inaccurate in the defects of a smaller thickness (0.3 mm). This was to be expected given the lower detectability of these defects and the lower thermal alteration they cause (also considering the limitations of the speed of capture). A tendency to overestimate the dimension was detected in 15 mm defects. As the defects are larger, the measurement zone is closer to the beginning of the defect, which can lead to a bias in the result due to the high influence of the transition zone (Fig. 3).

Finally, the experimental results may be affected by an irregular heat distribution and also by the fact that the specimens are manufactured with 3D printing (non-uniform material), which could cause an anisotropic behavior in the distribution of the heat depending on the characteristics and direction of the filling process. In addition, inaccuracies of thermographic cameras (within the range of uncertainty indicated by the manufacturer), environmental factors, and possible additional reflections, could provide uncertainty to the final prediction outcome. However, since the proposed algorithms allow self-learning, if the experimental data are used to feed the training dataset, it is possible that the accuracy of the method is improved. Finally, it should be noted that the defects used in this work simulate defects of lack of coating but are of ideal shapes. Therefore, the actual defects may have a different thermal response and the effectiveness of the procedure may be affected by complex geometries.

7. Conclusions

This work has presented the results of a methodology based on artificial intelligence (ML) that uses data from repeated numerical simulations (FEM) to generate prediction models of the size of defects in AM materials based on the thermal contrast (S-H thermography) and the physical characteristics of the material. The creation of these models was justified by a cause-and-effect analysis applied to the FEM model, in which it was found that the length of the defect is the variable with more weight for the calculation of the thermal contrast by numerical simulation.

These models have been applied separately to two different materials: Nylon and PLA, to firstly estimate the intrinsic performance parameters of the predictive method (RMSE, MAE, and R2) of three different types of predictive algorithms: linear regression, SVM, and Gaussian regression.

The algorithms designed and optimized have been applied experimentally to real specimens of both materials that have been ad-hoc manufactured including defects of different sizes (5x5, 10x10, and 15x15 mm) and thicknesses (0.3, 0.6, and 0.9 mm). With this, it is possible to carry out an in-depth study of the accuracy of the method taking into account the factors that can affect the actual application (explained in the Discussion section) and not just taking into account the intrinsic performance of predictive models.

The intrinsic error of the algorithms (MAE) was in the order of a millimeter. However, in the experimental validation, this error was overcome in some cases. This is to be expected since the error of the trained algorithms is calculated from a subset of the simulation process data. When experimental data are obtained and entered in the models, different physical phenomena cause the error for length predicted to be larger, although in some cases a deviation of the real results with respect to the predicted ones was compatible (even more favorable) with the intrinsic error of the models: in some cases, the predictive algorithm manages to predict the size of the defect with a deviation close to 1 % while in other cases that deviation increases significantly. In general terms, it can be said that the bigger the thickness of the defect, the greater the accuracy of the prediction. Furthermore, the prediction performance is less favorable for higher defect lengths.

The proposed method could be compatible with other methods fed from S-H thermography to estimate the depth of the defect. The obtained length using this method could even be used as a predictive input parameter for depth defect prediction. Additionally, Futures works

could address this issue. Furthermore, the results of this method applied to different internal structures and fills of additive manufacturing materials could also be addressed in future work and, also, noise could be considered in the FEM model to study if the final results are affected.

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CRediT authorship contribution statement

M. Rodríguez-Martín: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft. **J.G. Fueyo:** Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – original draft. **J. Pisonero:** Data curation, Investigation, Validation, Visualization, Writing – original draft. **J. López-Rebollo:** Data curation, Investigation, Validation, Visualization, Writing – original draft. **D. Gonzalez-Aguilera:** Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft. **R. García-Martín:** Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – original draft. **F. Madruga:** Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

- [1] J. Coykendall, M. Cottelee, J. Holdowsky, M. Mahto, 3D opportunity in aerospace and defense: Additive manufacturing takes flight, Deloitte Series Add. Manuf. (2014) 1.
- [2] E. Oztemel, S. Gursev, Literature review of Industry 4.0 and related technologies, J. Intell. Manuf. 31 (1) (2020) 127–182.
- [3] H. Chen, Z. Zhang, W. Yin, C. Zhao, F. Wang, Y. Li, A study on depth classification of defects by machine learning based on hyper-parameter search, Measurement 189 (2022) 110660.
- [4] X. Zhang, J. Saniee, A. Heifetz, Spatial temporal denoised thermal source separation in images of compact pulsed thermography system for qualification of additively manufactured metals, in: 2021 IEEE International Conference on Electro Information Technology (EIT), IEEE, 2021, pp. 209–214.
- [5] D.R. Gunasegaram, A.B. Murphy, A. Barnard, T. DeRoy, M.J. Matthews, L. Ladani, D. Gu, Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal additive manufacturing, Addit. Manuf. 46 (2021) 102089.
- [6] X. Maldague, Theory and practice of infrared technology for nondestructive testing, 2001.
- [7] F.J. Madruga, S. Sfarra, S. Perilli, E. Pivarčiová, J.M. López-Higuera, Measuring the water content in wood using step-heating thermography and speckle patterns—preliminary results, Sensors 20 (1) (2020) 316.
- [8] S. Dudzik, Two-stage neural algorithm for defect detection and characterization uses an active thermography, Infrared Phys. Technol. 71 (2015) 187–197.
- [9] J. Lin, X. Hong, Z. Ren, J. Chen, Scanning laser in-depth heating infrared thermography for deep debonding of glass curtain walls structural adhesive, Measurement 192 (2022) 110902.
- [10] M.S. Carvalho, A.P. Martins, T.G. Santos, Simulation and validation of thermography inspection for components produced by additive manufacturing, Appl. Therm. Eng. 159 (2019) 113872.
- [11] M. Rodríguez-Martín, J.G. Fueyo, D. Gonzalez-Aguilera, F.J. Madruga, R. García-Martín, A.L. Muñoz, J. Pisonero, Predictive models for the characterization of

- internal defects in additive materials from active thermography sequences supported by machine learning methods, *Sensors* 20 (14) (2020) 3982.
- [12] J. Peeters, C. Ibarra-Castanedo, S. Sfarra, X. Maldague, J.J.J. Dirckx, G. Steenackers, Robust quantitative depth estimation on CFRP samples using active thermography inspection and numerical simulation updating, *NDT and E Int.* 87 (2017) 119–123.
 - [13] H. Fernandes, H. Zhang, S. Quirin, J. Hu, M. Schwarz, H. Jost et al., Infrared thermographic inspection of 3D hybrid aluminium-CFRP composite using different spectral bands and new unsupervised probabilistic low-rank component factorization model 125 (2022) 102561.
 - [14] B. Azizinasab, R.P. Hasanzadeh, S. Hedayatrasa, M. Kersemans, Defect detection and depth estimation in CFRP through phase of transient response of flash thermography, *IEEE Trans. Ind. Inf.* 18 (4) (2021) 2364–2373.
 - [15] B.J. Manujesh, M.R. Prajna, Damage detection and classification for sandwich composites using machine learning, *Mater. Today Proc.* 52 (2022) 702–709.
 - [16] N.J. Wallace, N.B. Crane, M.R. Jones, Defect measurement limits using flash thermography with application to additive manufacturing, *NDT E Int.* 128 (2022) 102615.
 - [17] N. Saeed, N. King, Z. Said, M.A. Omar, Automatic defects detection in CFRP thermograms, using convolutional neural networks and transfer learning, *Infrared Phys. Technol.* 102 (2019) 103048.
 - [18] M.F. Beemer, S.M. Shepard, Aspect ratio considerations for flat bottom hole defects in active thermography, *Quant. InfraRed Thermogr. J.* 15 (1) (2018) 1–16.
 - [19] H. Wang, S.J. Hsieh, B. Peng, X. Zhou, Non-metallic coating thickness prediction using artificial neural network and support vector machine with time resolved thermography, *Infrared Phys. Technol.* 77 (2016) 316–324.
 - [20] R. Wang, C. Pei, R. Xia, Q. Wang, Z. Chen, A portable fiber laser thermography system with beam homogenizing for CFRP inspection, *NDT E Int.* 124 (2021) 102550.
 - [21] G. Silipigni, P. Burrascano, D.A. Hutchins, S. Laureti, R. Petrucci, L. Senni, L. Torre, M. Ricci, Optimization of the pulse-compression technique applied to the infrared thermography nondestructive evaluation, *NDT E Int.* 87 (2017) 100–110.
 - [22] J.E. Seppala, K.D. Migler, Infrared thermography of welding zones produced by polymer extrusion additive manufacturing, *Addit. Manuf.* 12 (2016) 71–76.
 - [23] J.L. Bartlett, F.M. Heim, Y.V. Murty, X. Li, In situ defect detection in selective laser melting via full-field infrared thermography, *Addit. Manuf.* 24 (2018) 595–605.
 - [24] A. Foudazi, M.T. Ghasr, K.M. Donnell, Measurement. Characterization of corroded reinforced steel bars by active microwave thermography 64 (2015) 2583–2585.
 - [25] M. Rodríguez-Martín, S. Lagueta, D. González-Aguilera, P. Rodríguez-González, Crack-depth prediction in steel based on cooling rate, *Adv. Mater. Sci. Eng.* 2016 (2016) 1–9, <https://doi.org/10.1155/2016/1016482>.
 - [26] C. Douellou, X. Balandraud, E. Duc, B. Verquin, F. Lefebvre, F. Sar, Rapid characterization of the fatigue limit of additive-manufactured maraging steels using infrared measurements, *Addit. Manuf.* 35 (2020) 101310.
 - [27] Y. Wei, L.i. Ding, Y. Han, Y. Luo, Z. Su, D. Zhang, Characterizing defects in materials with fusion of thermography and shearography, *Measurement* 182 (2021) 109736.
 - [28] X. Li, N. Tao, L. Feng, J.G. Sun, Thickness measurement research using transmission step-heating thermography, *NDT E Int.* 126 (2022) 102590.
 - [29] S. Fetni, Q.D.T. Pham, V.X. Tran, L. Duchêne, H.S. Tran, A.M. Habraken, Thermal field prediction in DED manufacturing process using Artificial Neural Network, 2021.
 - [30] R.C. Waugh, J.M. Dulieu-Barton, S. Quinn, Modelling and evaluation of pulsed and pulse phase thermography through application of composite and metallic case studies, *NDT E Int.* 66 (2014) 52–66.
 - [31] M. Krishnapillai, R. Jones, I.H. Marshall, M. Bannister, N. Rajic, NDTE using pulse thermography: Numerical modeling of composite subsurface defects, *Compos. Struct.* 75 (1–4) (2006) 241–249.
 - [32] K. Ghadermazi, M.A. Khozeimeh, F. Taheri-Behrooz, M.S. Safizadeh, Delamination detection in glass-epoxy composites using step-phase thermography (SPT), *Infrared Phys. Technol.* 72 (2015) 204–209.
 - [33] F. Khodayar, F. Lopez, C. Ibarra-Castanedo, X. Maldague, Optimization of the inspection of large composite materials using robotized line scan thermography, *J. Nondestruct. Eval.* 36 (2) (2017) 1–15.
 - [34] S. Grys, L. Vokorokos, L. Borowik, Size determination of subsurface defect by active thermography-Simulation research, *Infrared Phys. Technol.* 62 (2014) 147–153.
 - [35] P.D. Pastuszak, Characterization of defects in curved composite structures using active infrared thermography, *Proc. Eng.* 157 (2016) 325–332.
 - [36] D.L. Balageas, Thickness or diffusivity measurements from front-face flash experiments using the TSR (thermographic signal reconstruction) approach, in: *Proceedings of 10th Quantitative InfraRed Thermography conference, paper QIRT2010-011 Québec (Canada)*, 2010, July.
 - [37] J. Jiang, Y. Xiong, Z. Zhang, D.W. Rosen, Machine learning integrated design for additive manufacturing, *J. Intell. Manuf.* (2020) 1–14.
 - [38] J. Yang, W. Wang, G. Lin, Q. Li, Y. Sun, Y. Sun, Infrared thermal imaging-based crack detection using deep learning, *IEEE Access* 7 (2019) 182060–182077.
 - [39] X. Zhang, J. Sanjie, W. Cleary, A. Heifetz, Quality control of additively manufactured metallic structures with machine learning of thermography images, *JOM* 72 (12) (2020) 4682–4694.
 - [40] R. Marani, D. Palumbo, U. Galletti, T. D’Orazio, Deep learning for defect characterization in composite laminates inspected by step-heating thermography, *Opt. Lasers Eng.* 145 (2021) 106679.
 - [41] R. Marani, D. Palumbo, G. Bono, G. Cicirelli, U. Galletti, T. D’Orazio, Analytical model approximation for defect classification in fiberglass composites inspected by long-pulse thermography, in: *2020 IEEE International Conference on Industrial Technology (ICIT)*, IEEE, 2020, pp. 652–657.
 - [42] W. Dhhan, H. Midi, T. Alameer, Robust Support Vector Regression Model in the Presence of Outliers and Leverage Points, *Modern Appl. Sci.* 11 (8) (2017) 92.
 - [43] Y.u. Duan, C. Cooling, J.S. Ahn, C. Jackson, A. Flint, M.D. Eaton, M.J. Bluck, Using a Gaussian process regression inspired method to measure agreement between the experiment and CFD simulations, *Int. J. Heat Fluid Flow* 80 (2019) 108497.
 - [44] M.A. Chilenski, M. Greenwald, Y. Marzouk, N.T. Howard, A.E. White, J.E. Rice, J. R. Walk, Improved profile fitting and quantification of uncertainty in experimental measurements of impurity transport coefficients using Gaussian process regression, *Nucl. Fusion* 55 (2) (2015) 023012.
 - [45] K.O. Achieng, Modelling of soil moisture retention curve using machine learning techniques: Artificial and deep neural networks vs support vector regression models, *Comput. Geosci.* 133 (2019) 104320.
 - [46] D.P. Almond, S.L. Angioni, S.G. Pickering, Long pulse excitation thermographic non-destructive evaluation, *NDT E Int.* 87 (2017) 7–14.
 - [47] S.M. Shepard, J.R. Lhota, B.A. Rubadeux, D. Wang, T. Ahmed, Reconstruction and enhancement of active thermographic image sequences, *Opt. Eng.* 42 (5) (2003) 1337–1342.
 - [48] D.A. Gonzalez, S.G. Pickering, D.P. Almond, A low cost thermography NDT system based on long pulse excitation? development & evaluation. *NDT 2005-The Proceedings of the 44th Annual Conference of the British Institute of NDT*, 2005.

3.3 Detección de impactos en policarbonato a partir de termografía activa aplicando la modalidad flash

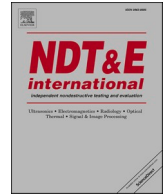
El policarbonato es uno de los materiales técnicos más interesantes que pueden ser empleados en las técnicas de impresión 3D más generalizadas para el público. Gracias a sus temperaturas de fusión, es posible imprimir filamento de este tipo de material con impresoras enfocadas al público general. Sin embargo, la configuración del proceso es clave para conseguir una calidad aceptable.

Este material es muy utilizado en procesos donde el grado de desgaste es elevado y también en productos dedicados a la absorción de impactos, tales como el sector aeronáutico, ingeniería de automóvil, defensa, etc. En este ámbito el Policarbonato desempeña una buena ratio entre energía absorbida y deformación. En este artículo se presenta la detección de defectología y deformaciones producidas en diferentes placas impresas por este material a partir de la técnica de termografía activa en su modalidad Flash sobre la cara opuesta de estos defectos para poder parametrizar las dimensiones del defecto y la energía de impacto con modificaciones tanto en la energía, como en las propiedades del material a partir del grado de relleno de este en el proceso de impresión.

Tras el registro de las imágenes, se realiza un procesado con el algoritmo PCA. Gracias a ello se puede estimar la influencia del infill, y la influencia de la energía de impacto sobre el resultado final.

En este trabajo se ha utilizado una cámara de alta tasa de refresco, necesaria para poder utilizar la técnica Flash, pero esta cámara cuenta con una resolución baja, de 128x128 píxeles. Una resolución mayor se traduciría en una capacidad de detección mayor, siendo la presentada aceptable. También, cuanto mayor es la energía del impacto, generando unas mayores deformaciones, más outliers aparecen perturbando el contraste estadístico presentado para la detección automática del defecto. Por este motivo también se han empleado análisis estadísticos no paramétricos.

Realizando análisis estadísticos sobre zonas de defecto y zonas de no defecto se observa que en todas las energías de impacto aparecen diferencias significativas entre ambas zonas. Analizando las medianas de las zonas de impacto, con un factor R2 de prácticamente 1 se puede demostrar la presencia de impacto y deformación en la zona.



Flash thermography to detect and evaluate impacts in polycarbonate parts produced by additive manufacturing

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ABSTRACT

In this work, active thermography has been evaluated for detecting impacts on polycarbonate parts produced by additive manufacturing with different fillers and under various impact energies. Polycarbonate is a material with very good impact resistance, very useful in sectors where security is critical (e.g., aeronautics, vehicle engineering, ballistics, defense, etc.). The impacts were specifically generated on the back face (non-visible) of the part, using a standardized test under controlled energy conditions. Specifically, flash thermography was used, and different processing techniques was applied. The most favorable results were obtained by principal component analysis (PCA). From a qualitative perspective, the proposed method allows to detect and evaluate the impact from the back side of the part (non-impacted side) taking into account the different material fillings. From a quantitative point of view, by using parametric and non-parametric tests, it can be shown that there are statistically significant differences between the image levels in the defect zone and the non-defect zone, and it is even possible to establish a correlation between the medians of the detected levels and the impact energy.

1. Introduction

Polycarbonate (PC) is a polymer that is easy to work with and is currently used in many applications in industry and for engineering tasks. It is highly deformable, so its energy absorption capacity is very high [1]. Therefore, polycarbonate is a material widely used for shock absorption, which is one of its main technical applications [2–7]. This, together with its 3D printing capacity, PC allows the production of very specific parts with complex and functional geometries [8–10] and with a slight weight due to the application of infill.

Therefore, PC is a material widely used in ballistic and other applications that require impact strength. Examples of use are bulletproof helmets and armored vehicles because of their good impact resistance. It is also being investigated for the development and manufacture of sandwich panels for bulletproof vests and armor systems [1].

