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Highlights in Practical Applications of Agents and Multiagent Systems

Springer

Advances in Intelligent and Soft Computing 89

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Highlights in Practical Applications of Agents and Multiagent Systems, 2011
ISBN 978-3-642-19916-5

Javier Bajo Pérez, Juan M. Corchado,
María N. Moreno, Vicente Julián,
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Highlights in Practical Applications of Agents and Multiagent Systems

9th International Conference on Practical Applications of Agents and Multiagent Systems

Springer

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ISBN 978-3-642-19916-5 e-ISBN 978-3-642-19917-2

DOI 10.1007/978-3-642-19917-2

Advances in Intelligent and Soft Computing ISSN 1867-5662

Library of Congress Control Number: 2011923213

Typeset & Cover Design: Scientific Publishing Services Pvt. Ltd., Chennai, India.

Printed on acid-free paper
5 4 3 2 1 0
springer.com

Preface

PAAMS'11 Special Sessions are a very useful tool in order to complement the regular program with new or emerging topics of particular interest to the participating community. Special Sessions that emphasized on multi-disciplinary and transversal aspects, as well as cutting-edge topics were especially encouraged and welcome.

Research on Agents and Multi-Agent Systems has matured during the last decade and many effective applications of this technology are now deployed. An international forum to present and discuss the latest scientific developments and their effective applications, to assess the impact of the approach, and to facilitate technology transfer, has become a necessity.

PAAMS, the International Conference on Practical Applications of Agents and Multi-Agent Systems is an evolution of the International Workshop on Practical Applications of Agents and Multi-Agent Systems. PAAMS is an international yearly tribune to present, to discuss, and to disseminate the latest developments and the most important outcomes related to real-world applications. It provides a unique opportunity to bring multi-disciplinary experts, academics and practitioners together to exchange their experience in the development of Agents and Multi-Agent Systems.

This volume presents the papers that have been accepted for the 2011 edition in the special sessions: Special Session on Agents Behaviours for Artificial Markets, Special Session on Multi-Agent Systems for safety and securit, Special Session on Web Mining and Recommender Systems, Special Session on Adaptative Multi-Agent System, Special Session on Integration of Artificial Intelligence Technologies in Resource-Constrained Devices, Special Session on Bio-Inspired and Multi-Agents Systems: Applications to Languages and Special Session on Agents for smart mobility.

We would like to thank all the contributing authors, as well as the members of the Program Committees of the Special Sessions and the Organizing Committee for their hard and highly valuable work. Their work has helped to contribute to the success of the PAAMS’11 event. Thanks for your help, PAAMS’11 wouldn’t exist without your contribution.

Juan Manuel Corchado
Javier Bajo
PAAMS’11 Organizing Co-chairs

Acknowledgements: This conference has been supported by Junta de Castilla y León (Spain).

Organization

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SS2 – Special Session on Multi-Agent Systems for safety and security
SS3 – Special Session on Web Mining and Recommender Systems
SS4 – Special Session on Adaptative Multi-Agent System
SS5 – Special Session on Integration of Artificial Intelligence Technologies in Resource-Constrained Devices
SS6 – Special Session on Bio-Inspired and Multi-Agents Systems: Applications to Languages
SS7 – Special Session on Agents for smart mobility

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Calibration of an Agent Based Model for Financial Markets

Annalisa Fabretti

Abstract. Agent based model are very widely used in different discipline. In financial markets they can explain very well known features called stylized facts and fit statistical properties of data. For such a reason in predicting future price movements they could perform better than standard models using gaussianity. At this scope calibration and validation in order to choose the model and the model parameters are very essential issues. However calibrating such models is a hard issue to tackle and not yet very well considered in literature. The present paper presents the attempt to calibrate the Farmer Joshi model by a Nelder Mead algorithm with threshold. Different objective function are considered in order to identify the best choice.

1 Introduction

Agent based models (ABM) are able to reproduce some of the statistical properties of returns seen in real stock markets [2]. These features include a distribution of returns that is more peaked than the Gaussian distribution, periods of persistent high volatility, period of persistent high trading volume and correlation between volatility and trading volume. Traditional economic models adopt gaussian distribution considering extreme events as outliers or build statistical process able to reproduce these features without providing any understanding of how these features are observed over all financial markets. The agent-based approach considers a population of intelligent adaptive agents and let them acting in order to maximize their financial performance. These kind of model are able to put attention on interactions, learning dynamics or herding behaviour very commons in markets. Heterogeneity is one of the key issue in modelling financial markets. ABM focus on describing different approaches to trade [9] [3], sometimes using oversimplified technical trading rules [4]. Some models put attention on the price formation, i.e. the way of matching

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J.B. Pérez et al. (Eds.): Highlights in PAAMS, AISC 89, pp. 1–8.
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orders, which matters in reproducing stylized facts [11]. A comprehensive view of the literature can be found in [7] and [8].

