ON AGENTS NEGOTIATION IN A TRADING COMPANY SIMULATION

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ABSTRACT
The aim of this paper is to propose an innovative approach to describe the customer behavior in the trading processes of a virtual company. Agent-based modeling and simulation techniques are used to implement a multi-agent system to serve as a simulation framework. The framework should be a basic part of a management system operating in the integration with real system of a company (e.g. ERP system) to investigate and to predict chosen business metrics of a company. This will ensure the management of a company to support their decision-making processes. The paper firstly presents some of the existing theories about consumer behavior and the types of factors influencing it. Secondly, characterizes multi-agent model of a virtual company, the agents participating in the seller-customer negotiation, and the production function. The production function is used to count the product price while negotiating. Lastly, the simulation results and their validation are described. To sum up, the proposed approach to consumer behavior in an agent-based model could properly contribute to better decision-making process.

Keywords: system modeling, multi-agent systems, agent negotiation, decision support, consumer behavior

1. INTRODUCTION
In the contemporary, dynamic, global and competitive market environment, consumer behavior depends on many different types of factors, which are difficult to grasp. With personal and social factors deals e.g. Enis (1974). With physical factors deals e.g. McCarthy and Perreault (1993). More complex view on the social, economic, geography and culture factors gave Keegan et al. (1992). Schiffman (2007) brought marketing mix and environment into the types of factors mentioned herein above. Previous discussions have so far either relied on an objectivist (complete information of customers, constant decision mechanism, constant consumer preferences) or a constructivist view (consumption discourses, consumption as a crucial aspect in the construction of identity). However, both have failed to integrate the consumers' interactions with their social behavior and physical environment as well as the materiality of consumption (Gregson et al. 2002, Jackson et al. 2006). The complexity of the factors influencing consumer behavior and their changes in the time shows relations between external stimuli, consumer's features, the course of decision-making process and reaction expressed in his choices. As a result, the investigation of consumer behavior seems to be too complicated for traditional analytical approaches (Forrester 1971, Challet and Krause, 2006).

Agent-based modeling and simulation (ABMS) provides some opportunities and benefits resulting from using multi-agent systems as a platform for simulations with the aim to investigate the consumers' behavior. Agent-based models are able to integrate individually differentiated types of consumer behavior. They are characterized by a distributed control and data organisation, which enables to represent complex decision processes with only few specifications. In the recent past there were published many scientific works in this area. They concern in the analysis of companies positioning and the impact on the consumer behavior (e.g. Tay and Lusch 2002, Wilkinson and Young 2002, Casti 1997). Often discussed is the reception of the product by the market (Goldenberg et al. 2010, Heath et al. 2009), innovation difussion (Rahmandad and Sterman 2008, Shaikh et al. 2005, Toubia et al. 2008). More general deliberations on the ABMS in the investigating of consumer behavior shows e.g. (Adjali et al. 2005, Ben 2002, Collings et al. 1999).

The approach introduced in this paper uses an agent-based model in the form of multi-agent system to serve as a simulation platform for the seller-customer negotiation in a virtual trading company. The overall idea comes from the research of Barnett (2003). He proposed the integration of the real system models with the management models to work together in real-time. The real system (e.g. ERP system) outputs proceed to the management system (e.g. simulation framework) to be used to investigate and to predict important company's results (metrics). Actual and simulated metrics are compared and evaluated in a management model that identifies the steps to take to respond in a manner that drives the system metrics towards their desired values. We used a generic control loop model of a company (Wolf 2006) and implemented multi-agent simulation framework, which represents the management system. This task was rather complex, therefore we took only a part of the model – trading processes and the negotiation of seller and customer.

The work described in this paper aims at proposing an approach to describe the customer behavior in the trading processes of a virtual company. Implemented simulation framework will be a basic part of a future management system simulating business metrics – key performance indicators (KPIs) of a real company's system. The paper is structured as follows. In the section 2 the multi-agent model is described. In the section 3 the seller-customer negotiation is introduced. The core of this section is the production function definition. The simulation results are presented in section 4.