In this context, some research has been conducted to apply thermography to analyze the plastic deformation during the impact [11], to estimate crack propagation [12] and even high-speed cameras have been used to study in detail the impacts and the material deformation

[13].

Due to the stress distribution during the impact, the impact region is generated in the impact face, but the tensile region is induced by the impact in the back face of the material. However, for low-energy impacts, this tensile region is not detectable by the naked eye but hypothetically it could be detected using non-destructive testing techniques.

Furthermore, the quantification of the impact energy is crucial in certain aspects, being very complicated to do in parts with complex geometries such as those obtained by 3D printing because their properties are anisotropic and vary depending on the infill and the problems inherent to layered manufacturing.

Active infrared thermography is becoming a disruptive methodology in the field of manufacturing quality control and predictive maintenance [14,15]. It has great applicability in polymeric materials used in AM due to its low thermal conductivity and diffusivity [16,17]. This makes it possible to detect and measure internal defects in the materials themselves without the need for contact or destructive testing [12,18–20]. Furthermore, integrating this type of maintenance and testing techniques into the life cycle of the material improves sustainability and

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environmental impact [21].

The active thermography setup can be widely adapted to the case of the study. For this purpose, there are different active thermography modalities and setups depending on the nature and characteristics of the external excitation source. Examples of these modalities can be step-heating, lock-in, flash thermography or thermography assisted by laser [22–26]. Each technique has a different use that is better suited to one type of material or another, consequently, it is necessary to adapt the case to the material. In many cases, ad hoc and portable devices have been used to collect data [27].

Another aspect of active thermography to be taken into account is the type of postprocessing depending on each type of case. Thermal Signal Reconstruction (TSR) [28,29], Pulse Phase Thermography (PPT) using the Fourier Transform [29], Signal to Noise Ratio (SNR) [30] or Differentiated Absolute Contrast (DAC) [31], among many others. Specifically, Principal Component Thermography (PCT) is used for many applications of noise elimination, such as dimension reduction, classification and others [32]. PCT has been also applied to numerous infrared subsurface detection applications [32]. In Ref. [33], it is evaluated the PCT for a variety of thermography methods [34], the PCT was also applied for automatic Infrared sequence processing for Teflon and carbon fiber reinforced plastic (CFRP) plates with defects [34,35]. PCT has been also applied for the thermography reliability assessment of composites [36]. Regarding metallic materials in Ref. [37], PCT has been used to detect corrosion in iron pipes.

These processing are not based on a single image. Instead, these use a sequence of thermograms captured during the stimulation process in order to consider the time and apply processing to visualize defects or characteristics that are not visible in a single thermographic image. Even, this processing phase can be supported by artificial intelligence techniques [16,17].

The aim of this work is to carry out a study to determine if it is possible to detect the impact and measure the impact energy from the backside of 3D printed polycarbonate parts with different infills since this would facilitate the detection/evaluation of impacts in those areas of vehicles, machines, protections and structures additively manufactured that are difficult to access or in those cases where the impact face is not accessible for visual inspection.

For this purpose, an experimental methodology on PC parts will be carried out with different energy-controlled impacts, using active thermography and based on PCT processing. The aim is to investigate the first time if it is possible to detect impacts from the back face using active thermography and, on the second time, if it is possible to quantify the defect caused by the impact with different printing parameters and to estimate the impact energy from the thermographic response.

2. Materials and methods

This section will describe the specimens tested, how they were made and impacted, and the explanation of the setup specifically designed to conduct the research.

2.1. Materials

The manufactured specimens were made from polycarbonate filament (PolyMax PC) with a diameter of 1.75 mm, whose printing temperature is between 250 and 270 °C, on a Prusa® Mk3s Printer. The mechanical properties of the filament were extracted from the datasheet provided by the manufacturer [38] and are shown in Table 1.

First, it is intended to evaluate the influence of the infill on the visualization and detection of the impact on the back face. For this purpose, 4 similar plates with dimensions of 70x70 × 4 mm have been designed and, thus, manufactured using 3D printing. These plates have been individually printed with a grid pattern with 25 %, 50 %, 80 % and 100 % infill respectively. For this analysis, they have been individually printed to prevent the higher energy impacts from altering the internal

Table 1

Mechanical properties of Printing Polycarbonate from the manufacturer datasheets.

Feature	Value	Testing Method
Young's Modulus (GPa)	2.048 ± 6 6	ASTM D638 (ISO 527, GB/T 1040)
Tensile Strength (MPa)	59.7 ± 1.8	ASTM D638 (ISO527, GB/T 1040)
Elongation at break (%)	12.24 ± 1.44	ASTM D638 (ISO527, GB/T 1040)
Impact resistance (Izod) (kJ/m ²)	25.1 ± 1.9	ASTM D256 (ISO 179, GB/T 1043)
Bending Strength (MPa)	94.1 ± 0.9	ASTM D790 (ISO 178, GB/T 9341)
Nozzle Temperature (°C)	250–270	
Bed Temperature (°C)	110	

structure of the lower energy impact zones.

Each plate was subjected to a 5 J impact by dropping a mass of 2.50 kg to a controlled and measured height of 0.2 m (Fig. 1). A standardized impact device, Proctor, according to ASTM D698, was used [39], using a small circular piece to better localize the impact by reducing its surface area.

Secondly, it is intended to correlate the thermographic information for different impact energies. For this purpose, a plate of larger dimensions than the previous ones, 150x150 × 6 mm, was printed with grid filling (25 % of density). On this specimen, a series of quadrants have been defined on which an impact has been applied with controlled energies of 5, 10, 15 and 20 J respectively, one in each quadrant (Fig. 1).

Once the specimens have been manufactured, data will be obtained using active thermography. For this purpose, the active thermography modality flash will be used [40–42]. The sequence of thermographic images is recorded with a high-frequency detector Thermosensorik CMT128. The lamps used (2 lamps of 600 W) have been operated at maximum power.

2.2. Methods

The research methodology has been designed to use flash thermography to firstly assess impact detection in specimens of different infill densities (Fig. 1a) and, secondly evaluate the effect of impact energy on detection (Fig. 1b) using a fixed infill.

In this way, the influence of two critical issues that affect the defect visualization will be evaluated from the thermographic signal generated: the influence of the infill and the influence of the impact energy (Fig. 1b). The diagram process followed for this work is shown in Fig. 2. In the first step, the specimens with different infills will be tested using flash thermography.

In order to choose the more adequate postprocessing, different processing methods have been used, such as PCT, Fourier Transform, TSR and PPT, being PCT is the one that shows the best defect determination in terms of qualitative detection. Since the results using the discarded methods offered no detective power, they are not reported.

Once the threshold infill at which the impact is detectable in the image is established, different specimens with the same infill will be impacted (according to ASTM D698) under different energy impact conditions (5, 10, 15 and 20 J). These specimens will be tested using flash thermography and the sequence for each specimen will be processed using PCT. Thus, the results will be statistically analyzed using parametric and non-parametric methods.

The thermography active modality (flash thermography) and the algorithm to process the thermographic sequences (PCT) will be explained below.

2.2.1. Flash thermography

Flash thermography is an active thermography modality. It requires the application of external energy, in this case using radiation in the

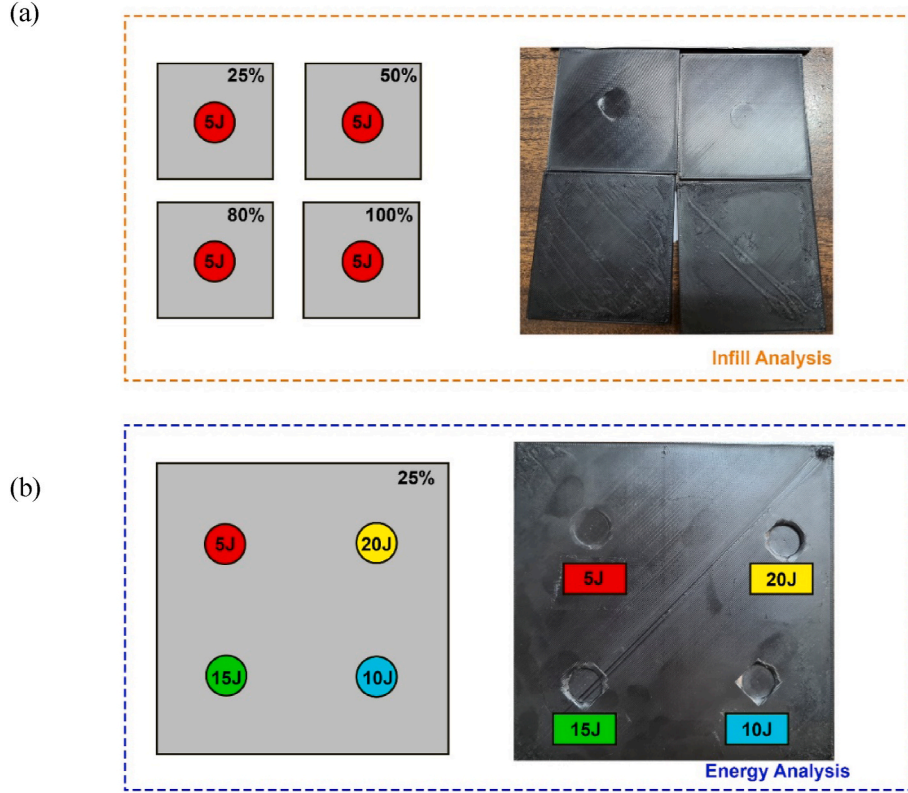


Fig. 1. Specimens impacted. The detection and assessment of the defect is carried out on the side opposite to the side that receives the impact. (a) Infill analysis with the configuration of the different infill percentages. (b) Energy analysis with the configuration of the different impact energy.

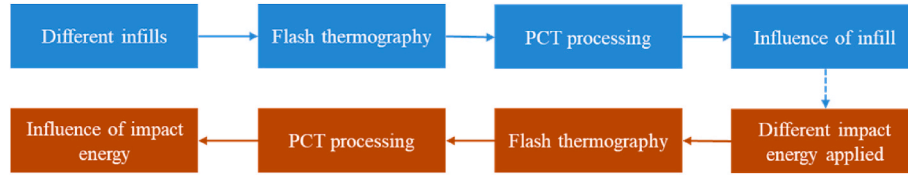


Fig. 2. Workflow applied to detect and evaluate impacts in polycarbonate parts produced by additive manufacturing. In the first experiment, specimens with different infills were tested. Based on the results, the infill was fixed and specimens tested with different impact energies were tested.

visible spectrum from lamps in reflection modality, which are activated for a very short period. The heating period is so short that, even if the camera used takes many frames, it cannot analyze sensitive variations (Fig. 3). Therefore, the period to be analyzed is the cooling. The test will be carried out by taking 4000 images synchronizing the flash firing with the start of data acquisition with an interval of 0.5 s. In this way, a cooling period of about 9.5 s is obtained, obtaining a total of 3800 images from the moment of application of the energy until its cooling. These features were established based on [43,44]. The images obtained have a resolution of 128x128 pixels. Please note that for all the experiments, the defect is located on the opposite side of the camera (Fig. 3).

From the sequence of thermographic images, a 3D matrix was generated as shown in Fig. 3 where each frame forms a 2D matrix with dimensions x , y in pixels and the depth is the number of images obtained.

2.2.2. Principal Component Thermography (PCT)

The data acquisition will collect different thermograms. Therefore, a 3D matrix will be generated in which the thermograms are ordered temporally, where the dimensions are x, y (N_u and N_v respectively) pixels and N_t images, as shown in Fig. 3. Each image has a total of 128x128 pixels and a total of 4000 frames have been obtained. The Principal

Component Thermography (PCT) algorithm [45] requires a transformation of this 3D matrix (the third dimension is the time) into a 2D matrix which can show the impact area. So, the scientific basis of the PCT technique consists of transforming the information collected in the time domain into a new domain where the temperature variation detected by the series of thermograms can be associated with defects within the internal structure.

For this purpose, each thermogram is placed in the form of a vector (eq. (1)):

$$x_t = (T_{1,1}, T_{1,2}, \dots, T_{u,v}) \quad (1)$$

Where x_t is each thermogram at instant t , and $T_{x,y}$ is the temperature of each pixel. After that, each thermogram is arranged in a row of a 3D matrix, known as raster-like matrix (eq. (2)):

$$\begin{pmatrix} T_{1,1} & \dots & T_{1,v} \\ \vdots & \ddots & \vdots \\ T_{u,1} & \dots & T_{u,v} \end{pmatrix} \begin{matrix} x_1 \rightarrow \text{First Thermogram} \\ \vdots \\ x_t \rightarrow \text{Last Thermogram} \end{matrix} \quad (2)$$

After obtaining this 2D matrix, the data must be normalized. If X is the matrix after normalization, covariance matrix is calculated (eq. (3)).

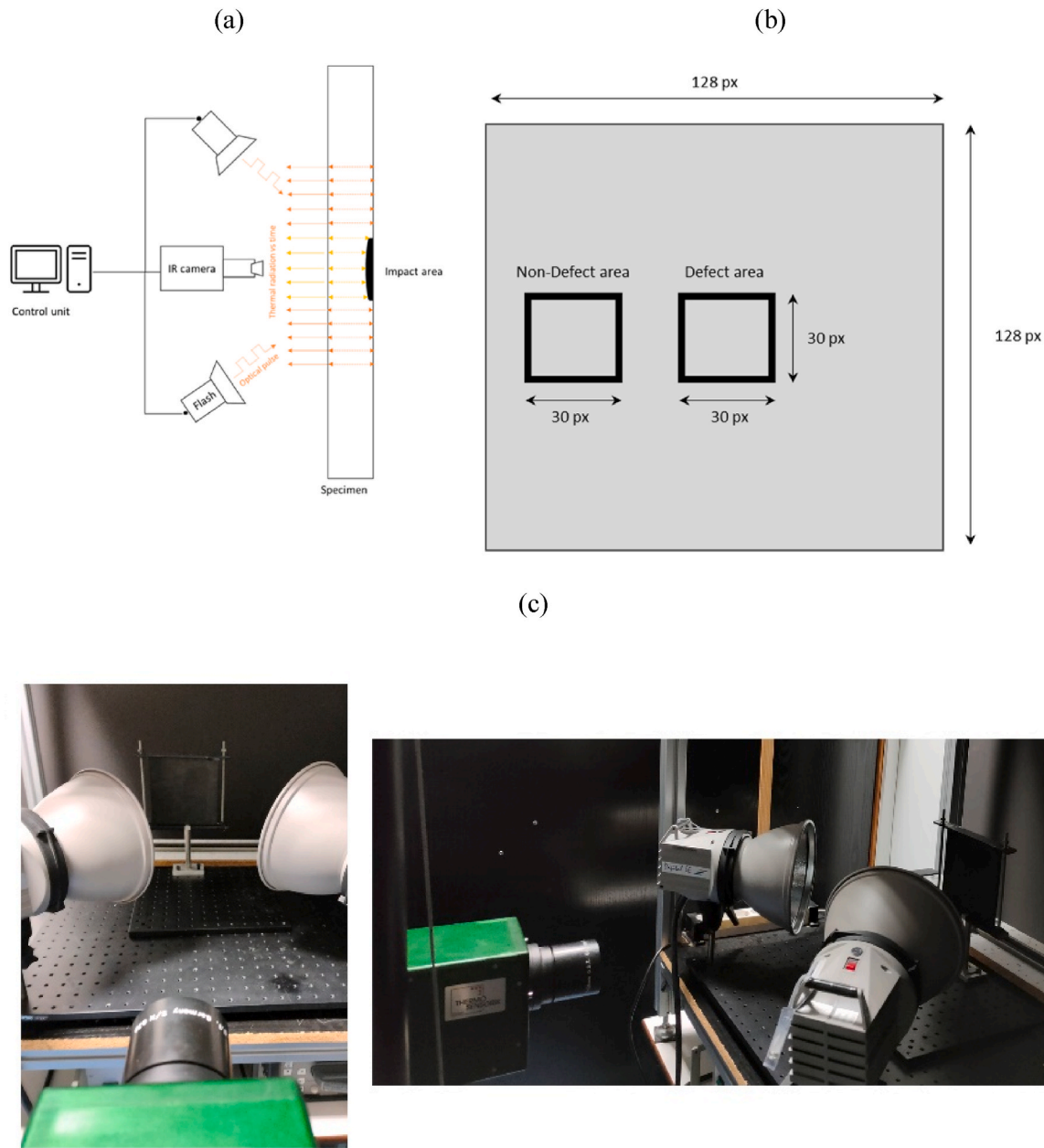


Fig. 3. Design of the flash thermography experiment. (a) Test scheme. (b) ROI used to evaluate the defect and non-defect area in the specimen. (c) Experimental test setup.

$$\text{cov} = \frac{1}{N_t} \mathbf{X} \mathbf{X}^T \quad (3)$$

The covariance matrix (cov) has dimension $N_{u,v} \times N_{u,v}$. The eigenvalues and eigenvectors are obtained from the diagonalization of the covariance matrix (eq. (4)):

$$\text{cov}_D = \mathbf{P}^{-1} \text{cov} \mathbf{P} \quad (4)$$

Where cov_D is the diagonalized matrix with eigenvalues on the diagonal and $\mathbf{P}$ is the matrix with eigenvectors placed in the columns. This gives a total of $N_u \times N_v$ eigenvalues.

Once these values have been obtained, the matrix cov_D is reordered, so that the eigenvalues are sorted in descending order. In the same way, the eigenvectors are reordered. The principal component is the largest eigenvector with the largest eigenvalue, obtaining, in most cases, that in the first 3 to 5 values have an excess of 95 % of the covariance. In this

way, the data can be directly compared with the principal components.

Depending on the size of each frame and the number of frames, the computational cost of this diagonalization algorithm can be very high. To alleviate this burden, Singular Value Decomposition (SVD) can be used, obtaining the same results, but with a lower computational cost.

First, the data are normalized to calculate the decomposed matrices $\mathbf{U}$, $\mathbf{S}$ and $\mathbf{V}$ to obtain the principal components (eq. (5)):

$$\mathbf{A} = \mathbf{U} \mathbf{S} \mathbf{V}^T \quad (5)$$

$\mathbf{A}$ is a matrix similar to the raster-like matrix presented above (eq. (2)). As can be seen, in this matrix the columns of $\mathbf{A}$ are temporal variations and the rows are spatial variations.

