Improving Production in Small and Medium Enterprises

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Abstract. Knowledge management has gained relevance during the last years to improve business functioning. However, there is still a growing need of developing innovative tools that can help small to medium sized enterprises to detect and predict undesired situations. This article present a multi-agent system aimed at detecting risky situations. The multi-agent system incorporates models for reasoning and makes predictions using case-based reasoning. The models are used to detect risky situations and an providing decision support facilities. An initial prototype was developed and the results obtained related to small and medium enterprises in a real scenario are presented.

Keywords: Hybrid neural intelligent system, CBR, MAS, Business Intelligence, business risk prediction.

1 Introduction

Knowledge Management is a fundamental asset for businesses in the contemporary economy. Knowledge takes into account the organization of the

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business, individuals and the information [12]. Knowledge management can be applied to different organizations and different contexts. In the present financial context, it is increasilly relevant to provide innovative tools and decision support systems that can help the small-medium enterprises (SMEs) to improve their functioning [8], [11]. These tools and methods can contribute to improve the existing business control mechanisms, reducing the risk by predicting undesiderable situations and providing recommendations based on previous experiences [2].

This article presents an innovative approach, based on multi-agent systems [10], to propose a model for risk management and prediction in SMEs. Multi-agent systems are the most prevalent solution to construct Artificial Intelligence distributed systems. Intelligent agents can incorporate advanced artificial intelligence models to predict risky situations. In this study we propose a distributed approach where the components of a SME are modeled as intelligent agents that collaborate to create models that can evolve over the time and adapt to the changing conditions of the environment. Thus, making possible to detect risky situations for the SMEs and providing suggestions and recommendations that can help to avoid possible undesiderable situations. The core of the multi-agent system are the evaluator and advisor agents, that incorporate new techniques to analyze the data from enterprises, extract the relevant information, and detect possible failures or inefficiencies in the operation processes.

The article is structured as follows: the next section briefly introduces the problem that motivates this research. Section 3 presents the multi-agent system for managing small and medium enterprises and Section 4 describes its implementation. Section 5 presents the results obtained after testing the system.

2 Enterprise Risk Management

"Risk Management" is a broad term for the bussiness discipline that protects the assets and profits of an organization by reducing the potential for risks before it occurs, mitigating the impact of a loss if it occurs, and executing a swift recovery after a loss occurs. It involves a series of steps that include risk identification, the measurement and evaluation of exposures, exposure reduction or elimination, risk reporting, and risk transfer and/or financing for losses that may occur. All organizations practice risk management in multiple forms, depending on the exposure being addressed [1].

The economic environment has increased the pressure on all companies to address risks at the highest levels of the organization. Companies that incorporate a strategic approach to risk management use specialized tools and have more structured and frequent reporting on risk management. As such, they are in a better position to ensure that risk management provides relevant and applicable information that meets the needs of the organization and executive team. But no matter what an organization's approach is, the tools used must be backed up by solid, actionable reporting addressed [1]. It's not always necessary for the risk managers to be conducting their own studies for their voices to be heard. Forging a strong relationship with internal auditors and other departments can allow risk practitioners to supplement their reports with the risk manager's own analysis [3]. Enterprise Risk Management (ERM) is defined as "a process, effected by an entity's board of directors, management and other personnel, applied in strategy-setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives." [4]. The managing of risks and uncertainties is central to the survival and performance of organizations. Enterprise risk management (ERM) is an emerging approach to managing risks across different business functions in an organisation that represents a paradigm shift from specialized approaches in managing specific risks [6], [7]. This paper provides a web intelligent model to ERM, which will subsequently lead to better organisational performance. ERM represents a revolutionary change in an organization's approach to risk. In addition, ERM encompasses all aspects of an organization in managing risks and seizing opportunities related to the achievement of the organization's objectives, not only for protection against losses, but for reducing uncertainties, thus enabling better performance against the organization's objectives [1].

3 Multi-agent System for Risk Management

In this article we propose a multi-agent system aimed at providing advanced capacities for risk management in SMEs. The multi-agent system provides a web system interface to facilitate the remote interaction with the human users involved in the risk management process. The core of the multi-agent system is a type of agent so called CBR-BDI agent. This agent type integrates a case-based reasoning mechanism (CBR) in its internal structure to take advantage of the reasoning abilities of the CBR paradigm. CBR-BDI agents are characterized by their capacities for learning and adaptation in dynamic environments. These agent types are used to evaluate the business' status and to generate recommendations that can help the business to avoid risky situations. CBR-BDI agents collaborate with other deliberative agents in the system to find optimum models for risk management. The agents in the system allow the users to access the system through distributed applications, which run on different types of devices and interfaces (e.g. computers, cell phones, PDA). Figure 1 shows the basic schema of the proposed architecture, where all requests and responses are handled by the agents in the platform. The system is modelled as a modular multi-agent architecture, where deliberative BDI agents are able to cooperate, propose solutions on very dynamic environments, and face real problems, even when they have a limited description of the problem and few resources available. These agents depend on beliefs, desires, intentions (BDI) and plan representations to solve problems. There are different kinds of agents in the architecture, each one with specific roles, capabilities and characteristics:

Business Agent. This agent was assigned for each firm in order to collect new data and allow consultations. The enterprise can interact with the system by means of this agent, introducing information and receiving predictions.

