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The impact of sales service in MAREA trading simulation under changing environment circumstances

JEL Classification: F1; F3

Keywords: multi-agent system; simulation; model; trading; MAREA

Abstract

Research background: Managerial scientists use a lot of modelling techniques for business processes. In this paper we are focused on agent-based modelling and simulations, which emerged in the last two decades as a new approach. Autonomous and interacting intelligent agents are able to model and simulate complex systems in the business sphere. With the use of agent-based modelling and simulations we are able to understand how macro level outcomes are affected by micro level processes and vice versa.

Purpose of the article: The purpose of the paper is to introduce recent development in the area of agent-based modelling and simulations focused on the business domain. Managers often have to make difficult decisions under the uncertainty and high risks. Agent-based modelling can provide powerful tools for lowering those risks through a possibility of running experiments, which is normally impossible in economics. In the second part we want to support the usefulness of agent-based simulations with our own simulations.

Methods: The method used in this article is an agent-based simulation in a multi-agent system. We use a framework called MAREA. It is a simulation environment with integrated ERP system based on REA ontology. Our simulation model is based on a retail company that sells electronics. For simplicity, in our setup we trade with computer cables.

Findings & Value added: In our simulations we experimented with the quality of sales service provided by company's sales representatives. We investigated the impact of quality of sales service on company KPIs under the changing environment circumstances represented by disturbance agent. The quality of sales service is a part of quality of service and thus it affects the perception of brand and loyalty of customers towards the company. In our simulation setup we work with two types of customers, long-term customers and new ones. The result is that quality of sales service has mostly positive effects on company KPIs.

Introduction

The purpose of the paper is to introduce a recent development in agent-based modelling and simulation (ABMS) domain focused on business. ABMS is a powerful tool for modelling and simulating complex systems. We think that this approach can be used especially well by managers of companies. In today's global and fast changing environment managers need to make fast and appropriate decisions under the pressure of all kinds of risks and uncertainty, often without well knowing the impact of those decisions on the company.

Knowledge and experiences of management may not always be there, and the method of trial and error might be quite costly. Here comes the place for ABMS, which can provide managers missing tools that can allow them to see the impact of those decisions without any risks for the company.

In the first part, we provide a general background in the ABMS area. We explain why we and many other researchers think the ABMS approach is very suitable for social sciences and the reasons behind this thinking, and we also focus on the strengths and weaknesses of ABMS approach. Then, we introduce a recent development and main focuses of researchers in ABMS in business sphere. The following chapter describes the methodology used in this paper. In the third chapter, we support our claim of the usefulness of ABMS approach by providing our own simulations in MAREA simulation framework. In this paper, we introduce MAREA framework just briefly, for more detailed description of used multi-agent system see, e.g. (Vymětal *et al.*, 2012, pp. 340-349). With our simulation setup, we will investigate impact of sales services on company KPIs under different circumstances in changing environment. While simulations can help to understand macro level process based on micro level processes and vice versa, in our simulation we are focused on the end state of our simulations rather than its dynamics. The last chapter presents results of the article and discussion.

Background research and related work

Modelling plays an irreplaceable role in modern economics. Economists model markets, consumers' behaviour, trading, supply chains and much more. The managements of business companies have to make decisions without knowing of impacts of such decisions. That may cost companies a lot, and therefore we think simulations may play a big difference, because management of companies can see impact of their decisions and lower the risks of their decisions. This is possible especially because of the rise of easy to use models and new technologies. There are two different paths towards modelling approaches, analytical and agent-based modelling. Analytical modelling approaches are based mostly on mathematical theories (Gries *et al.*, 2003, pp. 256–261; Liu & Trivedi, 2006, pp. 29–44). Even though mathematical and statistical modelling is an appropriate approach, it rarely contains the theory of consumer behaviour.