The columns of $\mathbf{U}$ represent a set of orthogonal statistical nodes known as Empirical Orthogonal Functions (EOFs) (Fig. 4).

Matrix $\mathbf{S}$ is the diagonal matrix representing the singular values of $\mathbf{A}$. These singular values are the eigenvalues corresponding to the eigen-

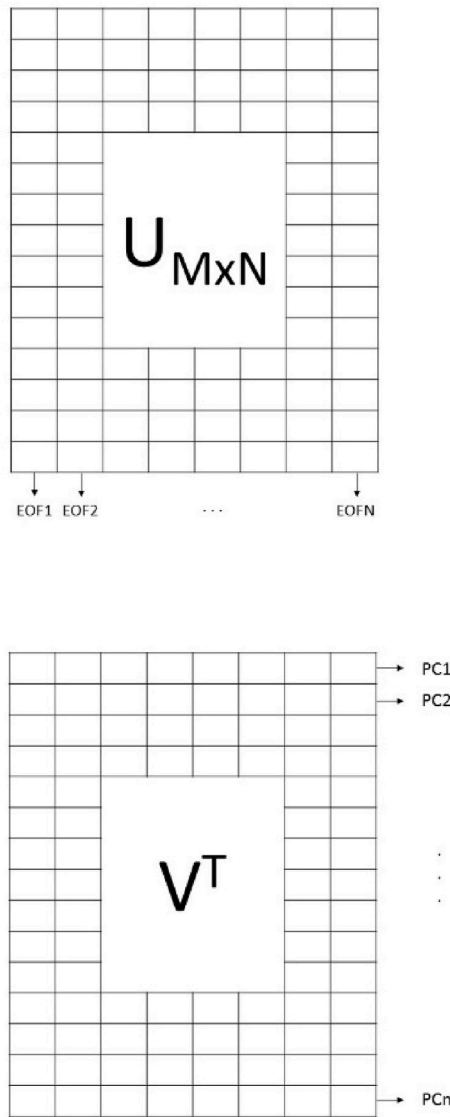


Fig. 4. U and V^T matrix configuration.

vectors, represented in matrix V . In this matrix V the principal components or eigenvectors of the data set are represented, where in each column the PC of each thermogram is represented. To provide spatial and temporal coherence, this matrix must be transposed so that these components are represented in the rows (Fig. 5).

In the matrix U , EOF_1 corresponds to the Most Characteristic Data Variability, EOF_2 is the second most Characteristic Data Variability. The first representation is characterized by a spatial Uniform Field with exponential decay where there is no variation with the RAW image. So, this first representation does not provide significant information. However, from the second one, it can be correlated with the signal contrast, where the defect can be determined. In this way, EOF_1 of PCT gives a similar signal to the original thermogram, but from there on the defect can be observed, since the contrast is compared.

3. Experimental results

In the first step, the flaw detection capability with different infills has been analyzed (Fig. 1a). Once this subject has been checked and studied, the detection capability of different impact energies concerning the same infill has been performed (Fig. 1b).

5J Impacts

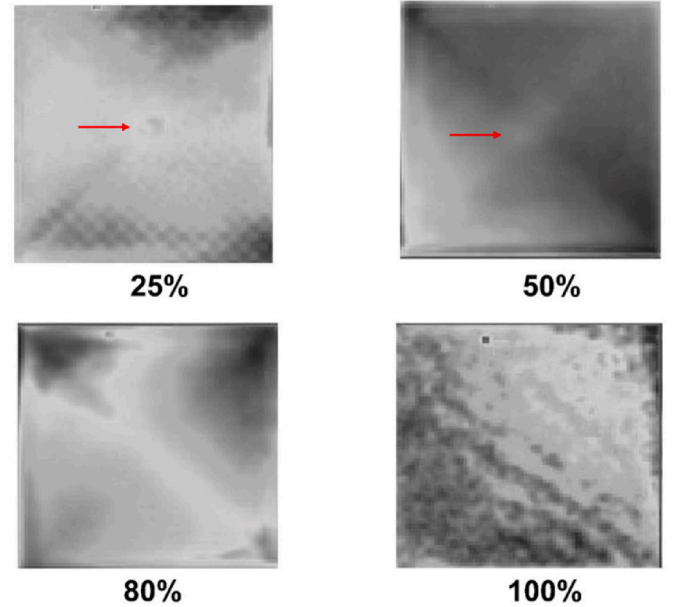


Fig. 5. Defect visualization in specimens on PCT image generated from each sequence (% of infill density).

3.1. Impact qualitative detection

A study was carried out on the specimens with different fillings by applying the PCT in order to be able to detect the impact. As already explained, 4000 images were taken, with a frequency of 400 images per second. In this way, a cooling period of about 9.5 s was obtained, giving a total of 3800 images. The results can be seen in Fig. 5. As the reader can see, the infill pattern is easily detected for 25 % of infill density. In the rest of the images, this can also be detected but more difficult to.

As can be seen, in the specimens (Fig. 5) with an infill density of 25 % and 50 %, the defect can be observed when PCT is applied. However, the visualization for the second (50 %) is more difficult. For all other infill densities (80 % and 100 %), the visualization of the defect was not possible. For this reason, the specimens to be studied with different impact energies were manufactured with a 25 % filler.

3.2. Impact characterization

Once the influence of infill has been studied (Fig. 2), in this section, different specimens tested with different impacts were evaluated using flash thermography to analyze the existence of correlation or characteristic attributes between the results obtained using PCT post-processing. This issue was addressed from a qualitative point of view, but also quantitatively. In the latter case, the aim is to avoid gross errors in the interpretation of the thermographic images due to false positives or the variation of the visualization levels.

In this manner, impacts in different quadrants of 5, 10, 15 and 20 J were applied on the same specimen. Based on the results reported in the previous section, the infill always remained at 25 % with a grid structure. Once the data were obtained, the PCT algorithm was applied to obtain the data from contrast. In the following subsections, both qualitative and quantitative results will be described.

3.2.1. Qualitative analysis

The thermographic images of the defect area (obtained after post-processing with PCT the thermograms taken from the back face) are shown below (Fig. 6). As the reader can observe, the impact zone can be clearly detected on the specimen impacted with 10 J. The reader also

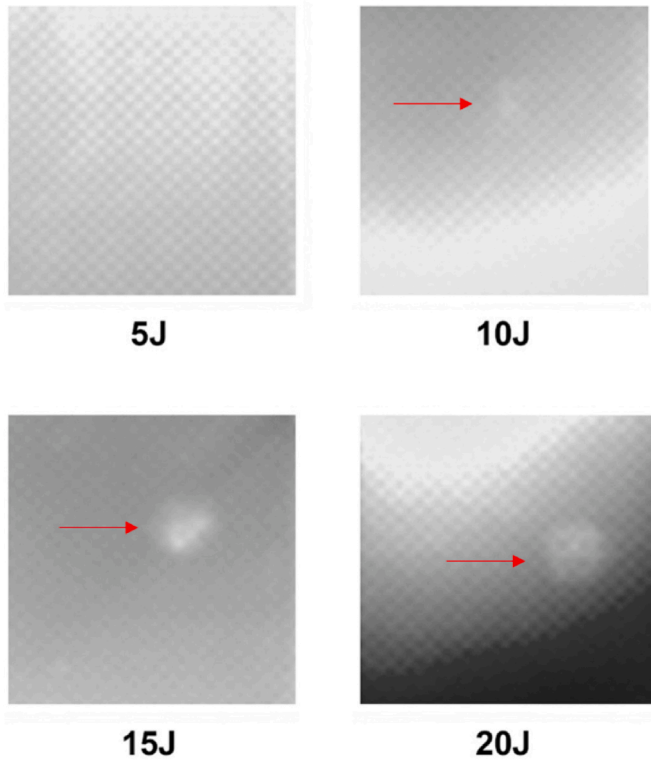


Fig. 6. Defect visualization in specimens based on PCT image generated from each sequence (for different impact energies).

can observe that, in this case, the internal infill shown on the image was not an obstacle to the detection of the impact. Please note that on the back face, it is not possible to detect any impact by the naked eye.

3.2.2. Quantitative analysis

To obtain a more detailed interpretation of the results and to avoid possible errors in the image visualization, a quantitative analysis was applied. This was based on parametric and non-parametric statistics methods.

Once data recorded for each pixel within the defect area were extracted from each one of the four specimens, 900 pixels levels were extracted for each specimen (a Region of Interest (ROI) of 300x300 pixels in the defect area as shown in Fig. 3).

Thus, the descriptive analysis was implemented and outlined in Table 2. Apparently, there were differences both in the centering of the data and their variability, so the statistical distribution of the data would not necessarily have to follow a normal distribution. To evaluate this issue, two normality tests were previously applied (Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-S)). These tests showed that the image response in the defect area for impacts of 5 J, 10 J, and 15 J follows a close to normal distribution (Table 2). However, for an impact of 20 J, the normality hypothesis was not verified and several outliers that affect the visualization results were detected (Fig. 7). For this reason, robust statistics were also calculated from data together with

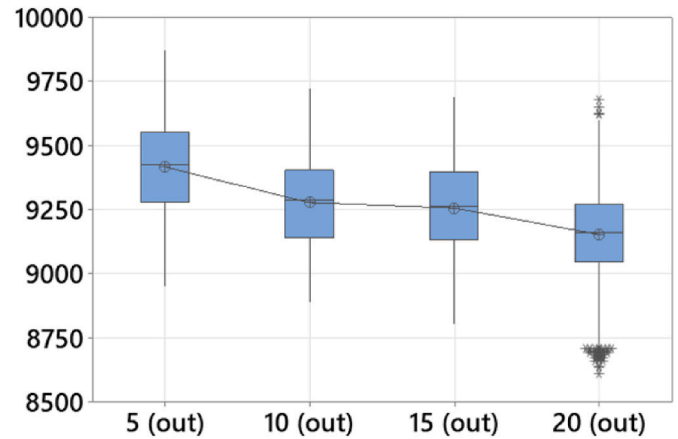


Fig. 7. Boxplot for the pixel levels obtained from each specimen within defect area. X-edge represent the impact energy (J) and Y-edge the values recorded within the ROI. Several outliers were detected for 30 J.

Gaussian statistics (Table 2).

Additionally, Tukey test (parametric) and Mann-Whitney test (non-parametric) were also used to evaluate if there were statistically significant differences between the values within the defect area (rest of pixels) with respect those within the non-defect area for each one of the specimens (Table 3).

Thus, robust to outliers' parametric tests were conducted to evaluate if there were significant statistical differences between the pixel information within each defect region. Robust Anova based on Welch test was applied (Table 3). This test showed that the means of the responses were significantly different between all the samples ($F(3, 1968) = 14113.6$, $p\text{-value} = 00.000$).

Since the data for 20 J were not close to normality and highly affected by outliers, in order to check the results from parametric tests using non-parametric tests, Kruskal-Wallis was also applied. Please note that the median test is powerful for the great sample sizes since it is less sensitive to the outliers. The results showed that the medians of the responses were significantly different (Table 4). So, the P-Value of Kruskal Wallis test was 3322,53 and it implies a P-Value of 0.00. For this reason, statistically significant differences between the impact areas also were detected.

3.2.3. Prediction of impact energy

On the one hand, parametric and non-parametric tests showed that the results of the defect area were significantly different from those located in the non-defect area. It implies the existence of quantitative differences in the images between the impacted and non-impacted area and these differences can be captured using the thermographic monitoring of the back face. On the other hand, the tests also showed the pixel values within the four defect areas were significantly different (Fig. 7). Furthermore, a significative linear relationship ($R\text{-Square} = 0.979$) was detected in the median values (robust to outliers) of each specimen (Fig. 8). For this reason, it is possible to conclude that the thermographic response using the PCT processing a priori allows for the estimation of the impact energy of the material on the back face.

Table 2

Descriptive analysis using Gaussian and robust statistics for the pixels that fall in the defect region.

Impact	Gaussian			Robust				Skewness	Kurtosis	K-S	A-D
	Mean	95 % CI	StDev	Median	95 % CI	MAD	IQR				
5	9575.6	9412.28; 9419.42	49.4	9578.76	9575.14; 9583.56	40.25	70.9	-0.03	-0.35	<0.01	<0.05
10	9376.2	9273.16; 9280.30	48.0	9373.24	9367.66; 9378.71	39.81	73.8	0.22	-0.43	<0.01	<0.05
15	9242.3	9251.88; 9259.02	61.0	9246.98	9243.29; 9250.11	49.15	85.7	-0.32	-0.44	<0.01	<0.05
20	8967.9	9149.42; 9156.56	79.8	8965.00	8959; 8971	62.63	104.0	0.18	0.26	0.045	0.136 ^a

^a $p\text{-value} > 0.05$.

Table 3

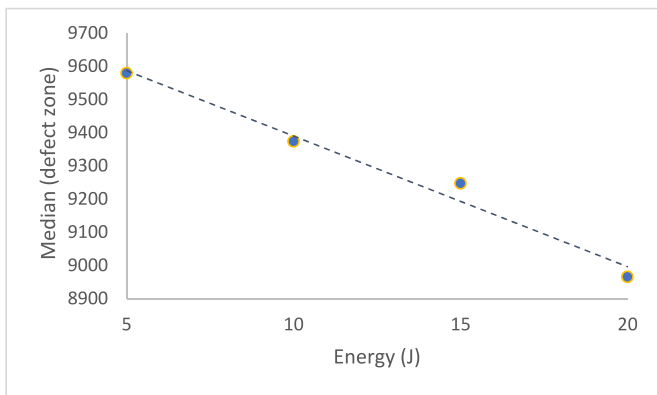
Comparison between the pixel values in defect and non-defect area.

Impact energy	Tukey			Mann-Whitney			
	Difference of means	T-Value	P-Value	Median (defect)	Median (non-defect)	W-value	P-value
5	−159.71	−26.25	0.000	9578.76	9423.04	7189419	0.000
10	−99.48	−16.60	0.000	9373.24	9286.62	6404378	0.000
15	13.18	2.20	0.000	9246.98	9263.98	4377436	0.000
20	185.05	30.88	0.000	8965.00	9161.21	12823570	0.000

Table 4

Z values from Kruskal-Wallis test.

Impact (J)	N	Median	Mean Rank	Z-Value
5	900	9578,76	3149,1	44,95
10	900	9373,24	2222,5	14,06
15	900	9246,98	1375,7	−14,16
20	900	8965,00	454,8	−44,85
Overall	3600		1800,5	


Fig. 8. Correlation between the median of the processed (using PCT) image and the impact energy (R-Square = 0.979).

4. Discussion

The results demonstrate that it is possible to detect impacts from the back face of the specimens using active thermography with a PCT postprocessing. A high-frequency IR camera with a resolution of 128 x 128 pixel was used for this research and the resolution was adequate for the proposed detection purpose. However, a higher resolution could provide more detail in the transition zone between defect and non-defect. On the other hand, signal noise has not been a problem for image processing, but in the case of the highest energy impact (20 J), different outliers have been detected in the statistical analysis of the affected area, as well as a different result in the normality tests (AD). This may be due to the inhomogeneous heat distribution and that, in this case (maximum applied energy) the no-defect zone was more affected by the high impact energy. In order to statistically work with this data, also non-parametric statistic methods have been used to analyze if there exist differences between defect and non-defect areas, and also between the different impacted areas (with different applied impacts energies).

5. Conclusions

Flash thermography was used to evaluate the back face of additively manufactured polycarbonate specimens. The specimens were impacted with different impact energies (using standardized testing). The objective was to enable a method for quantitative and qualitative evaluation of the impact from a non-impact face.

The thermographic data have been processed using different

techniques (PCT, Fourier Transform, TSR, and PPT). This led to the conclusion that the best technique for qualitative defect detection was PCT.

First, different specimens with different levels of filler were tested. At controlled energy, the impact was detected for the 25 % and 50 % infill specimens. In this way, the influence of the infill in the visualization of the impact was demonstrated and evaluated. As expected, with a higher infill density, lower the chance of detection. This was expected due to the higher impact resistance for high density infills. The infill is also detected in the image but is not an obstacle to the detection of the impacted area.

Subsequently, the infill was set at 25 % and the impact energy was varied (5–20 J) to assess both quantitative and qualitative detection on the processed thermographic image. Quantitative results were obtained using parametric and non-parametric statistical methods. Considering the quantitative analysis, the parametric and non-parametric statistical tests performed showed for all cases significant differences in the distribution of the defect and non-defect zone levels respectively. Non-parametric tests were applied to rule out false conclusions mainly due to outliers and inhomogeneity in heat distribution. Also, statistically significant differences between the provided levels value of the different specimens impacted with different impact energy. In this case, a high correlation (R-Square = 0.979) was obtained between medians of the values and impact energy demonstrating that it is possible to estimate the impact wear from the back face (when the effects of the impact are not visually visible). This subject opens the door to new methods for impact energy or deterioration prediction in manufactured-by-AM parts of PC. The qualitative results allowed to distinguish the impact zone adequately. This is compatible with the literature on defect detection in polymeric materials and composites [4,45].