Since ABM are useful in reproducing market statistics, validation and calibration cover an important role. According to Tesfatsion [13] there are three alternative ways of validating computational models: a descriptive output validation; a predictive output validation; and an input validation. But how can these be done in a scientifically meaningful manner? At the moment there are only a limited number of contributions dealing with it. An interesting and wide discussion of the literature can be found in [15]. A model can be validated if the statistical properties of simulated data match those of real data and the two series can be said to belong to the same distribution, but how can the model parameters be chosen? It is difficult to justify why to choose one specification of parameters and not another; this recalls the problem of calibration. Calibrating is also useful in selecting the best model in reproducing the real data. ABMs can have different ingredients and not any of them can fit well the qualitative and quantitative stylized fact [14]. Main methods of calibration presented so far in the literature are descriptive or heuristic based on similarity of generated sample [10]. Unfortunately classical calibrating model are subject to fail due to the irregularity of the simulated data, however Gilli and Winker in [6] propose a Nelder-Mead simplex algorithm with a local search heuristic called threshold accepting. Others methods, as genetic algorithms used in social science, are also proposed to calibrate agent based model [12] and could give useful improvement to the issue.

The aim of the present work is to study the issue of calibrating an ABM. The standard idea for calibrating this kind of model is to fit statistical properties as moments. For this reason another question addressed in this work is: which moments are to be preferred in the construction of the objective function? In [6] authors combined kurtosis and Arch(1)-effect in the objective function, in [12] mean and standard deviation, while in [16] a more wide discussion on the choice of the objective function is provided. In the present work using the Nelder Mead algorithm with threshold proposed in [6] different moments in the objective function are compared in calibrating the model in [4]. The Farmer Joshi model is choosn for its simplicity but at the same time for its capacity to reproduce market dynamics. The mechanism of price formation, if compared with more complex and realistic mechanism can be considered trivial, however it is out of the scope of the present work to discuss the goodness of Farmer Joshi model, instead it is an aim of the present work to verify the utility of the method proposed by Gilli and Winker in [6].

The paper is organized as follows: Sect. 2 presents briefly the Farmer Joshi Model; Sect. 3 describes data and explains the methodology; Sect. 4 explains results and finally concludes focusing on future researches.

2 The Farmer Joshi Model

The model [4] considers two type of agents characterized by common strategies in the market, fundamentalist and chartist; to aggregate demands the model also includes a risk neutral market maker. At the single time step t the traders observe the most recent prices $P_t, P_{t-1}, ..P_{t-d}$ and the information I_t and submit an order ω_t^i; then the market maker fills all the orders at the new price P_{t+1}. The market maker bases price formation only on the net order $\omega_t = \sum_{i=1}^{N} \omega_t^i$, where N is the number of agents in the market. The market maker fills price for the net order using the so called market impact function $P_{t+1} = P_t \cdot e^{\frac{\omega_t}{\lambda}}$, where λ is called the liquidity parameters. Letting $p_t = \log P_t$, and adding a noise term ξ_{t+1} the logarithm of the price is

$$p_{t+1} = p_t + \frac{1}{\lambda} \sum_{i=1}^{N} \omega_t^i + \xi_{t+1}. \quad (1)$$

The quantity ω_t^i consists in the difference $x_t^i - x_{t-1}^i$, where $x_t^i = x_t^i(p_t, p_{t-1}.., I_t)$ is the position at time t of the i-th trader.

Trend followers invest based on the belief that price changes have inertia. A trend strategy takes a positive (long) position if prices have recently been going up, and a negative (short) position if they have recently been going down. Their position is $x_{t+1}^i = c(p_t - p_{t-d})$, where c is a positive constant and d is the time lag.

Value investors make a subjective assessment of the value in relation to price. They believe that their perceived value may not be fully reflected in the current price, and that future prices will move toward their perceived value. They attempt to make profits by taking positive (long) positions when they think the market is undervalued and negative (short) positions when they think the market is overvalued.
Let the logarithm of the value v_t be a random walk: $v_{t+1} = v_t + \eta_{t+1}$, where η_t is a noise process IID with mean μ_η and standard deviation σ_η. The value investor takes the position $x_{t+1}^i = c(v_t - p_t)$, where $c > 0$ is a constant proportional to the trading capital.