2. MULTI-AGENT MODEL

To ensure the outputs of customer behavior simulations a simulation framework was implemented and used to trigger the simulation experiments. The framework covers business processes supporting the selling of goods by company sales representatives to the customers – seller-customer negotiation (Fig. 1). It consists of the following types of agents: sales representative agents (representing sellers, seller agents), customer agents, an informative agent (provides information about the company market share, and company volume), and manager agent (manages the seller agents, calculates KPI). Disturbance agent is responsible for the historical trend analysis of sold amount (using his influence on customer agent). All the agent types are developed according to the multi-agent approach. The interaction between agents is based on the FIPA contract-net protocol (FIPA 2002).

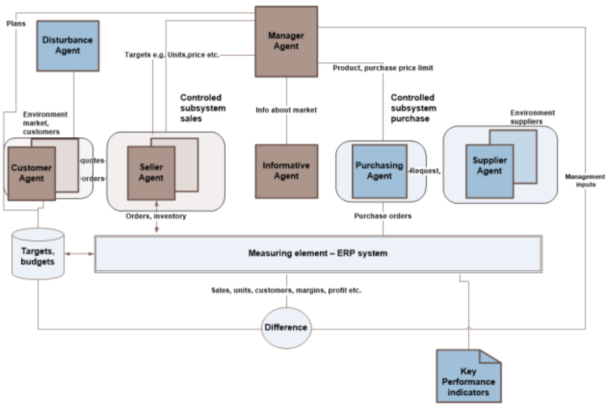

Figure 1: Generic Model of a Business Company (Source: adapted from Šperka et al. 2013).

The number of customer agents is significantly higher than the number of seller agents in the model because the reality of the market is the same. The behavior of agents is influenced by two randomly generated parameters using the normal distribution (an amount of requested goods and a sellers' ability to sell the goods). In the lack of real information about the business company, there is a possibility to randomly generate different parameters (e.g. company market share for the product, market volume for the product in local currency, or a quality parameter of the seller). The influence of randomly generated parameters on the simulation outputs while using different types of distributions was presented in (Vymetal et al. 2012).

3. SELLER-CUSTOMER NEGOTIATION

In this section, the seller-customer negotiation workflow is described and the mathematical definition of a production function is proposed. Production function is used during the contracting phase of agents' interaction. It serves to set up the limit price of the customer agent as an internal private parameter.

Only one part of the company's generic structure, defined earlier, was implemented. This part consists of the sellers and the customers trading with stock items (e.g. tables, chairs). One stock item simplification is used in the implementation. Participants of the contracting business process in our multi-agent system are represented by the software agents - the seller and customer agents interacting in the course of the quotation, negotiation and contracting. There is an interaction between them. The behavior of the customer agent is characterized in our case by proposed customer production function (Equation 1).

At the beginning disturbance agent analyzes historical data – calculates average of sold amounts for whole historical year as the base for percentage calculation. Each period turn (here we assume a week), the customer agent decides whether to buy something. His decision is defined randomly. If the customer agent decides not to buy anything, his turn is over; otherwise he creates a sales request and sends it to his seller agent. Requested amount (which was generated based on a normal distribution) is multiplied by disturbance percentage. Each turn disturbance agent calculates the percentage based on historical data and sends the average amount values to the customer agent. The seller agent answers with a proposal message (a certain quote starting with his maximal price: *limit price * 1.25*). This quote can be accepted by the customer agent or not. The customer agents evaluate the quotes according to the production function. The production function was proposed to reflect the enterprise market share for the product quoted (a market share parameter), seller's ability to negotiate, total market volume for the product quoted etc. (in e.g. Vymetal et al. 2012). If the price quoted is lower than the customer's price obtained as a result of the production function, the quote is accepted. In the opposite case, the customer rejects the quote and a negotiation is started. The seller agent decreases the price to the average of the minimal limit price and the current price (in every iteration is getting effectively closer and closer to the minimal limit price), and resends the quote back to the customer. The message exchange repeats until there is an agreement or a reserved time passes.