CRediT authorship contribution statement

Manuel Rodríguez-Martin: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Javier Pisonero:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **Diego González-Aguilera:** Writing – original draft, Supervision, Resources, Project administration, Funding acquisition. **Francisco Javier Madruga:** Validation, Software, Resources, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Manuel reports financial support was provided by Spain Ministry of Science and Innovation. Manuel reports financial support was provided by European Commission. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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References

- [1] Mullaoglu F, Usta F, Türkmen HS, Kazancı Z, Balkan D, Akay E. Deformation behavior of the polycarbonate plates subjected to impact loading. *Procedia Eng* 2016;167:143–50.
- [2] Allen G, Morley D, Williams T. The impact strength of polycarbonate. *J Mater Sci* 1973;8:1449–52.
- [3] Hu W, Wang Y, Yu J, Yen C-F, Bobaru F. Impact damage on a thin glass plate with a thin polycarbonate backing. *Int J Impact Eng* 2013;62:152–65.
- [4] Al-Lafi W, Jin J, Song M. Mechanical response of polycarbonate nanocomposites to high velocity impact. *Eur Polym J* 2016;85:354–62.
- [5] Torres JP, Frontini PM. Mechanics of polycarbonate in biaxial impact loading. *Int J Solid Struct* 2016;85:125–33.
- [6] Esfahlani SS. Ballistic performance of Polycarbonate and Polymethyl methacrylate under normal and inclined dynamic impacts. *Heliyon* 2021;7(4):e06856.
- [7] Shah QH. Impact resistance of a rectangular polycarbonate armor plate subjected to single and multiple impacts. *Int J Impact Eng* 2009;36(9):1128–35.
- [8] Vidakis N, Petousis M, Kechagias J. A comprehensive investigation of the 3D printing parameters' effects on the mechanical response of polycarbonate in fused filament fabrication. *Progress in Additive Manufacturing* 2022;7(4):713–22.
- [9] Cantrell JT, et al. Experimental characterization of the mechanical properties of 3D-printed ABS and polycarbonate parts. *Rapid Prototyp J* 2017;23(4):811–24.
- [10] Blanco I, Cicala G, Ognibene G, Rapisarda M, Recca A. Thermal properties of polyetherimide/polycarbonate blends for advanced applications. *Polym Degrad Stab* 2018;154:234–8.
- [11] Chen L, Zhang M, Li D, Li Y. Infrared thermographic evaluation of thermal release phenomena in polycarbonate during plastic deformation. *Advanced Industrial Engineering Polymer Research* 2023;6(1):39–48.
- [12] Vieira R, Gonz  les G, Freire J. Thermography applied to the study of fatigue crack propagation in polycarbonate. *Exp Mech* 2018;58:269–82.
- [13] Bian Y, et al. High-speed penetration dynamics of polycarbonate. *Int J Mech Sci* 2022;223:107250.
- [14] Metz C, Franz P, Fischer C, Wachtendorf V, Maierhofer C. Active thermography for quality assurance of 3D-printed polymer structures. *Quantitative InfraRed Thermography Journal* 2021;18(1):50–71.
- [15] Saeed N, Abdulrahman Y, Amer S, Omar MA. Experimentally validated defect depth estimation using artificial neural network in pulsed thermography. *Infrared Phys Technol* 2019;98:192–200.
- [16] Rodr  guez-Mart  n M, et al. Step heating thermography supported by machine learning and simulation for internal defect size measurement in additive manufacturing. *Measurement* 2022;205:112140.
- [17] Rodr  guez-Mart  n M, et al. Predictive models for the characterization of internal defects in additive materials from active thermography sequences supported by machine learning methods. *Sensors* 2020;20(14):3982.
- [18] Chen H, Zhang Z, Yin W, Zhao C, Wang F, Li Y. A study on depth classification of defects by machine learning based on hyper-parameter search. *Measurement* 2022; 189:110660.
- [19] Zhang X, Saniie J, Heifetz A. Spatial temporal denoised thermal source separation in images of compact pulsed thermography system for qualification of additively manufactured metals. In: 2021 IEEE international conference on electro information technology (EIT). IEEE; 2021. p. 209–14.
- [20] Maldague X. Theory and practice of infrared technology for nondestructive testing. 2001.
- [21] Zhou X, et al. Life cycle assessment of polycarbonate production: proposed optimization toward sustainability. *Resour Conserv Recycl* 2023;189:106765.
- [22] Badghaish AA, Fleming DC. Non-destructive inspection of composites using step heating thermography. *J Compos Mater* 2008;42(13):1337–57.
- [23] Breitenstein O, Langenkamp M. Lock-in thermography. *Basics Use for Functional Diagnostics of Electronics Components* 2003.
- [24] Wu D, Busse G. Lock-in thermography for nondestructive evaluation of materials. *Rev Gen Therm* 1998;37(8):693–703.
- [25] Shepard SM. Flash thermography of aerospace composites. *IV Conferencia Panamericana de END Buenos Aires* 2007;7:26. Citeseer.
- [26] Cerniglia D, Montinaro N. Defect detection in additively manufactured components: laser ultrasound and laser thermography comparison. *Procedia Struct Integr* 2018;8:154–62.
- [27] Wang H, Hsieh S-J, Peng B, Zhou X. Non-metallic coating thickness prediction using artificial neural network and support vector machine with time resolved thermography. *Infrared Phys Technol* 2016;77:316–24.
- [28] Balageas D, Chapuis B, Deban G, Passilly F. Improvement of the detection of defects by pulse thermography thanks to the TSR approach in the case of a smart composite repair patch. *Quantitative InfraRed Thermography Journal* 2010;7(2): 167–87.
- [29] Oswald-Tranta B. Time and frequency behaviour in TSR and PPT evaluation for flash thermography. *Quantitative InfraRed Thermography Journal* 2017;14(2): 164–84.
- [30] Madruga FJ, Ibarra-Castanedo C, Conde OM, L  pez-Higuera JM, Maldague X. Infrared thermography processing based on higher-order statistics. *NDT E Int* 2010; 43(8):661–6.
- [31] Ben  tez HD, Ibarra-Castanedo C, Bendada A, Maldague X, Loaiza H, Caicedo E. Definition of a new thermal contrast and pulse correction for defect quantification in pulsed thermography. *Infrared Phys Technol* 2008;51(3):160–7.
- [32] Yousefi B, Sfarra S, Sarasini F, Castanedo CI, Maldague XP. Low-rank sparse principal component thermography (sparse-PCT): comparative assessment on detection of subsurface defects. *Infrared Phys Technol* 2019;98:278–84.
- [33] Ibarra-Castanedo C, Gonzalez D, Klein M, Pilla M, Vallerand S, Maldague X. Infrared image processing and data analysis. *Infrared Phys Technol* 2004;46(1–2): 75–83.
- [34] Marinetti S, et al. Statistical analysis of IR thermographic sequences by PCA. *Infrared Phys Technol* 2004;46(1–2):85–91.
- [35] Fernandes H, Zhang H, Ibarra-Castanedo C, Maldague X. Fiber orientation assessment on randomly-oriented strand composites by means of infrared thermography. *Compos Sci Technol* 2015;121:25–33.
- [36] Duan Y, Servais P, Genest M, Ibarra-Castanedo C, X. P. J. o. m. s. Maldague, and technology. ThermoPoD: a reliability study on active infrared thermography for the inspection of composite materials. *J Mech Sci Technol* 2012;26:1985–91.
- [37] Liu Z, Genest M, Krysz D. Processing thermography images for pitting corrosion quantification on small diameter ductile iron pipe. *NDT E Int* 2012;47:105–15.
- [38] Polymaker. PolyMax PC-Fr DataSheet. Available: https://3d.nice-cdn.com/upload/file/Polymaker-PC-Max_TDS-v1.0.pdf.
- [39] D698-12 standard test methods for laboratory compaction. 2021.
- [40] Azizinasab B, Hasanzadeh RP, Hedayatrasa S, Kersemans M. Defect detection and depth estimation in CFRP through phase of transient response of flash thermography 2021;18(4):2364–73.
- [41] Wallace NJ, Crane NB, Jones MRJN, International E. Defect measurement limits using flash thermography with application to additive manufacturing, 128; 2022, 102615.
- [42] Balageas D. Thickness or diffusivity measurements from front-face flash experiments using the TSR (thermographic signal reconstruction) approach. In: *Proceedings of 10th quantitative InfraRed thermography conference*, paper qirt2010-011 qu  bec (Canada); 2010.
- [43] Madruga FJ, Ibarra-Castanedo C, Conde OM, L  pez-Higuera JM, Maldague X. Infrared thermography processing based on higher-order statistics. *NDT E Int* 2010; 43(8):661–6.
- [44] Madruga F, Ibarra-Castanedo C, Conde O, Lopez-Higuera J, Maldague X. Automatic data processing based on the skewness statistic parameter for subsurface defect detection by active infrared thermography. *Proc. QIRT* 2008;9:6. Citeseer.
- [45] Rajic N. Principal component thermography for flaw contrast enhancement and flaw depth characterisation in composite structures. *Compos Struct* 2002;58(4): 521–8.

CAPÍTULO IV

APLICACIÓN EN INDUSTRIA DE LAS METODOLOGÍAS ESTUDIADAS

4.1 Artículo 5. Smartvessel: A New Extinguisher Prototype Based on New Materials and IoT Sensors.

En este capítulo se pretende construir un prototipo optimizado de recipiente a presión fabricado a partir de composite por la técnica de FW. Gracias a los estudios realizados, se ha diseñado un prototipo con los parámetros optimizados a partir de modelos numéricos con un enfoque estocástico. En este trabajo se realiza una comparativa de prestaciones entre el prototipo presentado y productos similares instaurados en la industria, tales como los recipientes metálicos o los recipientes a partir de fibra de Aramida.

De cara a aumentar el número de aplicaciones del producto, se presenta también un prototipo de medida y control de recipientes a presión de CO₂ susceptible a ser utilizado en entornos complejos navales (ej. grandes embarcaciones). Este implementa una serie de sensores conectados a un microcontrolador dotado de un sistema de comunicaciones que es capaz de enviar una señal y poder obtener su medida instantánea en cualquier parte de manera remota.

Todo esto se realiza gracias a la implementación de tecnología IoT. A partir de un estudio de protocolos, se dedujo que para este tipo de aplicaciones el mejor protocolo es el LoRaWAN. Hay tres aspectos principales que definen el tipo de protocolo que mejor se adapta a la aplicación. El tamaño de dato a enviar, el consumo de batería y el alcance, son estos parámetros. Debido a su uso en embarcaciones, es crucial que estos sensores tengan un bajo consumo de batería para soportar largas travesías y puedan instalarse en ubicaciones poco accesibles. Además, es fundamental que el rango de envío de datos sea amplio, ya que las embarcaciones suelen tener zonas de difícil acceso y, con frecuencia, una considerable distancia entre la zona de control y otras áreas del barco. Sin embargo, el tamaño de los datos enviados no necesita ser grande, ya que basta con transmitir un valor que refleje el peso del dispositivo, lo cual requiere únicamente una variable numérica de 8 bits. Colocando antenas en la embarcación, sería posible hacer un punto de conexión IoT móvil, donde los sensores manden la señal a un terminal y este envíe la información a un servidor. Por estas razones el protocolo que mejor se adapta es LoRaWAN. Todo lo explicado se probó en un entorno real, en una embarcación de tamaño medio. Para ello se colocó una antena en el puente de control y se fue testeando la calidad de la señal enviada desde diferentes puntos de la embarcación, tanto de manera interior como exterior.

Además, se presenta un diseño de Dashboard que facilite la lectura e interpretación de los datos, además de servir como base para trabajos futuros de cara a que, a partir de lecturas anteriores, un sistema hecho a partir de inteligencia artificial sea capaz de predecir posibles incendios o fallos de los dispositivos, facilitando el mantenimiento y la seguridad de la embarcación. Este Dashboard representa la medida enviada por los sensores, tanto de peso como de presión. En el caso de los extintores de polvo y agua, el agente propulsor es N₂ en pequeñas proporciones, de manera que la presión es casi constante, sin verse demasiado afectada por las condiciones ambientales. De esta manera, en el Dashboard se ha programado un gradiente de colores que facilite la interpretación de esta presión a partir de los rangos de funcionamiento, de manera que se envíe un aviso o advertencia en caso de que el rango no sea el correcto. En el caso de los extintores de CO₂, el gas es susceptible a cambios bruscos de presión y, al operar bajo presión de vapor, las fugas no pueden detectarse debido a que la presión se mantiene constante. Por esta razón, este tipo de sensor no resulta adecuado, optándose en su lugar por medir el peso total del dispositivo, siguiendo el protocolo de aviso previamente descrito. Todo ello, sumado a sensores de temperatura y humedad, conformarían una red de datos que permita anticipar o avisar de diferentes problemáticas no solo de los dispositivos, sino también del entorno y de la embarcación.

Por lo tanto, las principales contribuciones a este nuevo prototipo son: (i) Innovación en el uso de nuevos materiales que consigan un producto ligero, pero más resistente, tanto mecánicamente como frente a la corrosión en ambientes agresivos. Para ello, se ha realizado una comparativa directa entre las características de recipientes fabricados en acero, fibra de aramida y fibra de carbono. (ii) Integración orgánica de sensores que permite monitorizar el estado actual y habilitar la posibilidad de mantenimientos predictivos.

Article

Smartvessel: A New Extinguisher Prototype Based on New Materials and IoT Sensors

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Abstract: Smartvessel is an innovative fire extinguisher prototype supported by new materials and IoT technology that seeks to improve the functionality and efficiency of conventional fire extinguishers. Storage containers for gases and liquids are essential for industrial activity as they enable higher energy density. The main contributions of this new prototype are (i) innovation in the use of new materials that provide lighter and more resistant extinguishers, both mechanically and against corrosion in aggressive environments. For this purpose, these characteristics are directly compared in vessels made of steel, aramid fiber and carbon fiber with the filament winding technique. (ii) The integration of sensors that allow its monitoring and provide the possibility of predictive maintenance. The prototype is tested and validated on a ship, where accessibility is complicated and critical. For this purpose, different data transmission parameters are defined, verifying that no data are lost. Finally, a noise study of these measurements is carried out to verify the quality of each data. Acceptable coverage values are achieved with very low read noise, on average less than 1%, and a weight reduction of 30% is obtained.

Keywords: extinguishers; new materials; CFRP; AFRP; additive manufacturing; IoT sensors



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1. Introduction

The storage of liquids and gases in pressure vessels is an important part of industrial activity today. Storing at high pressures, a higher energy density is achieved and, therefore, better energy–volume ratios. This has an impact on industrial performance: (1) greater autonomy of the user devices; (2) the optimization of transport and logistics; (3) increased efficiency in energy displacement; and (4) a reduced carbon footprint and lower environmental impact.

However, current standard extinguisher solutions have several drawbacks [1]: (1) they are heavy to handle; (2) they are prone to corrosion; and (3) they have an inefficient volume-to-weight ratio, decreasing their economic and environmental viability.

Typically, extinguishers are manufactured using alloy steel due to the knowledge in terms of properties and manufacturing techniques. This results in very heavy containers, where approximately 30% of a useful extinguisher is the weight of the empty bottle. Therefore, new manufacturing techniques are being studied, as well as different types of materials with a better strength-to-weight ratio. Additive manufacturing has found here an opportunity with the filament winding technique with composite materials [2–4], such as carbon-fiber-reinforced polymers (CFRPs), glass-fiber-reinforced polymers (GFRPs) or aramid-fiber-reinforced polymers (AFRPs), which have high strength and a much lower weight than bottles made of steel alloys [5].

Another problem to which conventional extinguishers are exposed is corrosion. Many of these pieces of equipment are located outdoors, in areas with high humidity, and in chemical environments that directly attack the steel surface, even the stainless steel [6].

In this sense, composite materials have demonstrated a great capacity to resist corrosion, even in very aggressive environments such as marine areas [7,8]. In addition, both for their mechanical behavior and chemical resistance, parameters can be varied in manufacturing to find an optimum design for each environment.

On the other hand, smart maintenance approaches, called Maintenance 4.0 [9], are being developed in the context of the Industry 4.0 paradigm and are fed by the most advanced tools in the field of data processing and storage, adding operational information concerning the context and large data sets that can be processed with techniques of the Internet of Things (IoT), artificial intelligence and big data. However, this predictive and intelligent maintenance approach is still pending in the fire extinguisher industry [10].

Regardless of the material, in fire extinguishers, it is mandatory to check through revisions of all their mechanical elements and the state of charge of the extinguisher to ensure proper service conditions. These revisions, which are necessary for the extinguisher to fulfill its mission in case of fire or explosion, are carried out by a specialized operator and performed periodically. This time-consuming task could be avoided with an intelligent real-time monitoring system, which would also contribute to economic savings [11], especially in hazardous and/or inaccessible areas (e.g., wind turbine towers, ships, etc.), where the inspection costs are very high. Although there are different initiatives for monitoring the status of fire extinguishers [11–13], the approach developed by the authors is only focused on detecting pressure changes as a parameter to be monitored and always under conventional extinguishers. Furthermore, they use wireless communication networks, which are limited due to coverage in complex scenarios (e.g., ships). These communication problems can be solved with low-power wide-area networks (LPWANs), which are characterized by achieving long ranges in communication with low energy consumption and low data transfer speed. Therefore, it is not a technology designed to transmit audio or video signals, but it is ideal for providing connectivity to devices in remote locations, powered by a battery and with a low volume of data transmissions [14]. Within LPWAN networks, there are different types of technologies (e.g., LTE-M, LoRaWAN, Sigfox and NB-IoT) [15], which have already been tested in different industrial applications [16–19]. While technologies that use licensed frequency bands, such as NB-IoT or LTE-M, excel in transmission time and roughness, technologies that use unlicensed frequency bands (i.e., ISM bands), such as Sigfox or LoRaWAN, stand out for network capacity, lower cost and device lifetime [20]. Specifically, LoRaWAN networks are configured with a star topology, where a gateway receives messages from different devices or nodes. Transfer rates range from 10 to 100 Kbps, transmitted data frames are tens of bytes and the transmission cycle is limited to prevent saturating ISM unlicensed frequency bands [21].

In this work, different extinguishers manufactured with new materials and methods are tested and analyzed. In addition, we design and integrate different IoT sensors so intelligent monitoring can be applied. As a result, a final prototype is designed and validated for providing the automatic and remote maintenance of the extinguisher, making the inspection tasks more efficient, saving costs and contributing to the optimization of logistics, transport and sustainability.

Finally, a study of the characteristics and behaviors of the different new materials is carried out, which is later evaluated on a pressure bottle with similar characteristics in terms of operation. Furthermore, a study and development of the sensor system that best suits this case study and its possibility of being embedded into the system is performed.

In this work, we seek to provide an answer to the ability to provide an IoT structure in complex environments, such as a large vessel. This paper is structured as follows: After this Introduction, from which the main contribution of the manuscript is motivated, Section 2 describes, in detail, the new materials and methods developed; Section 3 outlines and discusses the main results achieved. The final section is devoted to highlighting the main conclusions and future perspectives of the approach.