From the point of view of a practitioner, a concern with the simple position-based value strategies and the simple trend follower strategies is excessive transaction costs. Trades are made whenever the mispricing changes. To reduce trading frequency strategies a threshold for entering a position and another threshold for exiting it can be used. The goal is to trade only when the expected price movement is large enough to beat transaction costs. Assume that a short position $-c$ is entered when the mispricing exceeds a threshold T and exited when it goes below a threshold τ . Similarly, a long position c is entered when the mispricing drops below a threshold $-T$ and exited when it exceeds $-\tau$. In general, different traders will choose different entry and exit thresholds, the entry threshold T^i and exit threshold τ^i are extracted from uniform distributions of entry thresholds ranging from T_{min} to T_{max} and exit thresholds ranging from τ_{min} to τ_{max}, respectively. Finally, parameter c is chosen so that $c = a(T - \tau)$, where a is a positive constant called scale parameter for capital assignment.

3 Data and Methodology

An objective function considering moments not always well behaves to guarantee a global solution, hence standard methods are subject to fail. In such a situation in different fields of science and engineering, heuristics optimization have been applied successfully. Such heuristics includes simulated anealing, threshold accepting heuristic, neural networks and genetic algorithms [5]. These kind of methods require a strong computational power and for this are really time consuming. Due to the complexity of the problems and the stochastic elements of the algorithm and the model, they cannot pretend to produce exact solution in every case with certainty. However, a stochastic high-quality approximation of a global optimum is probably more useful than a deterministic poor-quality local minimum provided by a classical method or no solution at all. Here the methodology proposed by [6] is implemented to solve the problem

$$\min_{\theta \in \Theta} f(\theta), \tag{2}$$

where θ is the vector of parameters, Θ is the space of feasible parameters, and $f(\theta)$ is the objective function. The objective function is a weighted combination of estimating errors on some chosen moments. Let be $\mathbf{w}$ a vector of weights, the function takes the form

$$f(\theta) = \mathbf{w}'|\mathbf{m}^e - \mathbf{m}^m|, \tag{3}$$

where $\mathbf{m}^j$, with $j = e, m$, is the moments vector $\mathbf{m} = (k, m, \sigma, \alpha)'$, where k is the kurtosis, m the mean, σ the standard deviation and α is the Arch(1) effect. The index e identify the empirical value of data and m the value of the simulated time series, finally $'$ indicates transposition.

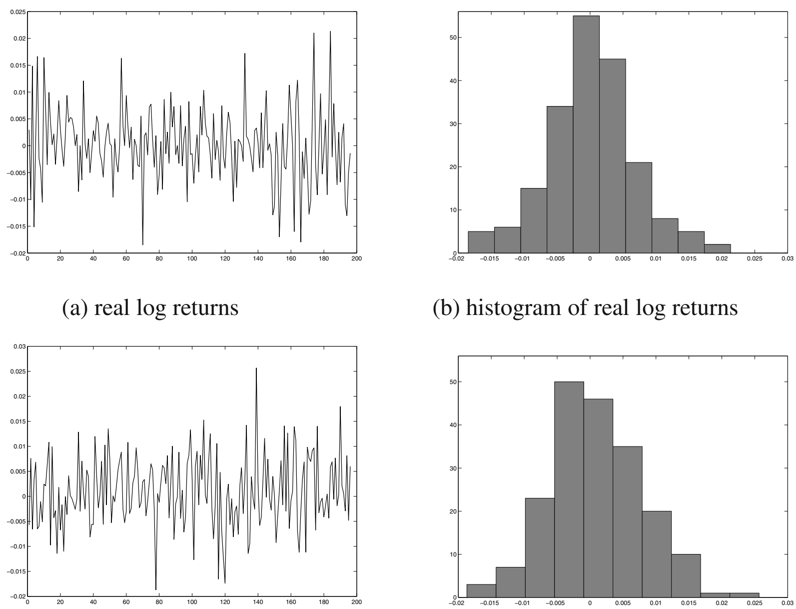
The vector of parameters to calibrate is $\theta = [\lambda, \mu_\eta, \sigma_\eta]$, the liquidity parameter, the drift and the volatility of the random walk driving the fundamental value v_t, respectively. Actually, the model have many parameters to be set, but a too many parameters estimation would easily fail, for this reason this first attempt of calibration is focused only on 3 parameters and keeps constant the others, see table 1. Note that the parameter σ_ξ is not mentioned, because the calibration is done on the "pseudo deterministic "part of the model, that is the log-price in (1) without the noise ξ. Hence the σ_ξ can be found fitting the residuals.