On the other hand, agent-based simulations used in this paper are able to simulate complex systems and give us the opportunity to study behaviour of a whole population of consumers, which helps to understand how micro level processes affect macro level outcomes and vice versa (Siebers *et al.*, 2008; Terano, 2008, pp. 175–187). The ABMS approach also allows to weaken some assumption used in economic theory like, e.g., rationality of agents, where it is assumed that agents are completely rational under all circumstances. Software agents can be programmed to have bounded rationality or agent heterogeneity (Axtell, 2007, pp. 105–122). Agent-based simulations allow us to capture the influences like, e.g., communication, experience level, cultural and social factors, etc., which typical business process models cannot (Rand & Rust, 2011, pp. 181–193) and help us to overcome limitations of commonly used economic methods including linearity, homogeneity and stationarity (Chhatwal & He, 2015, pp. 423–433). Runje *et al.* (2015, pp. 1561–1566) say that agent-based modelling can be used as a tool of understanding of dynamics of companies operating on global, complex and highly competitive markets. Twomey and Cadman (2002, pp. 56–63) summarized the main strengths of the ABMS approach as system assumptions (models are not limited by assumptions like linearity or stationarity), realism (models are realistic as world is made of interacting entities), natural representations (models are easy to understand because of strict correspondence between model and targeted system), heterogeneity (ABMS introduce very high degree of heterogeneity), bounded rationality (due to a limited information of software agents there is no need for agents to be perfectly rational), communication and social networking, object-

oriented analysis, design and programming and lastly maintenance and refinement.

The ABMS approach has also some weaknesses like the need for adequate data, identification of rules of behaviours of agents, demand for programming skills and technological demands related with computational time (Twomey & Cadman, 2002, pp. 56–63; Midgley *et al.*, 2007, pp. 884–893; Fagiolo *et al.*, 2007, pp. 189–194; Leombruni & Richiardi, 2005, pp. 103–109). Even though it is true that ABMS is able to model complex, non-linear systems and even behaviour, it is also true that validation and verification of such models is a big problem (Vanhaverbeke & Macharis, 2011, pp. 186–196). Complexity of ABMS models is also its weakness because one needs to be able to validate those complex models (Marks, 2007, pp. 265–290). Validation of models depends not only on goals of simulations. According to author there is always a trade between realism and parsimony, because with more realistic models one needs more variables which escalate to a greater level of freedom. Heppenstall *et al.* (2007, pp. 1051–1070) and Midgley *et al.* (2007, pp. 884–893) introduce a way to better validate models through use of genetic the algorithms. Another problem is that ABMS approach is often not able to find global optimal solution, one needs to search through space solution by performing high number of simulations with different parameters.

ABMS in business

While in previous chapter we wanted to provide general background in area of ABMS, we explained why we and many other researchers think the ABMS approach is very suitable for social sciences and reasons behind this thinking. Then, we provided strengths and weaknesses of the ABMS approach. In this chapter, we are focused on the recent work in area of agent-based modelling and simulation in business domain. Our search was focused mainly on prominent databases like Web of science and Scopus, where we were looking for work related to ABMS and business that were published in years 2007 and later.

Quite a big part of research in the ABMS area focused on business sphere is dedicated to analysing supply chains. Li *et al.* (2010, pp. 850–859) focused on analysing the behaviour of dominant player's in supply chains. Wang *et al.* (2009, pp. 1046–1055) used the ABMS approach to investigate the formation of supply chains on all levels of management, strategic, tactical and operational level. He *et al.* (2013, pp. 325–336) introduced agent-based retail model, where they investigated micro-scale inter-

actions between three types of agents (suppliers, retailers and consumers) and a macro-scale feedback of market transactions to get the optimal price strategy. Optimal behaviour of agents' in agent-based retail model is determined by the use of optimization methods and genetic algorithm. Sun *et al.* (2017, pp. 377–389) integrated agent-based modelling and discrete event modelling to model automotive supply chain network.