2. Materials and Methods

2.1. New Materials for Fire Extinguishers

As was mentioned, fire extinguishers are mostly manufactured from steel alloys. For this purpose, steel sheets with a thickness of 1 to 1.5 mm were conformed. The basic shape of the vessel was achieved by joining the two halves of the vessel by shaping, as shown in Figure 1. The two halves were joined by MIG/MAG wire welding, and the upper thread was prepared for the drive valve. The vessel was finally painted with RAL 3000 epoxy paint with a minimum thickness of 110 microns to prevent corrosion. In general, the weight of the bottle is about one-third of the total mass, with the rest being the extinguishing agent.

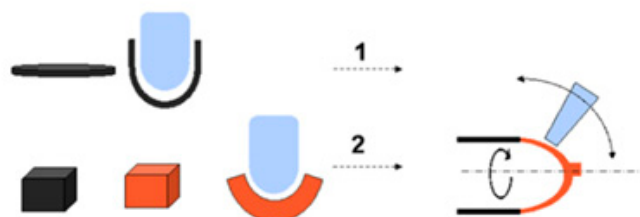


Figure 1. Manufacturing process of the steel vessel. (1) Halves manufacturing by cold drawing. (2) End caps manufactured by repulse technic.

To make it more resistant and lighter, equipment was manufactured with new composite materials, generally based on epoxy matrices, and with the filament winding manufacturing technique. This technique consists of winding on a mandrel of pre-impregnated fibers of this epoxy matrix. The results are products called composite overwrapped pressure vessels (COPVs). These vessels are classified into different types depending on the type of material and the inner vessel, called Liner. The different types of COPV are shown in Table 1.

Table 1. Types of COPV.

Type	Liner Material	Fiber Material	Kg/L
Type I	Aluminum	Aluminum	1.40
Type II	Aluminum	Glass fiber	0.98
Type III	Aluminum	Carbon fiber	0.74
Type IV	Polymer	Carbon/hybrid fiber	0.45
Type V	-	Carbon/hybrid fiber	0.32

Costs differ depending on the type of COPV used, with type V being the most expensive because more composite is needed for shaping and interior finishing. In all cases, the fibers support the full structural capacity of the vessel.

Depending on the type of application, more or less mechanical strength of the material to support the efforts is required. For the most common applications, such as wood or liquid acting as fuel, low-pressure extinguishers (i.e., 17 bar), mainly powder and hydric, are used; meanwhile, for fires where the fuel is gaseous, high-pressure extinguishers (i.e., 120 bar), mainly CO₂ extinguishers, are used. With the aim of using new materials in applications of this type, it is necessary to use type IV COPVs that guarantee structural resistance and weight reduction. In addition, these materials must have a minimum plastic deformation capacity. Therefore, the fibers used for the manufacture of these vessels should be carbon, aramid and glass fibers (Table 2) [5]:

Table 2. Mechanical properties of the fibers.

	Density	Young's Modulus (GPa)	Tensile Strength (MPa)	Elongation at Maximum Tensile Strength
Steel alloy	7.86	210	4830	38.0
Carbon fiber	1.76	230–260	≥4000	1.5
Glass fiber	2.44	100–230	≥3400	4.5
Aramid fiber	1.44	125	≥3400	2.4

Composites need a matrix to distribute the stresses, and epoxy matrices are usually used for the selected fibers [22]. These materials have different mechanical properties; therefore, from the rule of mixtures [23], it is possible to calculate the mechanical characteristics of the composite material, as well as the different combinations to obtain the desired configuration. In addition, there are manufacturing parameters, such as the number of layers, fiber orientation [24], etc., that significantly vary the performance of the final material of the product.

Differentiating between low-pressure extinguishers (i.e., 17 bar) and high-pressure extinguishers (i.e., 120 bar), the dimensions and bottle designs for these different types of equipment vary considerably. The material for manufacturing the equipment will have a considerable effect on the total weight of the equipment and the maximum allowable pressure. Therefore, a comparison of the different materials of interest for this equipment is made in Table 3.

Table 3. Principal properties of the materials employed to make pressure vessels.

	Low-Pressure			High-Pressure		
	Total Weight	Maximum Admissible Pressure (bar)	Price EUR/kg	Total Weight	Maximum Admissible Pressure (bar)	Price EUR/kg
Steel alloy	9.00	70	1.80	14.59	165.00	1.80
Carbon fiber	6.67	80	33.15	7.15	188.57	33.15
Glass fiber	6.93	68	16.23	7.98	160.29	16.23
Aramid fiber	0.55	68	15.73	6.76	160.29	15.73

2.2. Accessories, Sensors and Connectivity

For a correct verification of the condition of the extinguishers, it is necessary to distinguish between the different types of equipment on the market. On the one hand, there are extinguishers whose extinguishing agent is powder or water, and the propellant is nitrogen in the gaseous phase. On the other hand, there are CO₂ extinguishers whose extinguishing agent itself is the gas that displaces oxygen and interrupts the combustion process. In nitrogen extinguishers, the pressure value is constant, as has been established according to regulations around 17 bars [25], while in CO₂ extinguishers, the pressure varies considerably. This is due to the fact that, inside the container, CO₂ is in interphase, having fluid in liquid and gas phases at the same time, so the pressure value fluctuates constantly and is susceptible to change with the temperature of the environment. Therefore, the inspections of the different types of extinguishers are different: in those using nitrogen as a propellant, it is important to validate the value of the pressure, while in CO₂ extinguishers, it is necessary to check the weight of all equipment to rule out leaks.

2.2.1. Sensors

Different types of sensors have been used to measure the different parameters necessary to verify the status of the extinguishers. To measure pressure, three methods were used: (i) A commercial pressure sensor, in the 0–34 bar range, which is a low-cost solution; (ii) a strain gauge applied on the external part of the extinguisher. This is an expensive

solution, but it requires less space and can work in a wider pressure range (i.e., 0–140 bar) (Figure 2a); (iii) an ad hoc hook and special base printed in 3D for wall-mounted extinguishers (<20 kg) and bigger extinguishers placed on the floor (<100 kg), respectively (Figure 2b). The strain gauge used was a 120 Ω strain gauge from Hottinger Baldwin Messtechnik (HBM)® (Darmstadt, Germany). (Figure 2c).

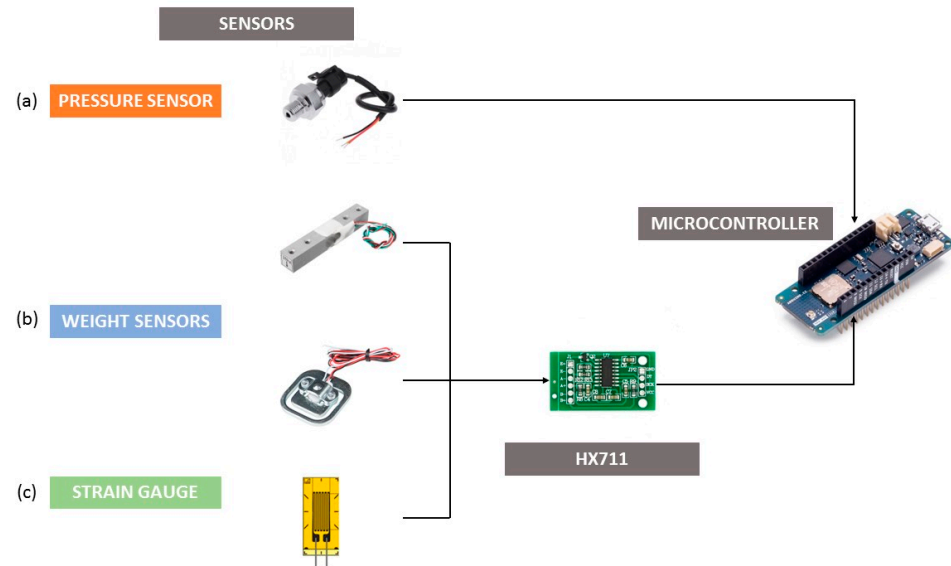


Figure 2. Sensors and controller used.

For measuring the internal pressure, the strain gauges were placed directly on the shell of the extinguisher. By applying the thin-walled rule in cylindrical vessels (Equation (1)), we can obtain the tensional state as a pressure function. Considering that the material works in an elastic regime, through Hooke's law (Equation (1)), we can express the deformation of the fire extinguisher as a pressure function (Equation (2)). Therefore, by knowing the material behavior, the inner pressure can be known by directly measuring the deformations of the material (Equations (1) and (2)):

$$\sigma_1 = \frac{Pr}{t}; \sigma_2 = \frac{Pr}{2t}, \text{ where } \sigma = E \cdot \epsilon \quad (1)$$

$$P = \frac{\sigma_1 \cdot t}{r}; P = \frac{E \cdot \epsilon_1 \cdot t}{r} \quad (2)$$

where:

$\sigma_1 \equiv$ transversal stress;

$\sigma_2 \equiv$ radial stress;

$P_r \equiv$ pressure;

$t \equiv$ thickness

$E \equiv$ Young's modulus of the material;

$\epsilon \equiv$ strain.

All the sensors using strain gauges operate based on a Wheatstone bridge [26]. In this bridge, where the strain gauge is one of the resistors, a balance is obtained. (Figure 3).

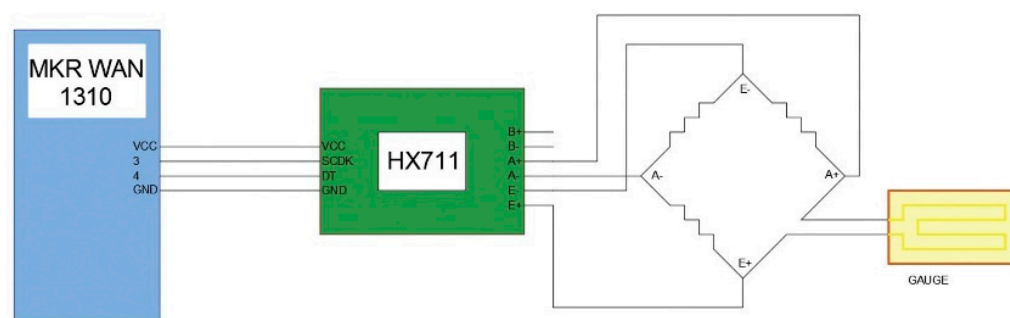


Figure 3. Wheatstone bridge prototype.

Any variation in the resistances translates into a variation in the voltage reading at the ends of the circuit. Therefore, the gauge will vary this bridge, and the voltage variation across the circuit can be read. This requires an amplifier to serve as a translator of this variation. For this purpose, an HX711 AD amplifier was used for all cases.

2.2.2. Accessories

As explained before, for extinguishers where nitrogen is the propellant agent, it is important to know the value of the pressure within the container. Meanwhile, for CO₂ extinguishers, it is important to know the total weight of the equipment so that possible leaks or damage to the shell can be ruled out. For this reason, three accessories were designed and manufactured with 3D printing to carry out the verification process of the equipment that incorporates different sensors connected by LoRaWAN.

On the other hand, an accessory was designed to be attached directly to the hook of the extinguisher to measure its weight. It consists of a piece made of Polyethylene Terephthalate Glycol (PETG) [27] and was printed in 3D with an Ender© 3 pro printer (Creality 3D, Shenzhen, China) that had a nozzle diameter of 4mm, accepts 1.75mm filament and a print volume of 220 × 220 × 250 mm [28]. This piece can be hung from a standard hook that is anchored to a wall and serves as an interconnection with the equipment, being compatible with any extinguisher and commercial solution (Figure 4). The weight sensor was placed so that the weight of the extinguisher applies a force perpendicular to it and can correctly measure its weight. Thus, even if there are movements (e.g., extinguishers placed on ships), the measurement of this sensor is correct, avoiding large fluctuations. All the accessories were manufactured with the following parameters: 6 perimeters, 5 bottom layers and 5 top layers, a grid filler with a 15% filler and a layer height of 0.2 mm [29].

To measure the state of the CO₂ extinguishers, a longitudinal load sensor was used based on strain gauge technology. A platform was designed (Figure 4) and printed in 3D, with PETG acting as a scale, where the weight was measured directly.

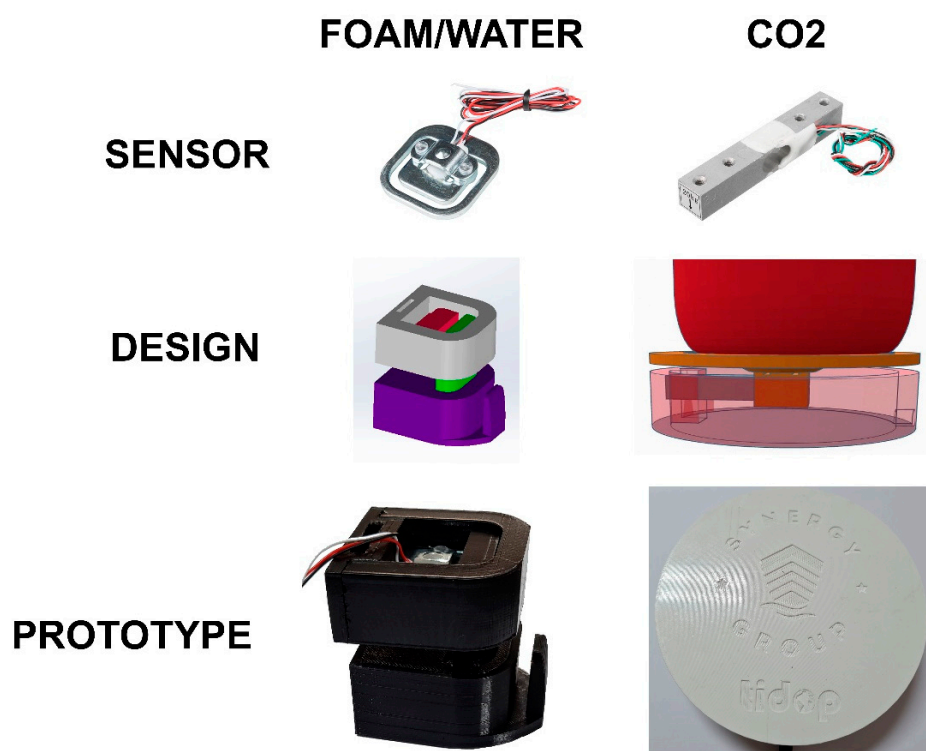


Figure 4. Sensors, designs and prototypes for the measurement of weight for different types of extinguishers (powder/water and CO₂).

2.2.3. Connectivity

Regarding communication networks, a LoRaWAN network was used. This network was chosen due to the great synergy between the characteristics of this network and the application requirements given in this work: long-range connectivity and energy autonomy, which implies low power consumption. Another reason for choosing LoRaWAN network was its scalability for being connected with other devices, thus, improving its coverage by adding more gateways [30].

An Arduino® MKR WAN 1310 (Arduino, Turin, Italy) was used to develop the device and to obtain and send the data. This device was placed in a small housing printed in 3D with PETG so that it could be easily placed anywhere near the extinguisher to obtain the sensor readings. Inside this board (Figure 3), an HX711 AD amplifier was connected, working as an interface for weight and deformation measurements together with some connectors for the pressure sensors. As a result, a part of the board was dedicated to the connection with the weight sensors and another to the connection with the pressure sensors, being a compact and multi-reading system. Next to the board, a compact and manageable battery provided independence and autonomy.

The choice of this microcontroller was motivated due to the fact that the IoT connection can be realized with LoRaWAN protocol. This protocol fits perfectly to the need of this application since the data size was not large. The transfer distance range needs to be wide, and finally, the power consumption must be small since the board was supported by a battery, and this must allow the battery life to be prolonged over time.

Last but not least, a small box with an antenna was designed and manufactured in 3D printing, integrating the microcontroller and the amplifier board. This box can be placed near the extinguisher or anywhere nearby without any problem. Different slots were designed to allow the different sensors to be connected to the corresponding pins without any mistakes (Figure 5).

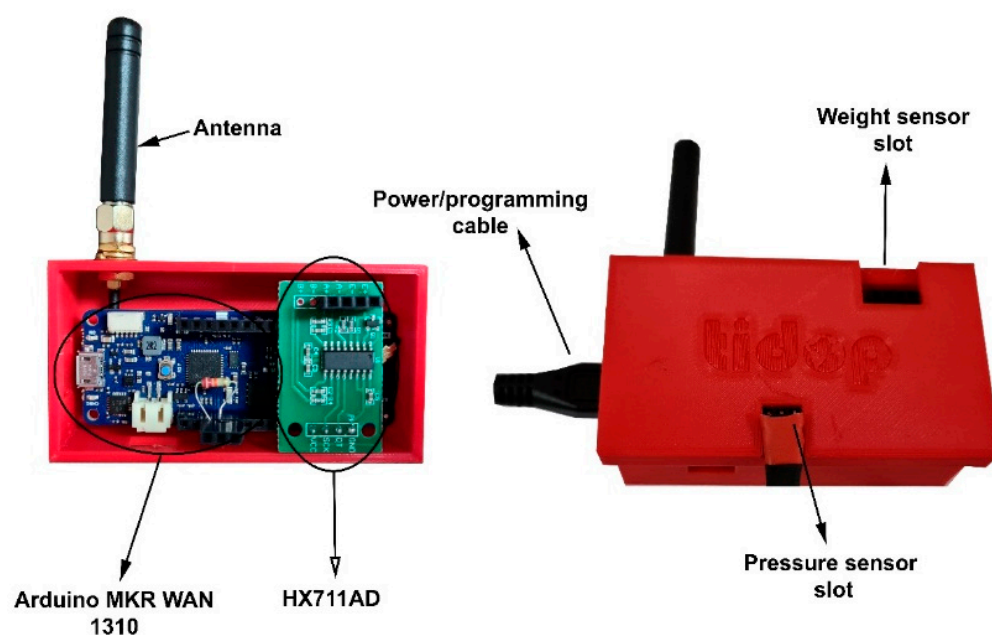


Figure 5. Data acquisition system and different slot designs. Sensors, designs and prototypes for the measurement of weight for different types of extinguishers (powder/water and CO₂).

3. Results

3.1. New Materials for Fire Extinguishers

Different bottles were manufactured, analyzed and compared with traditional bottles dedicated to fire extinguishers.

3.1.1. Steel Vessel

A steel bottle with a thickness of 1.5 mm was used as a test model. The characteristics of this bottle can be seen in Table 4:

Table 4. Steel Vessel Characteristics.