Evaluator Agent. It is responsible for the evaluation and predictions of potential risky situations. Every time that it is necessary to obtain a new estimate of the state of an activity, the agent evolves through several phases. On the one hand, this evolution allows the multi-agent system, to identify the latest situations most similar to the current situation in the retrieval stage, and to adapt the current knowledge in the reuse stage in order to generate an initial estimate of the state of the activity being analysed. On the other hand, it is possible to identify old situations that serve as a basis to detect the inefficient processes developed within the activity and to select the best of all possible activities. The activity selected will then serve as a guide for establishing a risk level for the activity, its function, and the company itself, to develop in a more positive way. The retain phase guarantees that the system evolves in parallel with the firm, basing the corrective actions on the calculation of the error previously made.

Advisor agent. The objective of this agent is to carry out recommendations to help the internal auditor decide which actions to take in order to improve the company's internal and external processes.

Expert Agent. This agent helps the auditors and enterprise control experts that collaborate in the project to provide information and feedback to the multi-agent system. These experts generate prototypical cases from their experience and they receive assistance in developing the Store agent case-base.

Store Agent. This agent has a memory that has been fed with cases constructed with information provided by the enterprise (through its agent) and with prototypical cases identified by 34 enterprises control experts, using personal agents who have collaborated and supervised the developed model.

4 A Practical Implementation

The application of agents and multi-agent systems provides the opportunity of taking advantage of the inherent capabilities of the agents. Nevertheless, it is possible to increase the reasoning and learning capabilities by incorporating a CBR [9] mechanism into the agents. In the case at hand, we will focus on the CBR-BDI agents [10], responsible for classifying the enterprise situation and predict possible risks as well as providing recommendations to manage risk situations. In the BDI model, the internal structure of an agent and its capability to choose is based on mental aptitudes: agent behaviour is composed of beliefs, desires, and intentions [10]. Case-based Reasoning is a type of reasoning based on the use of past experiences [9]. The fundamental concept when working with case-based reasoning is the concept of case. A case can be defined as a past experience, and is composed of three elements: A problem description which describes the initial problem, a solution which provides the sequence of actions carried out in order to solve the problem, and the final state which describes the state achieved once the solution was applied. The way in which cases are managed is known as the case-based reasoning cycle. This CBR cycle consists of four sequential steps: retrieve, reuse, revise and retain. The retrieve phase starts when a new problem description is received. Similarity algorithms are applied in order to retrieve from the case's memory the cases with a problem description more similar to the current one. Once the most similar cases have been retrieved, in the reuse phase the solutions of the cases retrieved are adapted to obtain the best solution for the current case. The revise phase consists of an expert revision of the solution proposed. Finally, the retain phase allows the system to learn from the experiences obtained in the previous phases and updates the case memory in consequence.

The Evaluator and Advisor agent use the same type of case and share the same memory of cases. The data for the cases were obtained by surveys conducted with enterprise experts in the different functional areas of various enterprises, using the Expert agents. This type of survey attempts to reflect the experience of the experts in their different fields. For each activity, the survey presents two possible situations: the first one tries to reflect the situation of an activity with an incorrect activity state, and the second one tries to reflect the situation of an activity with a satisfactory activity state. Both situations will be evaluated by a human expert using a percentage. Each activity is composed of tasks, and each task has an importance rate, and values of realization for both incorrect and satisfactory activity state. These parameters are explained below in the analysis of the case structure. Each case is composed of the following attributes:

- Case number: Unique identification: positive integer number.
- Input vector: Information about the tasks (n sub-vectors) that constitute an industrial activity: ((IR1,V1),(IR2,V2),...,(IRn,Vn)) for n tasks. Each task sub-vector has the following structure (IRi,Vi):
  - IRi: importance rate for this task within the activity. It can only take one of the following values: VHI (Very high importance) with a numeric value of 5, HI (High Importance) with a numeric value of 4, AI (Average Importance) with a numeric value of 3, LI (Low Importance) with a numeric value of 2, VLI (Very low importance) with a numeric value of 1.
  - Vi: Value of the realization state of a given task: a positive integer number (between 1 and 10).
- Function number: Unique identification number for each function
- Activity number: Unique identification number for each activity
- Reliability: Percentage of probability of success. It represents the percentage of success obtained using the case as a reference to generate recommendations.
- Activity State: degree of perfection for the development of the activity, expressed by percentage. This is the solution of a problem case.

The following sub-sections present the internal structure of the CBR-BDI Evaluator and Advisor agents used to predict and prevent crisis in SMEs.