The second area of use of ABMS in business is in marketing management mainly consumer markets and consumers' behaviour. North *et al.* (2010, pp. 37–47) emphasizes that even though regression-based and other models provided many important contributions, none of them were able to holistically represent the interdependencies of decisions made by consumers, retailers and manufacturers. In their work, the authors used the ABMS approach to model consumer market model. Their model was able to directly influence and support managerial decision making with the effect of saving costs. Several other authors have used the ABMS approach to investigate consumers' behaviour. Roozmand *et al.* (2011, pp. 1075–1095) investigated consumers' decision making process of buying cars, where the authors also provide deep insight to ABMS decision making of consumers based on psychological needs, culture and personality, trust and reputation and lifestyle. Zhang and Zhang (2007, pp. 912–922) modelled customers' decision making facing several brands based on socio-demographic (e.g., age, income, occupation, education, housing and marital status) and personality factors (e.g., price sensitivity, quality sensitivity, loyalty, susceptibility and follower tendency). Another work dedicated to modelling about brand decisions is Schramm *et al.* (2010, pp. 234–242). While Zhang and Zhang (2007, pp. 912–922) investigated decoys effect, Schramm *et al.* (2010, pp. 234–242) focused on diffusion of innovations. Because of the low acceptance of the ABMS approach for publication in top marketing journals Rand and Rust (2011, pp. 181–193) in their work discuss guidelines for rigorous agent-based modelling and the use of such models.

The third area of use is automated trading. Fatima *et al.* (2004, pp. 1–45) states three most important issues in negotiation as (1) time constraints, (2) information state of negotiators and (3) number of issues to be negotiated. Li and Shi (2012, pp. 13–22) used agent-based modelling to optimize one day ahead bidding on electricity market with respect to wind forecasting accuracy. Izumi *et al.* (2009, pp. 3469–3476) introduced artificial-market framework to evaluate automated trading strategies. Ren *et al.* (2009, pp. 704–716) introduced expanded market-driven model designing strategies with respect to the changes of environment by considering not only current environmental condition but also potential changes of envi-

ronment. Zhou *et al.* (2007, pp. 305–342) presented tools for agent-based simulations of electricity markets in their paper.

Another area of use of ABMS approach is in managerial science. Lots of scientist use ABMS, namely NK-type simulation agent-based model based in biology, to analyse decision-making biases and impact of decision-making processes on overall organizational performance (Behrens *et al.*, 2013, pp. 179–190). Davis *et al.* (2007, pp. 480–499) describe the usage of simulations in theory development and describe the position of simulation methodology and theoretical development within organizations and strategy. Gilbert *et al.* (2007, pp. 100–109) focused their simulations on organizations' ability of learn, which is in direct relation with management of innovation. A deep view into the use of ABMS in managerial science is provided by Wall (2014, pp. 135–193), where he focused his attention primarily on research questions of “exploration vs exploitation” and “differentiation vs integration”, which he considers as a recent main tensions in managerial science which is widely studied especially with use of ABMS.

Research methodology

In our simulation experiments, we model complex system of trading company composed of interacting, autonomous agents presented in Macal and North (2010, pp. 151–162), thus our model can be described as stochastic, dynamic and discrete. Behaviour of agents is defined by simple rules and their interactions within environment, which also influences their behaviour. Depending on the problem one wants to exploit, software agents in the ABMS approach can represent many different entities (e.g., companies, people, branches, etc.). In our setup software agents represent people (e.g., customers, sales representatives), departments within company (e.g., manager, accountant, etc.).

As mentioned in the previous chapter, for our experiments we use modelling and simulation framework called MAREA. The framework models a trading process of selling goods by company sales representatives to the customers and purchasing goods from suppliers by purchase representatives. The first sub-system is called sales representative-to-customer negotiation, and the second sub-system is called supplier-to-purchase representative negotiation (Figure 1). Modelled company consists of the following types of agents: sales representative agents, purchase representative agents, customer agents, supplier agents, accountant agent (takes care of bookkeeping of the company), manager agent (manages the sales representative agents, calculates KPIs) and disturbance agent (responsible for

historical trend analysis of sold amount). All agents are developed according to multi-agent approach and the interaction between agents is based on the FIPA contract-net protocol (Sandita & Popirlan, 2015, pp. 478–486).