Height (mm)	525
Diameter (mm)	150
Thickness (mm)	1.5
Volume (L)	6.70
Empty Weight (kg)	3.20
Total Weight (kg)	9.28

This is a bottle dedicated to storing powder or water as an extinguishing agent, with a total load of 6 kg. This bottle withstands an internal pressure of about 70 bar.

3.1.2. Aramid Vessel

A polymeric liner of polypropylene (PP) was used for the aramid COPV. An aramid fiber of 0.2 mm thickness was wound around it. This winding was made using the wet filament winding technique with the following configuration: A fiber angle of [90°/45°/−45°/45°/45°]. The epoxy resin, Sicomin® SR1500 (Sicomin, Chateaufort les Martigues, France), was used as the matrix. The result was a bottle with the following characteristics (Table 5):

Table 5. AFRP vessel characteristics.

Height (mm)	420
Diameter (mm)	170
Thickness (mm)	1
Volume (L)	6.5
Empty Weight (kg)	0.842
Total Weight (kg)	6.842

This is a bottle dedicated to storing powder or water as an extinguishing agent, with a total load of 6 kg. This bottle withstands an internal pressure of about 68 bar.

3.1.3. Carbon Fiber Vessel

The commercial carbon fiber, Toray© CC 200T-120 (Toray Industries, Tokyo, Japan), was used with a thickness of 0.2 mm as reinforcement in a polymeric matrix made with a commercial epoxy resin, Sicomin© SR1500 (Sicomin, Chateaufort les Martigues, France), and in combination with Hardener Biresin© SD2505 (Sika, Bar, Switzerland). The manufacturing parameters were a fiber angle of $[-45/45^\circ]_{10}$, a winding speed of 20 RPM and a curing temperature of 50°C. The result is a bottle with the following features (Table 6):

Table 6. CFRP vessel characteristics.

Height (mm)	310
Diameter (mm)	100
Thickness (mm)	2
Volume (L)	6
Empty Weight (kg)	0.503
Total Weight (kg)	6.503

This is a bottle dedicated to storing powder or water as an extinguishing agent, with a total load of 6 kg. This bottle withstands an internal pressure of about 68 bar. The different vessels are shown in Figure 6.



Figure 6. Vessels studied. (a) Conventional steel-based vessel; (b) AFRP-based vessel; and (c) CFRP-based vessel.

In brief, the results of the comparison of these three materials are outlined in Table 7:

Table 7. Comparison between different vessels.

	Steel	Aramid	Carbon
Height (mm)	525	420	310
Diameter (mm)	150	170	100
Thickness (mm)	1.5	1	2
Volume (L)	6.70	6.50	2
Empty Weight (kg)	3.20	0.842	0.503
Total Weight (kg)	9.28	6.842	6.503
Pressure (bar)	70	68	80

It should be noted that the added value of COPVs type IV (Table 1) is that they can store more pressure, so that, despite having less extinguishing agent, they can be used for a long time, providing similar benefits to more voluminous steel bottles, reducing its dimension and weight considerably.

3.2. Accessories, Sensors and Connectivity Results

As it was stated above, a distinction was made between accessories and sensors for powder/water extinguishers and CO₂ extinguishers.

3.2.1. Powder and Water Extinguishers

To check the condition of a foam or water extinguisher, it is necessary to know the internal pressure of the bottle. These extinguishers, in addition, are usually hung on a hook so as to know their weight or to know if the extinguisher is in the correct state or has been used and, therefore, if it is necessary to recharge or replace it.

For this purpose, pressure and load sensors were used, as explained above. The pressure sensor has a conical thread, which can be inserted directly into the pressure gauge slot of the valve. However, being tapered, it does not fit perfectly with the groove. For this reason, a connector was designed and manufactured to guarantee the tightness of a toroidal joint and a piece that serves as a union and adapter between threads.

For the load sensor, an ad hoc accessory was designed and manufactured, which serves as an interconnection between the wall hook and the extinguisher itself (Figure 7). In this hook, a load sensor was placed, which, through strain gauges, measures the deformation at this point and transcribes it directly to the applied load. This accessory is sensitive to the placement of the extinguisher, but by applying sufficient sensitivity and pressure, it is useful for checking if the extinguisher is loaded or if it has been removed from the hook.

On the other hand, strain gauges were installed directly on the vessel surface. In this way, by measuring the axial and transverse deformation, the internal pressure of the extinguisher can be determined. Specifically, the thin-walled theory can be applied.



Figure 7. Powder hook design and complete system assembled.

3.2.2. CO₂ Extinguishers

CO₂ extinguishers contain interphase fluid. The gas phase has great variability in terms of internal pressure, so measuring this parameter directly is not the most convenient way. For this reason, the total weight of the extinguisher must be measured directly. For this purpose, a device whose performance is similar to a scale was designed and manufactured with a load sensor inside so that the extinguisher can be placed on top and weighed directly. An ad hoc extinguisher charging system was developed that allows the internal charge of the equipment to be varied while it is being weighted by means of a pressure circuit.

3.2.3. Connectivity

The validation of connectivity and coverage tests were performed on a dredge ship located in a shipyard in Pontevedra (Spain). The LoRaWAN network coverage was tested by the placement of two antennas: one in the bridge (inside the cabin) and the other one in the highest area of the ship over the bridge (outside). In order to carry out the tests, data were sent from different points on the ship (Figure 8) with different levels of power transmission signal or spread factor (SF 7, SF 9 and SF 11) with the aim of comparing the signal and noise levels received by the different gateways installed (Tables 8–10).

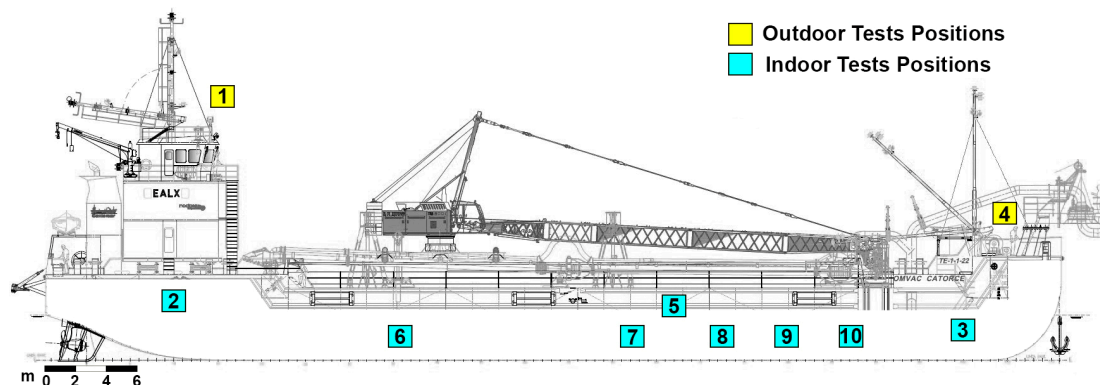


Figure 8. Antennas and coverage test placements within the ship.

Table 8. Coverture test results for SF 7.

Point	Airtime (s)	Gate Indoor		Gate Outdoor	
		RSS in (dBm)	SNR in (dB)	RSSI Out (dBm)	SNR Out (dB)
1	0.051456	−31	9.25	−64	9.25
1	0.051456	−27	9.25	−73	9.25
2	0.051456	−37	7.5	−47	7.5
2	0.051456	−75	7	−92	7
3	0.051456	−79	7.25	−89	9
3	0.051456	−83	7.25	−73	9
3	0.051456	−83	4	−86	7.25
4	0.051456	−84	3.5	−77	10.5
4	0.051456	−75	6.75	−79	8
4	0.051456	−73	7.5	−75	8.25
5	0.051456	−75	6.25	−65	6.5
5	0.051456	−85	3.25	−78	8.75
5	0.051456	−87	0.5	−77	7.25
6	0.051456	−85	5	−81	6.75
6	0.051456	−89	1	−83	7.25
7	0.051456	−85	2.75	−90	8.75
7	0.051456	−91	−5.25	−95	9.5
8*	0.051456	**	**	−97	8.75
8*	0.051456	**	**	−99	5.25
8*	0.051456	−87	−7.75	−93	9.25
9*	0.051456	**	**	−93	6
9*	0.051456	**	**	−95	8.5
10*	0.051456	−96	−6.5	−93	7.5
10*	0.051456	**	**	−93	6.75
10*	0.051456	**	**	−91	9
10*	0.051456	**	**	−97	5.5

* SNR above limit (7.5 dB). ** Lost packages.

Table 9. Coverture test results for SF 9.

Point	Airtime (s)	Gate Indoor		Gate Outdoor	
		RSS in (dBm)	SNR in (dB)	RSSI Out (dBm)	SNR Out (dB)
1	0.185344	9	−37	9	−65
2	0.185344	9	−72	9	−83
2	0.185344	9	−71	11.25	−85
2	0.185344	9	−77	10.5	−87
3	0.185344	9	−86	0.75	−79
3	0.185344	9	−85	1.25	−73
3	0.185344	9	−92	2.5	−80
4	0.185344	9	−74	11	−75
4	0.185344	9	−85	4.25	−67
4	0.185344	9	−73	9.25	−77
5	0.185344	9	−87	6	−91
5	0.185344	9	−86	6.75	−80
5	0.185344	9	−83	7.5	−78
6	0.185344	9	−90	−3	−79
6	0.185344	9	−90	−1.5	−87
6	0.185344	9	−91	5	−86
7	0.185344	9	−92	−5.75	−90
8*	0.185344	9	−88	−9.75	−96
8*	0.185344	9	−90	−6.5	−104

Table 9. Cont.

Point	Airtime (s)	Gate Indoor		Gate Outdoor	
		RSS in (dBm)	SNR in (dB)	RSSI Out (dBm)	SNR Out (dB)
8*	0.185344	9	**	**	−95
9*	0.185344	9	**	**	−97
9*	0.185344	9	**	**	−109
10*	0.185344	9	−89	−4.75	−99
10*	0.185344	9	**	**	−101
10*	0.185344	9	−89	−11	−101
10*	0.185344	9	**	**	−107

* SNR above limit (7.5 dB). ** Lost packages.

Table 10. Coverture test results for SF 11.

Point	Airtime (s)	Gate Indoor		Gate Outdoor	
		RSS in (dBm)	SNR in (dB)	RSSI Out (dBm)	SNR Out (dB)
1	0.659456	−13	10.75	−61	11.5
2	0.659456	−74	8.5	−86	10.5
3	0.659456	−83	2075	−73	11.25
3	0.659456	−74	6	−75	9025
3	0.659456	−74	805	−70	11
4	0.659456	−72	8025	−62	9
5	0.659456	−89	1	−78	10
5	0.659456	−87	−0025	−76	9.5
6	0.659456	−85	2075	−78	10.25
6	0.659456	−85	6.75	−104	5075
7	0.659456	−93	−7.5	−91	7
8*	0.659456	**	**	−89	7.25
9*	0.659456	**	**	−103	−0.25
9*	0.659456	**	**	−97	4.75
10	0.659456	−90	−9.5	−105	1.25

* SNR above limit (7.5 dB). ** Lost packages.

3.2.4. Monitoring Results

To monitor and graphically represent the data in real time, a dashboard was developed, showing the different measurements through time. This dashboard is fully adaptable and, in this case, has been designed to read weight and pressure, separately. The pressure sensor has absolute reading; therefore, it is not necessary to calibrate it at any time, and when connected, it will directly give correct readings in bar. However, for the load sensors, a prior calibration is required. For this purpose, a tare protocol was designed, which consists of connecting the sensor without any load. The data acquisition is allowed to stabilize for one minute because noise appears when the sensor is connected. After one minute, a fire extinguisher filled with a known weight will be placed for one minute to avoid the same noise. Once the taring protocol is completed, the sensor is ready to monitor data. In this case, the following programs, all of them open source, will be used: NodeRed software to make a connection through the Mqtt protocol and transmit the data to an Influxdb database with JavaScript. Once the data are registered in the database, the data are visualized through the Grafana platform (Figure 9).



Figure 9. Dashboard through a measurement test session. The graph above represents the percentage of load with respect to the setting. The bottom graph represents the actual pressure reading of the device.

Regarding data sending, for prototyping and functionality verification, a sending frequency of 10 s was defined. However, so that it can be used over a long period of time with batteries connected, the most advisable frequency is an automatic sending of one data acquisition per day, and a button will be included to send the data instantaneously if necessary. The statistical values of every step are shown in Table 11.

Table 11. Statistic study of the values.

Real Pressure	Value	Mean	Standard Deviation	Variation Coefficient	Mean Noise
17 bar	Load (%)	1.0041	0.0049	0.492	0.0025
	Pressure (bar)	17.1845	0.1216	0.708	0.0642
14 bar	Load (%)	0.8049	0.0031	0.382	0.0018
	Pressure (bar)	13.9940	0.1313	0.939	0.0724
11 bar	Load (%)	0.6055	0.0030	0.487	0.0017
	Pressure (bar)	10.8140	0.1172	1.084	0.0657
1 bar	Load (%)	0.0048	0.0029	0.602	0.0017
	Pressure (bar)	1.1933	0.1164	0.098	0.0696

4. Conclusions

The use of new materials in marine environments and even in mixed environments (e.g., oil tankers, transport of chemical compounds, etc.) is a viable alternative due to their resistance to corrosion, being much more cost-effective than the use of conventional materials (e.g., steel and stainless steel) because their useful life is much longer. On the other hand, there are additional advantages: These solutions are lighter, resulting in more ergonomic devices and lower logistics costs. Sensors can also be integrated more easily.

The use of the LoRaWAN network has proven to provide coverage at all locations on a ship, even in less accessible areas such as the engine room. The use of the LoRaWAN network allows for increased network capacity and coverage, as seen in field tests on a ship. Therefore, this solution is easily scalable to any situation by adapting the number of gateways to the required coverage area.

The use of low-cost technology has proven to be effective for the proposed application, where great accuracy is not required but we must guarantee a low-cost solution given the number of extinguishers to be monitored (e.g., 400 in the case of tankers). LoRaWAN has the advantage of being a scalable system, which allows the incorporation of additional devices depending on the demand of the application. At the same time, these low-cost devices based on the use of strain gauges are very versatile because different parameters can be measured with the same platform without any additional interface. The devices used, in turn, meet the requirement of low energy consumption, which makes them very suitable for preventive maintenance applications. The developed device could incorporate new parameters, such as temperature, humidity or CO₂ concentration, thereby adding more capacities for future possibilities, where these new signals treated from an artificial intelligence system, specifically in the case study presented in this work, allow beyond preventive maintenance to predict risk situations on ships (fires, gas leaks, leaks, structural failure, etc.).

The combination of the study of materials and wireless sensing allows a significant improvement in the manageability and predictive maintenance of the elements. The level of noise obtained by the sensors was sufficiently small to be able to obtain very good results, with SF7 being the one that gives the best results. Analyzing the signal and noise level data received by the gateways, there was no data loss for the gateway located on the bridge (outside); although, for the gateway located in the cabin (inside), there was a loss of some packets sent from the furthest positions (Tables 8–10).

On the other hand, the proposed system has some limitations: First, the sensitivity of the strain gauge requires a special circuit to amplify the signal, so we had to develop a special circuit to obtain the appropriate gain. In addition, it was necessary to protect the strain gauge from the environment. Another aspect to note is that each measurement will be made individually from each piece of equipment, using for each one a microcontroller. This is due to the use of amplifier boards that occupy a high number of pins in the microcontrollers. However, because this is a prototype, this aspect will be taken into account in future work in order to be able to make multiple measurements using as few controller boards as possible.

In this way, a much more complete predictive context can be created. In addition, numerical models can also be implemented through the finite element method (FEM). Thus, a mechanical behavior predictive model of the prototype (fire extinguisher) design will be available. Another future step will be managing all the collected data through artificial intelligence techniques to create a predictive algorithm that allows knowing the condition of the extinguishers and also to anticipate situations where the possibility of fire occurrence is high.