5 Results

A case study aimed at providing innovative web business intelligence tools for the management of SMEs was carried out in the Castilla y León region, in Spain. The experiment consisted on the construction of the initial prototype of cases memory, predicting potential risky situations for the enterprises taken into consideration and providing recommendations. The case study presented in this work was oriented to detect possible risky situations in SMEs, taken into account the crisis that affects the market. A multi-agent system was implemented and 22 SMEs participated in the experiment and were assigned a personal business agent. The enterprises were situated in different sectors of the Spanish market. The system was tested during 24 months, from January 2008 to January 2010, tuned and improved taking into account the experience acquired using a total of 238 cases.

To validate the overall functioning of the system it was necessary to individually evaluate the Evaluator and Advisor agents. These agents provide predictions on the performance of the activities and detect those tasks that can be improved for each activity in order to get an overall improvement of the activity. In the following paragraphs we will focus on the evaluation of the CBR-BDI agents and their influence in the multi-agent system. To validate the performance of the Evaluator agent, an estimation of the efficiency of the predictions provided by this agent was carried out. To evaluate the significance of the different techniques integrated within the Evaluator agent, a cross validation was established, following the Dietterich's 5x2- Cross-Validation Paired t-Test algorithm [5]. The value 5 in the algorithm represents the number of replications of the training process and value 2 is the number of sets in which the global set is divided. Thus, for each of the techniques, the global dataset S was divided into two groups S1 and S2 as follows: $S = S_1 \cup S_2$ y $S_1 \cap S_2 = \emptyset$. Then, the learning and estimation processes were carried out. This process was repeated 5 times and had the following steps: the system was trained using S1 and then it was used to classify S1 y S2. In a second step, the system was trained using S2 and then it was used to classify S1 y S2. The results obtained by the evaluator agent using the mixture of experts, presented in section 4, were compared to the results obtained using an individual RBF and an individual MLP to the same dataset and the same 5x2 Cross-Validation process. Table 1 shows the error rate obtained for each of the techniques, using the test in each of the 5 repetitions. As can be seen in Table 1, the estimated error was lower for the Evaluator agent than for the rest of the evaluated techniques.

Table 1 Absolute error for the estimation of the status of the activities.

Method	**S_2**	**S_1**	**S_2**	**S_1**	**S_2**	**S_1**	**S_2**	**S_1**	**S_2**	**S_1**
Advisor agent	0.297	0.309	0.210	0.281	0.207	0.355	0.226	0.343	0.239	0.302
MLP	0.677	0.669	0.489	0.507	0.513	0.806	0.530	0.696	0.506	0.485
RBF	1.009	0.833	0.656	0.985	0.878	0.959	0.620	0.831	0.643	0.783

A Paired t-Test was applied to check that the difference between the methods can be considered as significant if a value α=0.05 is established. To evaluate the Advisor agent it is necessary to take into account that the aim of this agent is to detect inefficient tasks by means of gain functions. The evaluation of the functioning of the Advisor agent was carried out by selecting those tasks with higher values for the gain function. The selected tasks were used to estimate the

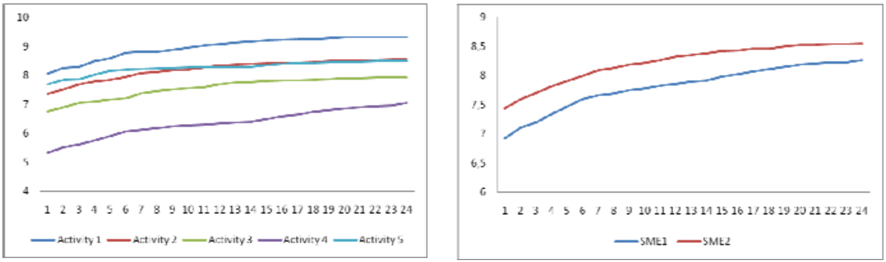

Fig. 1 a) Evolution of the average status of 5 activities during 12 months. b) Evolution of the average status of 2 SMEs during 12 months.

different scenarios for different execution values for the task. In this way, Figure 1a presents the evolution of the system for the average status of 5 activities along 12 months. As shown, the evolution for the 5 activities can be considered as positive. Looking at the evolution of the global efficiency for the activities analysed for two SMEs, shown in Figure 1b, it is possible to observe a growing tendency in the average status of the business along the time, which indicates a reduction of inefficient tasks in each of the activities. The results obtained demonstrate that the multi-agent system caused a positive evolution in all enterprises. This evolution was reflected in the reduction of inefficient processes. The indicator used to determine the positive evolution of the companies was the state of each of the activities analysed. After analysing one of the company's activities, it was necessary to prove that the state of the activity (valued between 1 and 100) had increased beyond the state obtained in the previous three month period. The system considers small changes in the tasks performed in the SMEs, and all the experts that participated in the experiments considered 3 months as a significant time to evaluate the evolution of a SME related to these changes.

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