The calibration method consists of two phases. First a Nelder-Mead algorithm is run, later the neighbourhood of the solution found at the first step is explored by a threshold algorithm. For a full description of the algorithm see [6]. The stopping criterium for the Nelder-Mead phase imposes a stop if the number of maximum iteration N_{iter}^{max} or the maximum admissible error err are reached. The first case is considered a failure because often occurs when the algorithm is not able to find the direction in which the objective function decreases. The second case instead is a success because the algorithm is able to find a θ^* minimizing the objective function; when this situation occurs the calibration procedure passes to the second phase, the threshold algorithm, exploring n_R rounds (with n_S steps for each round) of the neighbourhood of θ^*. In the trials presented N_{iter}^{max} has been set to 100, err to $1 \cdot 10^{-1}$, R to 20 and both n_R and n_S to 20.

Data considered are closing prices of S&P500 Composite index from 14/10/2005 to 28/09/2006. In Figure 1(a) logarithmic returns and (b) their histogram are shown. In table 2 a summary of the statistics of interest are reported.

Table 1 Parameters of the model

Name of Parameter	Symbol	Value
Number of agents	N^{trend} N^{fund}	100
Maximum threshold for entering positions	T^{trend}_{max} T^{fund}_{max}	4
Minimum threshold for entering positions	T^{trend}_{min} T^{fund}_{min}	0.2
Maximum threshold for exiting positions	τ^{trend}_{max} τ^{fund}_{max}	0
Minimum threshold for exiting positions	τ^{trend}_{min} τ^{fund}_{min}	-0.2
Maximum offset for log of perceived value	v_{max}	0.5
Minimum offset for log of perceived value	v_{min}	-0.5
Scale parameter for capital assignment	a^{trend} a^{fund}	0.001
Time delay for trend followers	d	5



(a) real log returns

(b) histogram of real log returns

(c) simulated log returns

(d) histogram of simulated log returns

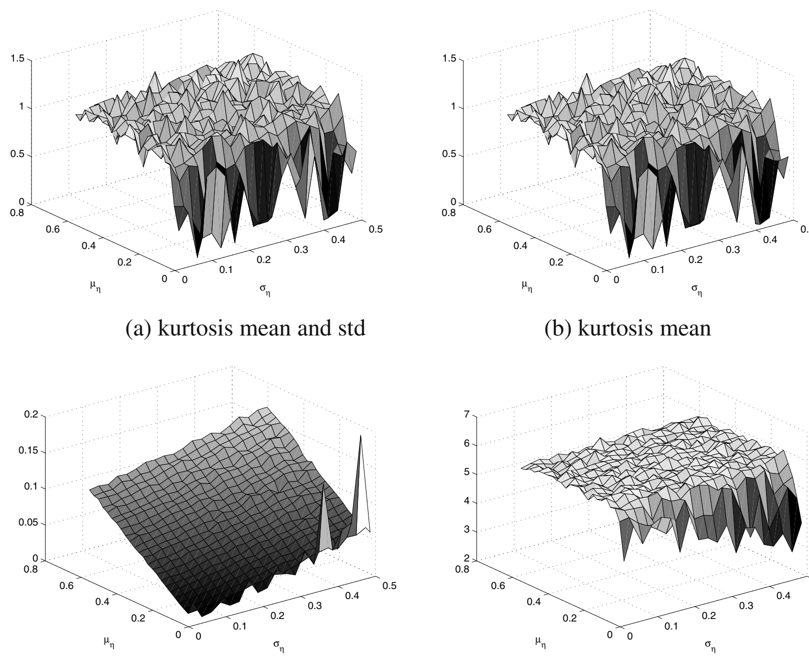
Fig. 1 Log returns of real data (a) and relative histogram (b) from 14/10/2005 to 28/09/2006 and simulated log returns (c) and relative histogram obtained with parameters $[1.0003, 0.0103, 0.0203]$.