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References

1. Toudeshdehghan, A.; Hong, T.W. A Critical Review and Analysis of Pressure Vessel Structures. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *1235*, 12009.
2. Alam, S.; Yandek, G.R.; Lee, R.C.; Mabry, J.M. Design and development of a filament wound composite overwrapped pressure vessel. *Compos. Part C Open Access* **2020**, *2*, 100045. [\[CrossRef\]](#)
3. Kartav, O.; Kangal, S.; Yüçetürk, K.; Tanoğlu, M.; Aktaş, E.; Artem, H.S. Development and analysis of composite overwrapped pressure vessels for hydrogen storage. *J. Compos. Mater.* **2021**, *55*, 4141–4155. [\[CrossRef\]](#)
4. Torab, H.; Aggarwal, M.C. Application of Composite Materials in High Pressure Technology. In Proceedings of the Pressure Vessels and Piping Conference: American Society of Mechanical Engineers, Anaheim, CA, USA, 20–24 July 2014; p. V005T05A13.
5. Edition, F.; Ashby, M.F. *Material Selection in Mechanical Design*; Elsevier Ltd.: Burlington, MA, USA, 2011.
6. Yeh, C.-P.; Tsai, K.-C.; Huang, J.-Y. Influence of chloride concentration on stress corrosion cracking and crevice corrosion of austenitic stainless steel in saline environments. *Materials* **2020**, *13*, 5640. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Lim, K.S.; Azraai, S.; Noor, N.; Yahaya, N. An overview of corroded pipe repair techniques using composite materials. *Int. J. Mater. Metall. Eng.* **2015**, *10*, 19–25.
8. Kara, M.; Uyaner, M.; Avci, A. Repairing impact damaged fiber reinforced composite pipes by external wrapping with composite patches. *Compos. Struct.* **2015**, *123*, 1–8. [\[CrossRef\]](#)
9. Jasiulewicz-Kaczmarek, M.; Gola, A. Maintenance 4.0 technologies for sustainable manufacturing-an overview. *IFAC-PapersOnLine* **2019**, *52*, 91–96. [\[CrossRef\]](#)
10. Kavitha, B.; Vallikannu, R. IoT based intelligent industry monitoring system. In Proceedings of the 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 7–8 March 2019; IEEE: New York, NY, USA, 2019; pp. 63–65.
11. González-Briones, A.; Garcia-Martin, R.; Alba FLd Corchado, J.M. Agent-Based Platform for Monitoring the Pressure Status of Fire Extinguishers in a Building. In Proceedings of the International Conference on Practical Applications of Agents and Multi-Agent Systems, L'Aquila, Italy, 7–9 October 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 373–384.
12. Zhai, L.; Jiang, W. Intelligent Environment Monitoring System for University Laboratories. *Future Internet* **2018**, *10*, 110. [\[CrossRef\]](#)
13. Garcia-Martin, R.; González-Briones, A.; Corchado, J.M. Smartfire: Intelligent platform for monitoring fire extinguishers and their building environment. *Sensors* **2019**, *19*, 2390. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Raza, U.; Kulkarni, P.; Sooriyabandara, M. Low power wide area networks: An overview. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 855–873. [\[CrossRef\]](#)
15. Aldahdouh, K.A.; Darabkh, K.A.; Al-Sit, W. A survey of 5G emerging wireless technologies featuring LoRaWAN, Sigfox, NB-IoT and LTE-M. In Proceedings of the 2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), Xi'an, China, 23–25 October 2019; IEEE: New York, NY, USA, 2019; pp. 561–566.
16. Cano, J.C.; Berrios, V.; Garcia, B.; Toh, C.K. Evolution of IoT: An industry perspective. *IEEE Internet Things Mag.* **2018**, *1*, 12–17. [\[CrossRef\]](#)
17. Sherazi, H.H.R.; Grieco, L.A.; Imran, M.A.; Boggia, G. Energy-efficient LoRaWAN for industry 4.0 applications. *IEEE Trans. Ind. Inform.* **2020**, *17*, 891–902. [\[CrossRef\]](#)
18. Nsiah, K.A.; Amjad, Z.; Sikora, A.; Hilt, B. Performance evaluation of latency for NB-LTE networks in industrial automation. In Proceedings of the 2019 IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Istanbul, Turkey, 8–11 September 2019; IEEE: New York, NY, USA, 2019; pp. 1–7.
19. Tange, K.; De Donno, M.; Fafoutis, X.; Dragoni, N. Towards a systematic survey of industrial IoT security requirements: Research method and quantitative analysis. In Proceedings of the Workshop on Fog Computing and the IoT 2019, Montreal, QC, Canada, 15–18 April 2019; pp. 56–63.
20. Mekki, K.; Bajic, E.; Chaxel, F.; Meyer, F. Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT. In Proceedings of the 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (Percom Workshops), Athens, Greece, 19–23 March 2018; IEEE: New York, NY, USA, 2018; pp. 197–202.

21. Sanchez-Gomez, J.; Gallego-Madrid, J.; Sanchez-Iborra, R.; Santa, J.; Skarmeta, A.F. Impact of schc compression and fragmentation in lpwan: A case study with lorawan. *Sensors* **2020**, *20*, 280. [[CrossRef](#)] [[PubMed](#)]
22. Bello, S.; Hassan, S.; Kana, M.; Raheem, I. Epoxy resin based composites, mechanical and tribological properties: A review. *Tribol. Ind.* **2015**, *37*, 500.
23. Fan, Z.; Tsakiroopoulos, P.; Miodownik, A. A generalized law of mixtures. *J. Mater. Sci.* **1994**, *29*, 141–150. [[CrossRef](#)]
24. Colombo, C.; Vergani, L. Optimization of filament winding parameters for the design of a composite pipe. *Compos. Part B Eng.* **2018**, *148*, 207–216. [[CrossRef](#)]
25. Pérez Guerrero, A. *NTP-368: Extinción de Incendio: Plan de Revisión de Equipos*; Ministerio de Trabajo y Asuntos Sociales: Madrid, Spain, 1995.
26. Hoffmann, K. *Applying the Wheatstone Bridge Circuit*; HBM: Darmstadt, Germany, 1974.
27. Velasco, M.A.; Quevedo, Y.N.; Bonilla, C.A. Determinación de propiedades mecánicas a tensión y compresión de PETG procesado mediante fabricación por filamento fundido. In Proceedings of the XXVIII Congreso Internacional Anual de la SOMIM, Bogotá, Colombia, 21–23 September 2022; pp. 170–175.
28. Karthik, M.S.K.; Karanam, H.K.R.; Prabu, S.S. Experimental and Thermal Analysis of Desktop FDM 3D Printers” Ender 3” and” CR-10S Pro” Hot Ends. *ECS Trans.* **2022**, *107*, 12851. [[CrossRef](#)]
29. Portoaca, A.; Nae, I.; Zisopol, D.G.; Ramadan, I. Studies on the Influence of FFF Parameters on the Tensile Properties of Samples Made of ABS. *IOP Conf. Ser. Mater. Sci. Eng.* **2022**, *1235*, 12008. [[CrossRef](#)]
30. Bor, M.C.; Roedig, U.; Voigt, T.; Alonso, J.M. Do LoRa low-power wide-area networks scale? In Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, Malta, 13–17 November 2016; pp. 59–67.

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CAPÍTULO V

CONCLUSIONES Y TRABAJOS FUTUROS

5.1 Conclusiones

Durante la presente Tesis Doctoral se han presentado una serie de retos y de objetivos que se han ido desarrollando y cumpliendo a lo largo de los trabajos presentados. Cabe destacar que se han empleado diferentes metodologías de manera armónica entre ellas para dar un sentido completo a todo el trabajo realizado. Como elemento común se puede concluir que **el uso de técnicas de imagen, de no contacto, en la industria 4.0 es imprescindible para un correcto proceso de caracterización, diseño y control debido a la complejidad de los nuevos elementos empleados**, como pueden ser los materiales compuestos o los nuevos procesos de fabricación.

Combinación DIC y modelos numéricos

La comparación entre DIC 2D y 3D confirma que la DIC 3D logra una precisión similar a la 2D, validándola para caracterizar materiales incluso en probetas con geometrías complejas. Esto permite estudiar comportamientos específicos de materiales en condiciones más realistas.

La integración del DIC con materiales compuestos y métodos estocásticos permite conseguir resultados que serían inalcanzables mediante métodos deterministas. Más concretamente, la caracterización de campo completo (Full-Field) de materiales compuestos anisotrópicos, con su alta variabilidad, posibilita la construcción de PDF que incorporan esta variabilidad y ofrecen un enfoque probabilístico para el comportamiento de los materiales.

La conjunción de todos estos aspectos ha llevado a la propuesta de **una nueva metodología de diseño** para depósitos a presión fabricados a partir de materiales compuestos. Gracias a la validación del DIC 3D, la fabricación de útiles con un carácter modular adaptables a diferentes aplicaciones ha permitido registrar un tipo de ensayo que simula mejor los esfuerzos de un recipiente a presión como es el RHTT y el posterior empleo de los métodos estocásticos.

Por otra parte, la comparación entre los modelos FEM y los datos de DIC ha permitido ajustar y mejorar los modelos teóricos, logrando una mayor precisión en la simulación del comportamiento real y optimizando la metodología de diseño para obtener resultados más representativos y fiables.

Aplicaciones en industria

Gracias a todo este desarrollo se ha podido construir un prototipo de extintor a partir de materiales compuestos por la técnica de FW que mejora las prestaciones de los extintores convencionales fabricados a partir de materiales convencionales como el acero. Este prototipo mejora la presión de servicio, mejorando por tanto el tiempo de uso y su propia resistencia, reduciendo considerablemente el volumen y por tanto el peso del dispositivo.

Además, estos nuevos métodos de fabricación facilitan la implementación de diferentes tipos de sensores embebidos que permiten aplicar el Internet de las Cosas, IoT, haciendo que el prototipo sea un nodo de esta red. Utilizando sensores que ofrezcan una sinergia con este tipo de dispositivos, como son los sensores de peso, deformación, temperatura y humedad, se puede conocer el estado del dispositivo en cualquier momento haciendo la pertinente consulta al controlador y además y más importante.

Termografía Activa

En cuanto a la otra gran base de esta Tesis Doctoral, la termografía activa aplicada en diferentes materiales empleados en la fabricación aditiva a partir de deposición fundida se puede llegar a las siguientes conclusiones.

La correlación entre los modelos teóricos FEM y los datos obtenidos por los ensayos de termografía activa realizados permiten construir modelos predictivos inteligentes capaces de analizar, interpretar y predecir el tamaño del defecto gracias a diferentes algoritmos incorporados de Machine Learning.

Los ensayos realizados y los resultados obtenidos han permitido optimizar la técnica de termografía activa en su relación material-técnica y ajustar sus parámetros específicos, lo cual representa un avance significativo. Ante la falta de normativa en la detección de defectos mediante termografía activa, estos hallazgos pueden sentar las bases para una futura estandarización del método.

Se ha propuesto un algoritmo de detección automática de defectos en termogramas sin el uso de Machine Learning, logrando una detección instantánea y eliminando el proceso de entrenamiento. En termografía activa, la simplificación del algoritmo permite una identificación rápida y precisa de defectos gracias a los bordes claramente visibles en la imagen.

5.2 Trabajos futuros

Aprovechando todo lo desarrollado en la presente Tesis Doctoral se plantean diferentes líneas de investigación y aplicación a futuro.

Por un lado, todo lo desarrollado en referencia a la DIC permite su aplicación directa sobre los sistemas optomecánicos del láser VEGA del Centro de Láseres Pulsados Ultracortos (CLPU). De esta manera se pretende caracterizar la deformación y desplazamientos de estos sistemas debido al calor generado por el paso del haz, al igual que la influencia de los bombeos de la metodología Chirped Pulse Amplifier, CPA, necesaria para alcanzar la potencia del petavatio (PW). En este sentido se plantea realizar, por un lado, un modelo predictivo capaz de corregir el beampointing del haz a partir de datos medibles directamente como puede ser temperatura o tiempo de funcionamiento, a partir de modelos avanzados de Machine Learning que sean capaces de predecir la posición de los sistemas y corregir la desviación del láser. Por otro lado, aprovechando todos los datos que se plantean, se podría llegar a realizar un gemelo digital del láser que permita facilitar la operabilidad y mantenimiento de este.

Siguiendo esta línea de colaboración con el CLPU, se puede aplicar todo el conocimiento generado en el campo de la termografía activa en los sistemas optomecánicos y de refrigeración. De esta manera, se podría llegar a realizar un mantenimiento avanzado, intentando automatizar la toma de datos, para simplificar las labores detectando posibles puntos de fallo que se escapan del rango visible.

Siguiendo con las técnicas visuales presentadas, DIC y termografía activa, se pretende avanzar en la investigación de una nueva combinación de materiales como son fibras procedentes de madera con polímeros para poder realizar procesos de fabricación aditiva, concretamente impresión 3D, aprovechando los recursos regionales. En este sentido, todo el trabajo desarrollado permitirá dar una caracterización general, tanto mecánica como térmica de este tipo de materiales. También, se podrá analizar la configuración óptima del proceso de impresión de cara a diferentes aplicaciones, tanto estructurales como para otro tipo de funcionalidades.

Bibliografía

- [1] Shackelford J F 2000 Materials science for engineers *Upper Saddle River, New Jersey*
- [2] Edition F and Ashby M F 2011 Material Selection in Mechanical Design
- [3] Hashin Z and Wendt F 1970 Theory of composite materials *Mechanics of composite materials* 201–42
- [4] Singh J, Kumar M, Kumar S and Mohapatra S 2017 Properties of glass-fiber hybrid composites: a review *Polymer-Plastics Technology and Engineering* 56 455–69
- [5] Newcomb B A 2016 Processing, structure, and properties of carbon fibers *Composites Part A: Applied Science and Manufacturing* 91 262–82
- [6] Barile C, Casavola C and De Cillis F 2019 Mechanical comparison of new composite materials for aerospace applications *Composites Part B: Engineering* 162 122–8
- [7] Fan Z, Tsakiroopoulos P and Miodownik A 1994 A generalized law of mixtures *Journal of materials science* 29 141–50
- [8] Beaman J, Bourell D L, Seepersad C and Kovar D 2020 Additive manufacturing review: early past to current practice *Journal of Manufacturing Science and Engineering* 142(11) 110812
- [9] Bikas H, Stavropoulos P and Chrysosolouris G 2016 Additive manufacturing methods and modelling approaches: a critical review *The International Journal of Advanced Manufacturing Technology* 83 389–405
- [10] Singh S, Ramakrishna S and Berto F 2020 3D Printing of polymer composites: A short review *Material Design & Processing Communications* 2(2) e97
- [11] Hossain M A, Zhumabekova A, Paul S C and Kim J R 2020 A review of 3D printing in construction and its impact on the labor market *Sustainability* 12(20) 8492
- [12] Azeem M, Ya H H, Alam M A, Kumar M, Stabla P, Smolnicki M, Gemi L, Khan R, Ahmed T and Ma Q 2022 Application of filament winding technology in composite pressure vessels and challenges: a review *Journal of Energy Storage* 49 103468
- [13] Carosella S, Hügle S, Helber F and Middendorf P 2024 A short review on recent advances in automated fiber placement and filament winding technologies *Composites Part B: Engineering* 111843
- [14] Gascons M, Blanco N and Matthys K 2012 Evolution of manufacturing processes for fiber-reinforced thermoset tanks, vessels, and silos: a review *IIE Transactions* 44(6) 476–89
- [15] Günaydın K and Türkmen H S 2018 Common FDM 3D printing defects International congress on 3D printing (additive manufacturing) technologies and digital industry pp 19–21
- [16] Alam S, Yandek G R, Lee R C and Mabry J M 2020 Design and development of a filament wound composite overwrapped pressure vessel *Composites Part C: Open Access* 2 100045

- [17] Kartav O, Kangal S, Yüçetürk K, Tanoğlu M, Aktaş E and Artem H S 2021 Development and analysis of composite overwrapped pressure vessels for hydrogen storage *Journal of Composite Materials* 55(28) 4141–55
- [18] Colombo C and Vergani L 2018 Optimization of filament winding parameters for the design of a composite pipe *Composites Part B: Engineering* 148 207–16
- [19] Wang H, Bouchard R, Eagleson R, Martin P and Tyson W R 2002 Ring hoop tension test (RHTT): A test for transverse tensile properties of tubular materials *Journal of Testing and Evaluation* 30(5) 382–91
- [20] Arellano M T, Crouzeix L, Douchin B, Collombet F, Moreno H H and Velázquez J G 2010 Strain field measurement of filament-wound composites at $\pm 55^\circ$ using digital image correlation: an approach for unit cells employing flat specimens *Composite Structures* 92(10) 2457–64
- [21] Pan B 2018 Digital image correlation for surface deformation measurement: historical developments, recent advances and future goals *Measurement Science and Technology* 29(8) 082001
- [22] He T, Liu L and Makeev A 2018 Uncertainty analysis in composite material properties characterization using digital image correlation and finite element model updating *Composite Structures* 184 337–51
- [23] Orell O, Vuorinen J, Jokinen J, Kettunen H, Hytönen P, Turunen J and Kanerva M 2018 Characterization of elastic constants of anisotropic composites in compression using digital image correlation *Composite Structures* 185 176–85
- [24] Garcia-Martin R, Bautista-De Castro Á, Sánchez-Aparicio L J, Fueyo J G and Gonzalez-Aguilera D 2019 Combining digital image correlation and probabilistic approaches for the reliability analysis of composite pressure vessels *Archives of Civil and Mechanical Engineering* 19 224–39
- [25] Garcia-Martin R, Lopez-Rebollo J, Sánchez-Aparicio L J, Fueyo J G, Pisonero J and Gonzalez-Aguilera D 2020 Digital image correlation and reliability-based methods for the design and repair of pressure pipes through composite solutions *Construction and building Materials* 248 118625
- [26] He Y, Makeev A and Shonkwiler B 2012 Characterization of nonlinear shear properties for composite materials using digital image correlation and finite element analysis *Composites Science and Technology* 73 64–71
- [27] Comer A, Katnam K-B, Stanley W and Young T 2013 Characterising the behaviour of composite single lap bonded joints using digital image correlation *International Journal of Adhesion and Adhesives* 40 215–23
- [28] Joshi S and Harle S M 2017 Linear variable differential transducer (LVDT) & its applications in civil engineering *Int. J. Transp. Eng. Technol* 3(4) 62–6
- [29] Schlichting J, Maierhofer C and Kreutzbruck M 2012 Crack sizing by laser excited thermography *NDT & E International* 45(1) 133–40
- [30] Gdoutos E E and Gdoutos E E 2022 Coherent Moiré and Moiré interferometry *Experimental Mechanics: An Introduction* 103–13

- [31] Post D, Han B, Ifju P, Post D, Han B and Ifju P 1994 Moiré interferometry *High Sensitivity Moiré: Experimental Analysis for Mechanics and Materials* 135–226
- [32] Hoffmann K 1974 *Applying the wheatstone bridge circuit* (HBM Darmstadt, Germany)
- [33] Seif M A, Khashaba U A and Rojas-Oviedo R 2007 Measuring delamination in carbon/epoxy composites using a shadow moiré laser based imaging technique *Composite structures* 79(1) 113–8
- [34] Gallage C and Gunasekara Jayalath C P 2019 Use of particle image velocimetry (PIV) technique to measure strains in geogrids Proceedings of the 7th International Symposium on Deformation Characteristics of Geomaterials (IS-Glasgow 2019)(E3S Web of Conferences, Volume 92) (EDP Sciences) pp 1–6
- [35] Rullman I, Patyna M, Janssen B and Willershausen B 2017 Determination of polymerization shrinkage of different composites using a photoelastic method. *American Journal of Dentistry* 30(1) 16–22
- [36] Sánchez-Arévalo F and Pulos G 2008 Use of digital image correlation to determine the mechanical behavior of materials *Materials characterization* 59(11) 1572–9
- [37] Leclerc H, Périé J-N, Roux S and Hild F 2009 Integrated digital image correlation for the identification of mechanical properties Computer Vision/Computer Graphics Collaboration Techniques: 4th International Conference, MIRAGE 2009, Rocquencourt, France, May 4-6, 2009. Proceedings 4 (Springer) pp 161–71
- [38] Pan B, Dafang W and Yong X 2012 Incremental calculation for large deformation measurement using reliability-guided digital image correlation *Optics and Lasers in Engineering* 50(4) 586–92
- [39] Zhao J, Sang Y and Duan F 2019 The state of the art of two-dimensional digital image correlation computational method *Engineering reports* 1(2) e12038
- [40] Solav D, Moerman K M, Jaeger A M, Genovese K and Herr H M 2018 MultiDIC: An open-source toolbox for multi-view 3D digital image correlation *Ieee Access* 6 30520–35
- [41] Reu P 2014 All about speckles: speckle size measurement *Experimental Techniques* 38(6) 1–2
- [42] Reu P 2015 All about speckles: contrast *Experimental Techniques* 39(1) 1–2
- [43] Reu P 2015 All about speckles: edge sharpness *Experimental techniques* 39(2) 1–2
- [44] Blaber J, Adair B and Antoniou A 2015 Ncorr: open-source 2D digital image correlation matlab software *Experimental Mechanics* 55(6) 1105–22
- [45] Huang C, Jin W, Xu Q, Liu Z and Xu Z 2020 Sub-pixel edge detection algorithm based on canny–zernike moment method *Journal of Circuits, Systems and Computers* 29(15) 2050238
- [46] Pan B, Qian K, Xie H and Asundi A 2009 Two-dimensional digital image correlation for in-plane displacement and strain measurement: a review *Measurement science and technology* 20(6) 062001