In the reality of a market, the number of customers is usually significantly higher than the number of sales representatives. In our simulation experiments, the number of customer agents is also significantly higher than the number of sales representative agents. The simulations are based on the sales representative-to-customer negotiation. Customer agents initiate negotiations at random by sending request message with demanded quantity of goods to sales representative agents. The requested amounts of demanded goods are generated randomly (Vymětal *et al.*, 2012, pp. 340–349). As a response to customer request, a sales representative sends back a message with the quoted price. Customer decides if he is willing to accept the quote based on the evaluated value of decision function (1). The behavior of customer agents is therefore characterized primarily by decision function. For simplification, only one stock item is used in the implementation. If customer agent decides not to buy anything, his turn is over.

In the text to follow we propose the mathematical definition of a decision function. Decision function for i -th customer determines the quantity that i -th customer accepts. If $x_i < \text{quantity demanded}$ by customer, the customer realizes that according to his preferences and budget, offered quantity is not enough, he reject the sales quote (Vymětal & Ježek, 2014, p. 3):

$$x_i^m = \alpha_i^* \frac{m_i}{p_x} \quad (1)$$

where:

x_i – quantity offered by m -th sales representative to i -th customer,
 α_i^* – preference of i -th customer (randomized),
 m_i – budget of i -th customer (randomized),
 p_x – price of the product x .

Vymětal and Ježek (2014, p. 3) derived their (1) decision function based on Marshallian demand function, Cobb-Douglas preferences and an utility function, where they assume the sold goods to be normal goods, as we do in our simulations. The aforementioned parameters represent global simulation parameters set for each simulation experiment. Other global simulation parameters are: limit sales price, number of customers, number of purchase representatives, number of suppliers, number of sales representatives, number of iterations, and mean sales request probability. The more exact parameters can be delivered by a real company, the more realistic simulation results can be obtained.

Each group of customer agents is served by concrete sales representative agent, and none of them can change the counterpart. Sales representative agents are responsible to the manager agent. Each turn, the manager agent gathers data from all sales representative agents and stores KPIs of the company. The data is the result of a simulation and serves to understand the company behavior in a time — depending on the agents' decisions and behavior.

The MAREA framework consists of the simulation of multi-agent system (MAS) and ERP system. Simulation designer is used to design a simulation model and adjust the simulation parameters. The ERP system stores data. Through the ERP system one can read and insert data. The ERP system also keeps track of KPIs like — cash level, turnover or profit, by summing up other values. The ERP system in MAREA is different from the ERP systems used in real companies, because it is based on principles of the REA models, which means that it does not use double-entering bookkeeping. The benefit of using the ERP system based on REA principles is that we are able to perform simulations in a few minutes instead of several hours. The cash level is calculated as a total of all transactions that change it — payments for purchases, income from sales, payment of bonuses, initial cash, etc. Turnover and Gross profit is calculated as a total of gross profits and turnovers of specific product types.

Simulations and simulation results

To demonstrate the usefulness of ABMS approach in the business sphere we experimented with several simulations. We investigate sales service quality provided by a company to their customers under changing environment circumstances. In our simulation, disturbance agent is responsible for changing environment. Environment is changing randomly with the use of even distribution (Vymětal *et al.*, 2012, pp. 340–349). Since we are focused on investigating the quality of service provided by sales representative agents, we consider changing environment to have impact only on the sales representative agents' performance that influences customers.

In our setup, we consider two types of customers — long-term customers and new customers. the difference between long-term customers and new customers is in relation with their willingness to buy a product and their loyalty to the store brand. Long-term customers are willing to pay higher prices for goods from favourite brands towards which they are loyal. In our simulation, we model retail high-tech company that sells electronics. For simplicity, we do not have any other company, as we assume that if

a customer did not negotiate successfully with a sales representative, he bought the goods he needed somewhere else. Since the competition on markets with electronics is very high and products are easily substitutable, companies on the market need to distinguish themselves from competition by providing many different services to customers with different levels of quality. We are also selling only one product, namely computer cables.