Table 2 Descriptive statistics of Data. S&P500 Composite Index from 14/10/2005 to 28/09/2006

Variable	Price	Log Return
Maximum Value	1339.2	0.0213
Minimum Value	1177.8	-0.0185
Kurtosis	3.7553	3.948
Mean	1273.6	4.8582e-004
Standard Deviation	31.6027	0.0066
α arch(1) effect	1.0005	0.99972

4 Results, Comments and Further Research

In the following the results are reported and commented. In Figure 2 objective functions considering different moments are shown plotted for μ_η in $[0.02, 0.6]$ and σ_η in $[0.02, 0.5]$ and λ fixed to 1. More precisely the objective functions considered are a linear combination of the kurtosis, the mean and the standard deviation (a),



(a) kurtosis mean and std

(b) kurtosis mean

(c) mean and std

(d) kurtosis and α

Fig. 2 Different objective functions are plotted for μ_η in $[0.02, 0.6]$ and σ_η in $[0.02, 0.5]$ and $\lambda = 1$. The objective functions considered are a combination of the kurtosis, the mean and the standard deviation (a), of the kurtosis and the mean (b), of the mean and the standard deviation (c) and of the kurtosis and α(d).

of the kurtosis and the mean (b), of the mean and the standard deviation (c) and of the kurtosis and α effect (d). It is notably to observe that where the kurtosis is considered the surface is very rough with higher values respect with the smoothest objective function obtained by the couple m and σ, that unfortunately is not able to catch the well known stylized facts of financial data.

Many trials have been done for the objective function with weights vector $\mathbf{w} = [1,2,1,5]$ and all of them have failed. Indeed the algorithm is unable to find the direction of descending of the objective function. This failure can be attributed either to the algorithm or to the model. In fact some ABMs are able to reproduce qualitative feature of the market but could be not adapt to reproduce the quantitative feature of the market as observed in [14] and here it could be the case. The Farmer Joshi model considers, for example, a very simple price formation mechanisms where more complex market microstructure better can reproduce stylized facts. More investigations are needed to understand how to improve the calibration or why it fails. In table 3 two successful calibration trials are presented, for each successful trial the moments of simulated data are provided. A successful calibration is obtained for the objective function with $\mathbf{w} = [1,0,0,5]$, while the threshold algorithm alone has been used in minimizing the objective function with $\mathbf{w} = [0,1,1,0]$. Data analysis is necessary to test the goodness of the resulting calibrated parameters; it can be seen comparing moments in table 3 with those in table 2 that only $\theta^* = [1.0003, 0.0103, 0.0203]$ fits real data, while $\theta^* = [0.7921, 0.9752, 0.6337]$ gives unsatisfactory results, suggesting that the algorithm stopped in a local minimum. In Figure 1 simulated data (c) for $\theta^* = [1.0003, 0.0103, 0.0203]$ are plotted in comparison with real data (a), see also their histograms (b) (d).

Some observations are due: first, it is worth to note that the choice of weights of the objective function would require a more rigorous criterium; second, attempts to calibrate data on a longer time window (14/10/2005 - 14/10/2010) has been done without success. A so long data interval in fact includes events like the recent financial crisis, the total kurtosis and the standard deviation of these data are so high that even a long time interval simulation is not able to catch completely the oscillations. This drawback may be bypassed evaluating moments using bootstrap.

In conclusion, even if the results presented are still preliminary they can offer a starting point for future investigations. The procedure implemented is still very slow to converge and often fails. The minimization of the objective function must be improved with a reasonable choice of the weights and a robust estimation, like the bootstrap, of the moments. By this first study it can be concluded that, when used for rough objective function, the Nelder Mead algorithm, even if coupled with an heuristic, can easily fail reaching a local minimum instead than a global one. A further test can be done by using this method for a model which it is possible to derive a closed form solution for the distribution of returns as in [1]. Other heuristic calibration methods can also successfully replace the one studied here. In particular interesting results are given by the genetic algorithms, which also allow the simultaneous calibration of many parameters. Future research are intended to be in such directions. The hope is to present in future more exhaustive studies on methods and their comparison.

Table 3 Calibration results of successful trials. The time is indicated in minutes.

Obj Fun	$\theta^* = [\lambda^*, \mu_\eta^*, \sigma_\eta^*]$	min Obj Fun	time	mean	std	kurtosis
k, α	$[0.7921, 0.9752, 0.6337]$	0.9235	167.12	0.1103	0.0968	2.9650
m, σ	$[1.0003, 0.0103, 0.0203]$ [1]	0.0012	44.43	0.0010	0.0070	3.2990

[1]Obtained with the threshold algorithm alone.