- [47] Schreier H, Orteu J-J and Sutton M A 2009 *Image correlation for shape, motion and deformation measurements: Basic concepts, theory and applications* vol 1 (Boston: Springer US)
- [48] Bing P, Hui-Min X, Bo-Qin X and Fu-Long D 2006 Performance of sub-pixel registration algorithms in digital image correlation *Measurement science and technology* 17(6) 1615
- [49] Szymanik B, Psuj G, Hashemi M and Lopato P 2021 Detection and identification of defects in 3D-printed dielectric structures via thermographic inspection and deep neural networks *Materials* 14(15) 4168
- [50] Saeed N, Omar M A, Abdulrahman Y, Salem S and Mayyas A 2018 IR thermographic analysis of 3D printed CFRP reference samples with back-drilled and embedded defects *Journal of Nondestructive Evaluation* 37 1–8
- [51] Moskovchenko A, Vavilov V, Bernegger R, Maierhofer C and Chulkov A O 2020 Detecting delaminations in semitransparent glass fiber composite by using pulsed infrared thermography *Journal of Nondestructive Evaluation* 39 1–10
- [52] Azizinasab B, Hasanzadeh R P, Hedayatrasa S and Kersemans M 2021 Defect detection and depth estimation in CFRP through phase of transient response of flash thermography *IEEE Transactions on Industrial Informatics* 18(4) 2364–73
- [53] Shepard S M 2007 Flash thermography of aerospace composites IV Conferencia Panamericana de END Buenos Aires vol 7 (Citeseer) p 26
- [54] Shepard S M, Lhota J R and Ahmed T 2009 Measurement limits in flash thermography *Thermosense XXXI* vol 7299 (SPIE) pp 209–15
- [55] Wallace N J, Crane N B and Jones M R 2022 Defect measurement limits using flash thermography with application to additive manufacturing *NDT & E International* 128 102615
- [56] He Z, Wang H, He Y, Zhang G, Wang J, Zou G and Chady T 2019 Joint scanning laser thermography defect detection method for carbon fiber reinforced polymer *IEEE Sensors Journal* 20(1) 328–36
- [57] Balageas D L and Roche J-M 2014 Common tools for quantitative time-resolved pulse and step-heating thermography—part I: theoretical basis *Quantitative InfraRed Thermography Journal* 11(1) 43–56
- [58] Badghaish A A and Fleming D C 2008 Non-destructive inspection of composites using step heating thermography *Journal of composite materials* 42(13) 1337–57
- [59] D'Accardi E, Dell'Avvocato G, Palumbo D and Galietti U 2021 Limits and advantages in using low-cost microbolometric IR-camera in lock-in thermography for CFRP applications *Thermosense: Thermal Infrared Applications XLIII* vol 11743 (SPIE) pp 151–65
- [60] Laureti S, Bison P, Ferrarini G, Zito R and Ricci M 2024 Simultaneous Multi-frequency lock-in Thermography: a new flexible and effective Active Thermography scheme *NDT & E International* 103144
- [61] Oswald-Tranta B 2017 Time and frequency behaviour in TSR and PPT evaluation for flash thermography *Quantitative InfraRed Thermography Journal* 14(2) 164–84

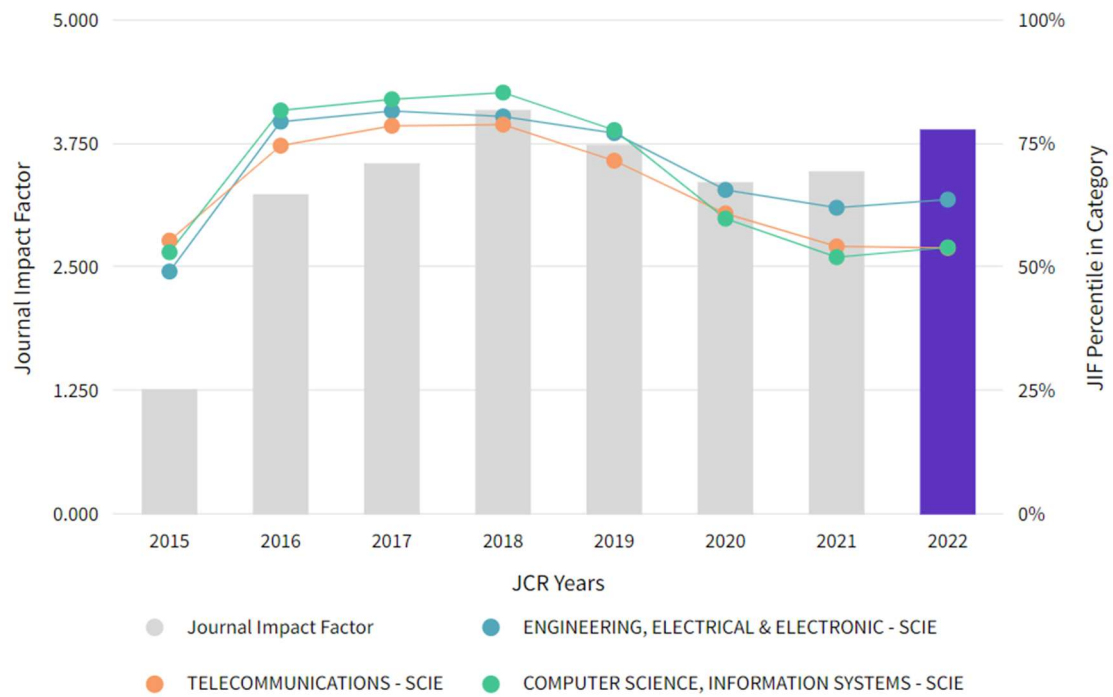
- [62] Huh J, Mac V H, Tran Q H, Lee K-Y, Lee J-I and Kang C 2018 Detectability of delamination in concrete structure using active infrared thermography in terms of signal-to-noise ratio *Applied Sciences* 8(10) 1986
- [63] Gonzalez D, Ibarra-Castanedo C, Madruga F and Maldague X 2006 Differentiated absolute phase contrast algorithm for the analysis of pulsed thermographic sequences *Infrared physics & technology* 48(1) 16–21
- [64] Thapa M, Mulani S B and Walters R W 2019 Stochastic multi-scale modeling of carbon fiber reinforced composites with polynomial chaos *Composite Structures* 213 82–97
- [65] Wang B, Cai Y, Li Z, Ding C, Yang T and Cui X 2020 Stochastic stable node-based smoothed finite element method for uncertainty and reliability analysis of thermo-mechanical problems *Engineering Analysis with Boundary Elements* 114 23–44
- [66] Gutiérrez M A and Krenk S 2018 Stochastic finite element methods *Encyclopedia of Computational Mechanics Second Edition* 1–25
- [67] Zheng Z, Dai H and Beer M 2023 Efficient structural reliability analysis via a weak-intrusive stochastic finite element method *Probabilistic Engineering Mechanics* 71 103414
- [68] Papadopoulos V and Giovanis D G 2017 *Stochastic finite element methods: an introduction* (Springer)
- [69] Tsai S W and Wu E M 1971 A general theory of strength for anisotropic materials *Journal of composite materials* 5(1) 58–80
- [70] Rackwitz R 2001 Reliability analysis—a review and some perspectives *Structural safety* 23(4) 365–95
- [71] Choi K and Youn B 2002 On probabilistic approaches for reliability-based design optimization (RBDO) 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization p 5472
- [72] Novak L and Novak D 2018 Polynomial chaos expansion for surrogate modelling: Theory and software *Beton-und Stahlbetonbau* 113 27–32
- [73] Fukunaga K and Hummels D M 1989 Leave-one-out procedures for nonparametric error estimates *IEEE transactions on pattern analysis and machine intelligence* 11(4) 421–3

Anexo I

Factor impacto publicaciones

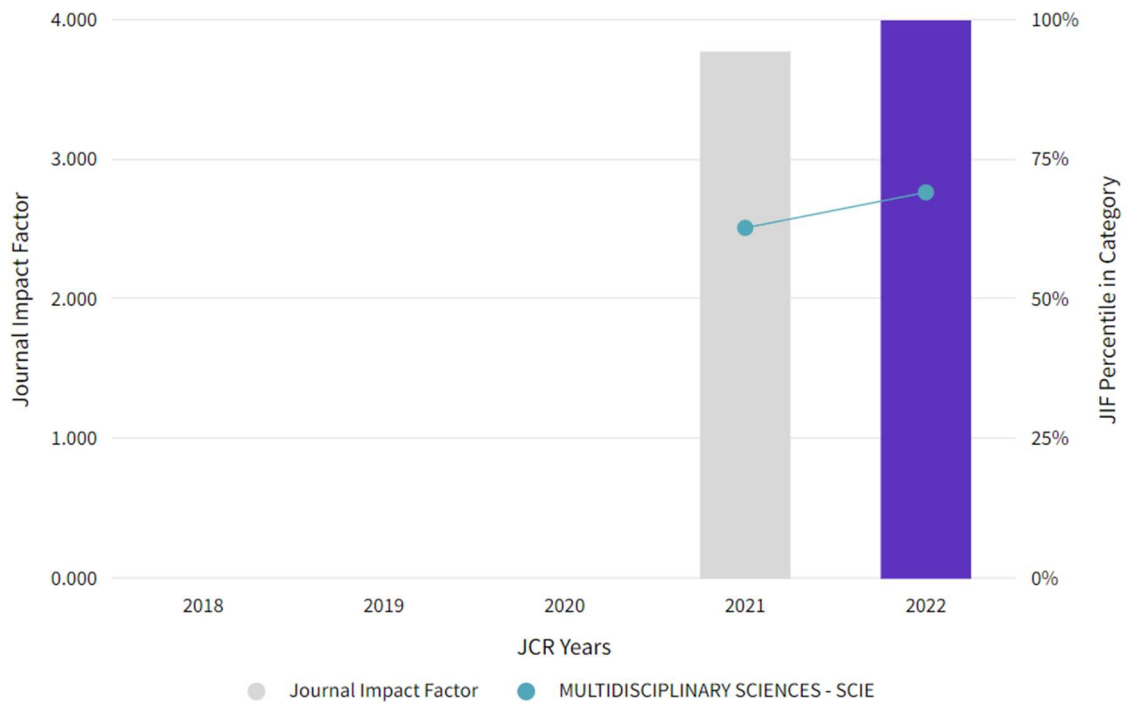
Artículo 1. A comparative study of 2D and 3D Digital Image Correlation approaches for the characterization and numerical analysis of composite materials.

Revista	IEEE Access
URL	https://ieeaccess.ieee.org/
Editorial	IEEE
Factor de impacto JCR	3.9
SJR 2022	0.89
Quartil	Q2
Ranking	100/275



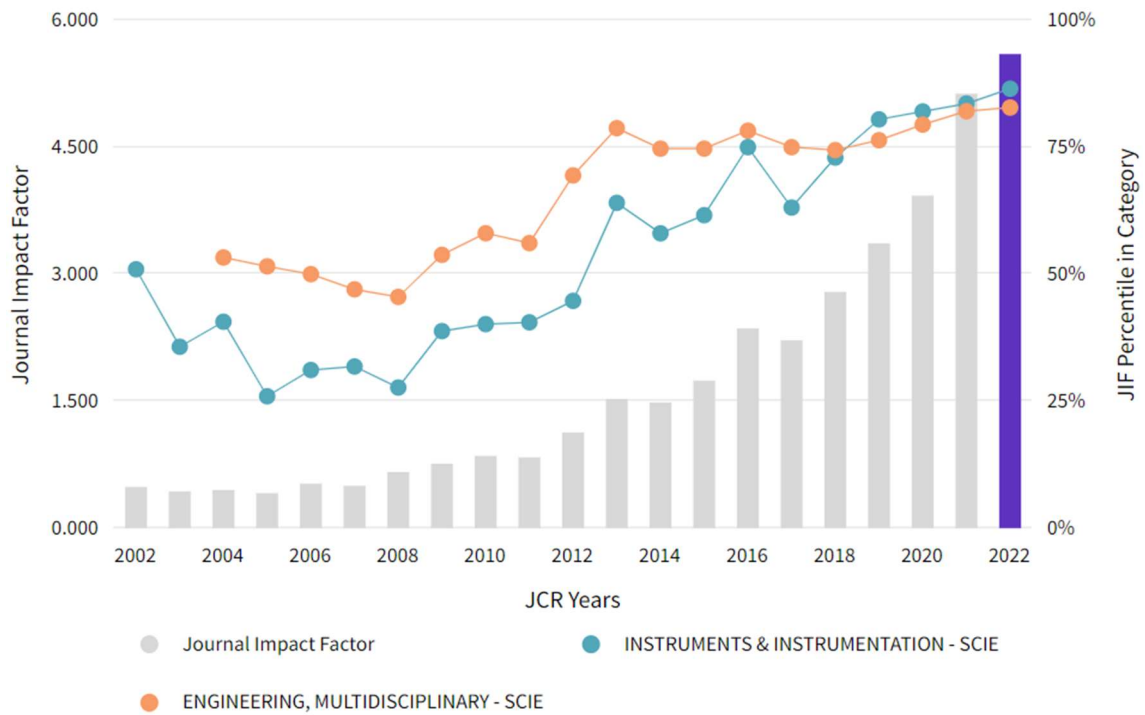
Artículo 2. Surrogate metamodels from digital image correlation for testing high-performance composite vessels.

Revista	Elsevier
URL	https://www.cell.com/heliyon/home
Editorial	Elsevier
Factor de impacto JCR	4.0
SJR 2022	0.80
Quartil	Q2
Ranking	23/73



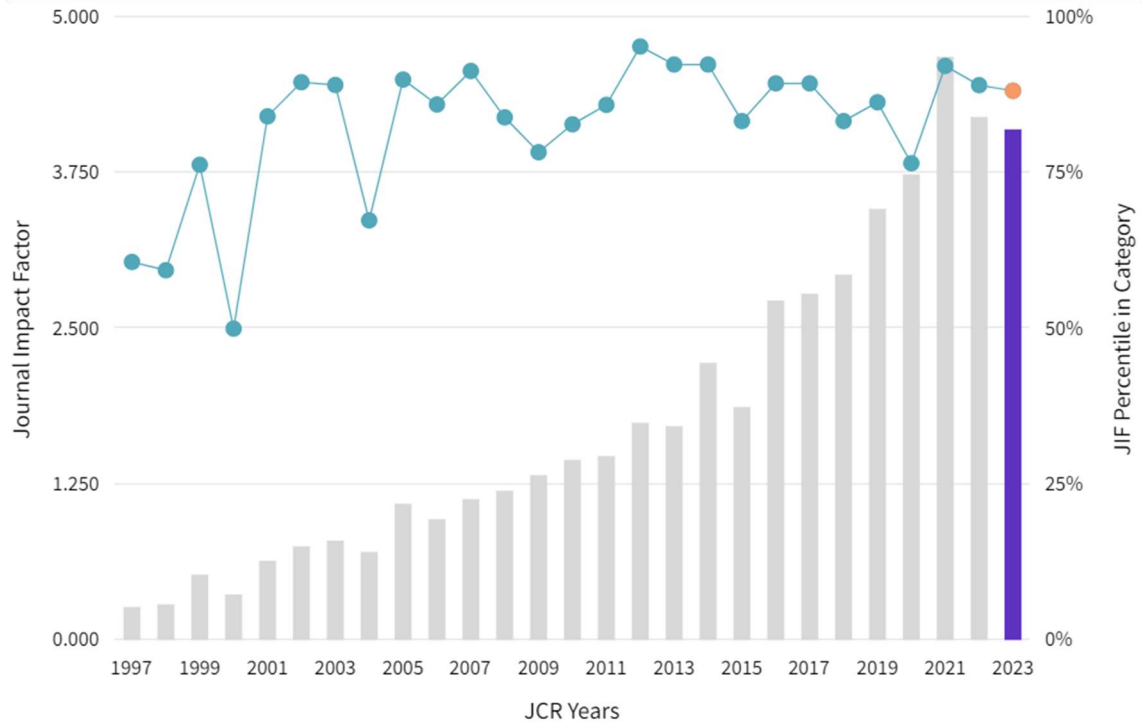
Artículo 3. Step heating thermography supported by machine learning and simulation for internal defect size measurement in additive manufacturing

Revista	Measurement
URL	https://www.sciencedirect.com/journal/measurement
Editorial	Elsevier
Factor de impacto JCR	5.6
SJR 2022	1.63
Quartil	Q1
Ranking	16/90



Artículo 4. Flash thermography to detect and evaluate impacts in polycarbonate parts produced by additive manufacturing.

Revista	NDT & E International
URL	https://www.sciencedirect.com/journal/ndt-and-e-international
Editorial	Elsevier
Factor de impacto JCR	4.1
SJR 2022	1.30
Quartil	Q1
Ranking	5/38



Artículo 5. Smartvessel: A New Extinguisher Prototype Based on New Materials and IoT Sensors.

Revista	Sensors
URL	https://www.mdpi.com/journal/sensors
Editorial	MDPI
Factor de impacto JCR	3.9
SJR 2022	0.89
Quartil	Q2
Ranking	26/86