According to Kotler and Keller (2016, pp. 150–174), American Association for Quality defines quality as follows: “Quality is the totality of features and characteristics of product or service that bear its ability to satisfy stated or implied need”. Service quality and customer satisfaction are directly connected to profitability of companies. Wong and Tjosvold (1995, pp. 189–205) also show that service quality directly affects customer loyalty, positive word of mouth, competitive product differentiation, and helps to generate repeat sales. We do not work with product quality in our simulation setup, because as we stated, we consider products on markets concentrated in electronics retail to be highly substitutable and thus companies has to differentiate through provided services.

According to Alan *et al.* (2015, pp. 715–735), customers do not buy in a given store just to purchase goods or services, but also to have a pleasant experience. Consumption experiences of customers are strictly personal and in our model preferences in equation (1) are setup for every customer randomly again within even distribution. Due to a competitive business environment, companies are trying to build long-term relationships with customers, which also involves education of such sales representatives. Customer satisfaction, which is demonstratively very important to a customer, is defined as an emotional state that occurs in response to an evaluation of interaction experiences and as a positive affective state (Ahearne *et al.*, 2007, pp. 603–616).

We were investigating 3 research questions:

1. Will education of sales representatives positively influence company KPIs?
2. What influence will the initial distribution of new and long-term customers have on company KPIs?
3. What influence will changing environment have on the company KPIs?

In our simulation we do not distinguish between repeated purchases in relationship with brand loyalty and simple repeated purchase behavior explicitly with respect to the quality of sales service provided by sales representatives. This is particularly done implicitly through equation (1) with the use of preferences parameter. The preferences are assigned to all customers by random with the use of even distribution. Customers that are not loyal to a brand will not accept higher prices because of their preferences, while

loyal long-term customers will be willing to accept higher prices. Nevertheless, we are not able to distinguish between repeated purchases and brand loyalty.

Simulation model of a trading company in MAREA consists of a lot of parameters. In this simulation, we were interested in the number of customers, loyalty coefficient for both types of customers, and the disturbance probability. The rest of the parameters fulfilled condition *ceteris paribus*. We always worked with 100 customers, but in two scenarios. There were 30 new customers (30N in Table 1) and 70 long-term customers (70L in Table 1) and vice versa, the same with probability of disturbance we used values of 5 % and 20 %. After 3 repeated purchases new customers' loyalty coefficient was changed to 1 and after 5 repeated purchases new customer was considered to be long-term customer. All simulations were set up for 365 days and every scenario was simulated 30 times.

In Table 2, scenario 70N_30L_5D_E means that the parameters of this scenario were 70 new customers, 30 long-term customers, 5D means that the value of probability of disturbance was 5 % and E means that sales representatives were educated, similarly to the rest of scenarios and through the rest of this paper. As one can see, transformation of new customers to long-term customers were higher, on average, in scenarios where we were educating sales representatives, but not significantly higher. It should be kept in mind that we are also not able to distinguish between repeated purchase behavior and loyal customers.

Figure 2 shows time series of profit throughout one year of simulating. We simulated each scenario 30 times. Time series in Figure 2 for every scenario are composed from daily averages of those 30 simulations. As one can see from Figure 2 and Table 3, education of sales representatives has an overall positive influence on company KPIs especially in long-run. But it is necessary to keep in mind that in our simulation we did not investigate the potential of losing educated sales representatives that can be quite costly for the company, and its influence on company. Company has to make several hard decisions with respect to the education like, which employees to educate, which type of education to choose, general education that can be applied in every company or education specific to the company and so on, which are not part of our simulations.

From Figure 2 and Table 3 one can also see that the company reaches higher KPIs when the distribution of customers was 70 long-term customers and 30 new customers. This makes sense, because long-term customers are a source of stable and high revenues. Recent research in the area of marketing shows that maintaining long-term customers is cheaper than gaining new ones. That was the reason for the emergence of CRM (Cus-

tomers Relationship Management) that focuses on keeping long-term relationships with customers and its implementation in many companies. It is desirable and convenient for companies to have a base of long-term customers, rather than focus only to getting new ones.