References

1. Alfarano, S., Wagner, F., Lux, T.: Estimation of Agent-Based Models: The Case of an Asymmetric Herding Model. Computational Economics 26, 19–49 (2005)
2. Cont, R.: Empirical properties of asset returns:stylized facts and statistical issues. Quant. Fin. 1, 223–236 (2001)
3. Day, R.H., Huang, W.: Bulls, Bears and Market Sheep. J. of Econ. Behav. and Org. 14, 299–329 (1990)
4. Farmer, J.D., Joshi, S.: The price dynamics of common trading strategies. J. of Econ. Behav. and Org. 49, 149–171 (2002)
5. Fonseca, C.M., Fleming, P.J.: Genetic Algorithms for multi-objective optimization: Formulation, Discussion, Generalization. In: Proceedings Fifth International Conference on Genetic Algorithm, pp. 416–423 (1993)
6. Gilli, M., Winker, P.: A global optimization heuristic for estimating agent based models. Comp. Stat. & Data Anal. 42, 299–312 (2003)
7. Hommes, C.H.: Heterogeneous Agent Models in Economics and Finance. In: Tesfatsion, L., Judd, K.L. (eds.) Handbook of Computational Economics, vol. 2, pp. 10–13. Elsevier Science B.V., Amsterdam (2006)
8. LeBaron, B.: Agent based computational finance: Suggested readings and early research. J. Econ. Dyn. Contr. 24, 679–702 (2000)
9. Lux, T., Marchesi, M.: Scaling and criticality in a stochastic multi-agent model of a financial market. Nature 397, 498–500 (1999)
10. Palin, J.: Agent-Based Stockmarket Models: Calibration Issues and Application. PhD thesis, University of Sussex, UK (2002)
11. Pellizzari, P., Dal Forno, A.: A comparison of different trading protocols in an agent based market. J. of Econ. Inter. and Coord. 2, 27–43
12. Rogers, A., Von Tessin, P.: Multi-Objective calibration for and agent-based model. In: Agent-Based Simulation, Lisbon, Portugal (May 2004)
13. Tesfatsion, L.: Website on ACE: Verification and Empirical Validation of Agent-Based Computational Models, http://www2.econ.iastate.edu/tesfatsi/empvalid.htm
14. Veryzhenko, I., Brandouy, O., Mathieu, P.: Agent's Minimal Intelligence Calibration for Realistic Market Dynamics. In: Li Calzi, M., Milone, L., Pellizzari, P. (eds.) Progress in Artificial Economics, pp. 3–14. Springer, Heidelberg (2002)
15. Windrum, P., Fagiolo, G., Moneta, A.: Empirical Validation of Agent-Based Models: Alternatives and Prospects. J. of Art. Soc. and Social Sim. 10(2) (2007)
16. Winker, P., Gilli, M., Jeleskovic: An objective function for simulation based inference on exachange rate data. J. Econ. Interac. Coord. 2, 125–145 (2007)

A Multiagent System for Web-Based Risk Management in Small and Medium Business

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Abstract. Business Intelligence has gained relevance during the last years to improve business decision making. However, there is still a growing need of developing innovative tools that can help small to medium sized enterprises to predict risky situations and manage inefficient activities. This article present a multiagent system especially conceived to detect risky situations and provide recommendations to the internal auditors of SMEs. The core of the multiagent system is a type of agent with advanced capacities for reasoning to make predictions based on previous experiences. This agent type is used to implement an evaluator agent specialized in detect risky situations and an advisor agent aimed at providing decision support facilities. Both agents incorporate innovative techniques in the stages of the CBR system. 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

Nowadays, the organization systems employed in enterprises are increasing in complexity. In the present financial context, it is increasilly relevant to provide innovative tools and decision support systems that can help the small-medium

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J.B. Pérez et al. (Eds.): Highlights in PAAMS, AISC 89, pp. 9–17.
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enterprises (SMEs) to improve their functioning (Khashman 2009, Li and Sun in press, Li et al. in press, Sun and Li 2009a, Sun and Li 2009b). 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 (Chi-Jie 2009, Li and Su 2008, Sun and Li 2008a, Sun and Li 2008b).

The processes carried out inside a company are grouped into functional areas (Corchado et al. 2000) denominated "Functions". A Function is a group of coordinated and related activities that are systematically and iteratively carried out during the process of reaching the company's objectives (Li and Sun 2009). The functions that are usually carried out within a company, as studied within the framework of this research, are: Purchases, Cash Management, Sales, Information Technology, Fixed Assets Management, Compliance to Legal Norms and Human Resources. Each one of these functions is broken down into a series of activities. For example, the Information Technology function is divided into the following activities: Computer Plan Development, Study of Systems, Installation of Systems, Treatment of Information Flows, and Security Management.