The disturbance agent was set up to evenly distribute disturbances with positive and negative impact on company. From Table 3 it is also visible that if one compares scenarios on top with scenarios beneath, it can be seen that through all pairs of levels of disturbances overall better performance is demonstrated in scenarios with bigger base of long-term customers with the exception of scenarios 30N_70L_20D and 70N_30L_20D. This also makes sense, because one would expect that long-term loyal group of customers will stabilize a company during bad times. On the other hand, a base of new customers will kick in and boost a company's KPIs during good times.

Conclusions

The paper presented the main strengths and weaknesses of the ABMS approach and its advantages for modeling and simulation of complex systems in general. We explored the question why this topic is not so much covered in high-tier economic journals, where we found that researchers sometimes have problems with determining where it is the best to use ABMS, and also with understanding of the topic itself. Another problem is also related to validation and verification of those very complex models, which is often not an easy task to do.

We also focused on the usage and recent development of ABMS approach in the business sphere. We discovered that the main usage of ABMS in business in the last ten years was in the areas of modelling supply chains, marketing management with interest especially in consumers' behavior, because communication and integration between agents is part of the definition of ABMS approach. Another business area where ABMS is frequently used is managerial science, where the main goal of ABMS is to provide decision support to the managers. The last area is automated trading, which is the result of technological development and raise of e-commerce in recent years.

In the second part of the paper, we decided to support our claims of the usefulness of ABMS with our own simulations. For this purpose, we used a framework called MAREA that provides us with the possibility of both modelling and simulating. We were investigating the impact of provided quality of service of sales representatives on a company's KPIs. The overall impact of education and provided quality of service by sales representatives

has a positive influence on a company's KPIs under changing environment. One can also see from simulations that a company's KPIs are also affected by distribution of new and long-term customers.

In the future research, we will focus more on the customers and their behaviour. We would like to incorporate coalitions in our model to better simulate interactions between agents like, e.g., communication through social networks, word of mouth etc. Another future we would like to add is symbolic paradigm that would help us, among other things, with historic experiences of customers with buying products, and this feature would provide a tool for better simulations of, for instance, a branding, or to determine customers' loyalty in a more sophisticated manner. We would also like to add other factors that affect customers' behavior especially in relationship with brand and brand loyalty.

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Annex

Table 1. Parameters of simulations

	30N and 70L	30L and 70N
Number of customers	30:70	70:30
Loyalty coefficient for New customers	0.8	0.8
Loyalty coefficient for Long-term customers	1.4	1.44
Probability of disturbance	0.05; 0.2	0.05; 0.2

Table 2. Descriptive statistics of number of new long-term customers

	30N_70L_5D	30N_70L_20D	30N_70L_5D_E	30N_70L_20D_E
Average	6.10	4.73	6.10	5.43
Median	6.50	5.50	6.50	5.50
Std. deviation	2.45	2.21	2.78	3.16
	70N_30L_5D	70N_30L_20D	70N_30L_5D_E	70N_30L_20D_E
Average	6.83	5.23	8.57	6.43
Median	7.50	5.00	8.50	6.00
Std. deviation	3.31	2.61	2.65	2.45

Table 3. Final values of profit and cash level of the company after 365 days for each scenario

	30N_70L_5D	30N_70L_20D	30N_70L_5D_E	30N_70L_20D_E
Cash level	23608.72	19884.03	25515.32	24152.62
Profit	18608.72	14884.03	20515.32	19152.62
	70N_30L_5D	70N_30L_20D	70N_30L_5D_E	70N_30L_20D_E
Cash level	18644.67	19900.67	23202.05	22481.18
Profit	13644.67	14920.25	18202.04	17481.18

Figure 1. Generic model of a business company

Source: Šperka & Vymětal (2013, pp. 140-147).

Figure 2. Development of profit of the company in 365 days for each scenario