This article propose an innovative approach, based on multiagent systems (Bajo et al. 2009), to propose a model for risk management and prediction in SMEs. Multiagent systems are the most prevalent solution to construct Artificial Intelligence distributed systems. Agents are computational entities that can be characterized through their capacities in areas such as autonomy, reactivity, pro-activity, social abilities, reasoning, learning and mobility (Bajo et al. 2009). These capacities make the multi-agent systems very appropriate for constructing intelligent environments. An agent can act as an interface between the user and the rest of the elements of the intelligent environment. Moreover, intelligent agents can incorporate advanced artificial intelligence models to predict risky situations.

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. Section 4 presents the results obtained after testing the system and the conclusions of this study.

2 Application of Business Web Intelligence to Enterprise Risk Assessment and Management

"Risk Management" is a broad term for the business discipline that protects the assets and profits of an organization by reducing the potential for loss 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 (Calderon and Cheh 2002, Risk and Insurance Management Society 2008).

The economic environment has increased the pressure on all companies to address risk at the highest levels of the organization. Companies with a strategic approach to risk management use more tools and have more structured and frequent reporting on risk management than do firms with other approaches. 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 (Calderon and Cheh 2002, Risk and Insurance Management Society 2008). 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 (Colbert 1995).

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." (Committee of Sponsoring Organizations of the Treadway Commission -COSO 2009).

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 organization that represents a paradigm shift from specialized, silo-ed approaches in managing specific risks (Ding et al. 2008, Huang et al. 2008, Li and Sun 2009, Lin et al. 2009, Ramamoorti et al. 1999). This paper provides a web intelligent model to Enterprise risk assessment, which will subsequently lead to better organizational performance.

3 Multiagent Web System for Risk Management

Agent and multi-agent systems (SMEs) have become increasily relevant during the last decades and have gained relevance in different areas (Bajo et al. 2009, Sun and Li 2008).

In this article 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. The multiagent system provides a web system interface to facilitate the remote interaction with the human users involved in the risk management process.

Thus, making possible to detect risky situations for the SMEs and providing suggestions and recommendations that can help to avoid possible undesiderable situations. 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.

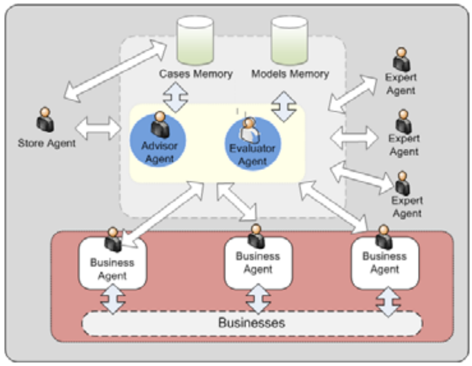


Fig. 1 Crisis multiagent architecture basic schema.

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 enterprise 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.
- 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 multiagent 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.

The core of the multiagent 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 evaluator and advisor agents are CBR-BDI agents (Corchado and Laza 2003) that make use to past experiences to resolve new problems. As such, it is perfectly suited for solving the problem at hand. In addition, CBR (Case-Based Reasoning) makes it possible to incorporate the various stages of expression analysis into the reasoning cycle of the CBR (Kolodner 1993), thus facilitating the creation of strategies similar to the processes followed in small and medium enterprises.

On one hand the evaluator agent is specialized in detecting risky situations. The recovery of information from previous experiences simplifies the prediction process by detecting and eliminating relevant and irrelevant patterns detected in previous analyses. The retrieve phase of the hybrid neural intelligent system incorporates a novel Expectation Maximization clustering technique (Dellaert 2002). The reuse stage incorporates an innovative mixture of experts that makes use of multilayer perceptron, support vector regression and radial basis function neural network. The revise and retain stages implement a decision support system for experts. Moreover, the knowledge obtained during the prediction process is of great importance for subsequent predictions. On the other hand, the advisor agent is specialized in providing recommendations to avoid risky situations and improve the overall functioning of the SME. The retrieve phase recovers similar cases and their corresponding solutions. The reuse phase incorporates a novel approach based on decision trees and probabilistic gain functions to ponder efficient and inefficient tasks. The revise and retain stages also implement a decision support system for experts. There are various artificial intelligence techniques such as artificial neural networks (Bianchia et al. 2007, Sawa and Ohno-Machado 2003), Bayesian networks (Baladandayuthapani et al. 2005), and fuzzy logic (Avogadri and Valentini 2009) which have been applied to business failure prediction. While these techniques can be applied to failure detection and prediction, the knowledge obtained cannot be incorporated into successive tests and included in subsequent analyses. The approach presented in this article is an evolution of our previous works and proposes an innovative perspective (Borrajo et al. 2005, Corchado et al. 2005). The new approach proposes a multiagent system to model the organizational structure of a SME. Moreover, the core of the system is a CBR-BDI agent type with the ability to adapt to the changes in the environment. In (Borrajo et al. 2005) we presented a system composed of two case-based reasoning systems to detect the associate risk in the activities of SMEs in the textile sector and generate recommendations to improve the erroneous processes. In (Corchado et al. 2005) we presented a decision support tool based on a case-based reasoning system that automates the internal control processes of a SME. The new approach proposes new methods for the retrieval stage of the CBR systems, as the Expectation Maximization clustering, that notably improves the case's recovery reducing the final quantity of cases stored and making it easier to recover the most similar cases to the problem introduced. Moreover, the approach proposes very innovative reuse mechanisms, based on mixture of experts and probabilistic decision trees.

4 Results and Conclusions

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 memory of cases and then in predicting potential risky situations for the enterprises taken into considerations 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 multiagent system was implemented and 22 SMEs participated in the experiment and were assigned a personal business agent. The enterprises were situated in different sectors and located in the Spanish region of Castilla y León. The economic context is the same for all the SMEs. 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. The evolution of the enterprise is monitored through its internal activities and the predictions are made based on the previous experiences and on the status of the market (the possible crisis that affect the market). To provide information about the Enterprise, the experts have to complete a survey.

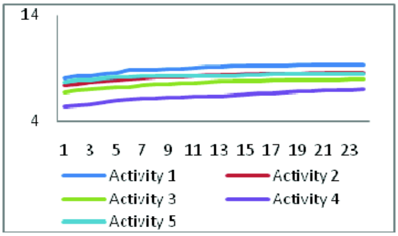
To validate the overall functioning of the system it was necessary to individually evaluate the Evaluator and Advisor agents. These agents provide predictions on the performance of the activities and detect those tasks that can be improved for each activity in order to get an overall improvement of the activity. To validate the performance of the Evaluator agent, an estimation of the efficiency of the predictions provided by the Evaluator 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 (Dietterich 1998). 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 S_1 and S_2 as follows: $S = S_1 \cup S_2$ y $S_1 \cap S_2 = \phi$. 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 S_1 and then it was used to classify S_1 y S_2. In a second step, the system was trained using S_2 and then it was used to classify S_1 y S_2. The results obtained by the evaluator agent using the mixture of experts 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
Evaluator 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 significative if a value $\alpha = 0.05$ 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, as explained in Section 3. 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 different scenarios for different execution values for the task. The estimation was performed using the values provided by the Evaluator agent, obtaining a concrete value for the task. In this way, Figure 2a 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.



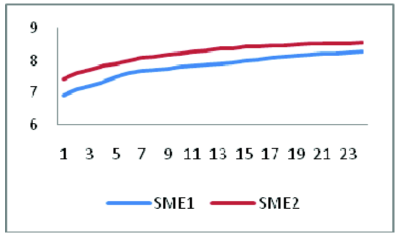


Fig. 2 a) Evolution of the average status of 5 activities during 12 months. b) Evolution of the average status of 2 SMEs during 12 months.

Looking at the evolution of the global efficiency for the activities analyses for two SMEs, shown in Figure 2b, 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 multiagent 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 analyzed. After analyzing 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.

We had certain problems implementing the system, partly because the management and experts were not familiar with the use of computational devices and multiagent systems, so some courses were given to introduce them to these technologies and teach them how to use the system interface. The proposed novel multiagent system is a unique system useful for dynamic environments and open enough to be used in other enterprise environments. The experts noted that the behavior of the system improves as the number of cases in the memory of cases grows. This is a typical behavior in CBR-based systems. We found some difficulties with the surveys, because some of the SMEs were reticent to complete surveys.

The users indicated that the use of a web-based interface facilitates the use of the new system. However, some of them were reticent about trusting the system because they were reluctant to facilitate their internal data and because updating the information about the enterprise requires specialized human resources and time. However, the auditors and experts believe that the CBR-BDI agents may support their work and provide a highly appreciated decision support tool. They