The customer production function for the m-th seller pertaining to the i-th customer determines the price that the i-th customer accepts (adjusted according to Vymetal et al. 2012).

$$c_n^m = \frac{\tau_n T_n \gamma \rho_m}{O v_n} \tag{1}$$

c_n^m - price of n-th product offered by m-th seller,
τ_n - market share of the company for n-th product $0 < \tau_n < 1$,
T_n - market volume for n-th product in local currency,
γ - competition coefficient, lowering the success of the sale $0 < \gamma \leq 1$,
ρ_m - m-th sales representative ability to sell, $0.5 \leq \rho_m \leq 2$,
O – number of sales orders for the simulated time,
v_n - average quantity of the n-th product, ordered by i-th customer from m-th seller.

The aforementioned parameters represent global simulation parameters set for each simulation experiment. Other global simulation parameters are: lower limit sales price, number of customers, number of sales representatives, number of iterations, and mean sales request probability. The more exact parameters can be delivered by the real company, the more realistic simulation results can be obtained. In case we would not be able to use the expected number of sales orders O following formula can be used

$$O = ZIp \text{ where}$$

Z - number of customers
I - number of iterations,
p - mean sales request probability in one iteration.

Customer agents are organized in groups and each group is being served by concrete seller agent. Their relationship is given; none of them can change the counterpart. Seller agent is responsible to the manager agent. Each turn, the manager agent gathers data from all seller agents and stores KPIs of the company. The data is the result of the simulation and serves to understand the company behavior in a time – depending on the agents' decisions and behavior. The customer agents need to know some information about the market. This information is given by the informative agent. This agent is also responsible for the turn management and represents outside or controllable phenomena from the agents' perspective.

4. SIMULATION RESULTS

Agent count and their parameterization are listed in Table 1.

Table 1: Multi-agent System Parametrization

AGENT TYPE	AGENT COUNT	PARAMETER NAME	PARAMETER VALUE
Customer Agent	500	Maximum Discussion Turns	10
		Mean Quantity	40 m
		Quantity Standard Deviation	32
Seller Agent	25	Mean Ability	1
		Ability Standard Deviation	0.03
		Minimal Price	0.36 EUR
Manager Agent	1	Purchase Price	0.17 EUR
Market Info	1	Item Market Share	0.15
		Item Market Volume	1 033 535EUR
		Competition coefficient	0.42
		No items sold in one iteration	1 330
		Iterations count	52
Disturbance Agent	1		

Agents were simulating one year – 52 weeks of interactions. As mentioned above – manager agent was calculating the KPIs. Total gross profit was chosen as a representative KPI. Figure 2 contains the month sums of total gross profit for real and generated data. As can be seen from this figure, the result of simulation was quite similar to the real data.

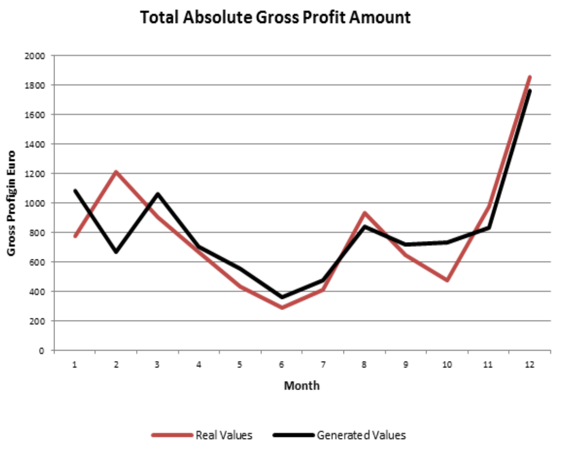

Figure 2: The Generation Values Graph – Monthly (Source: own)

To prove the relationship between the real and generated data – two instruments were chosen – Correlation Analysis to show the correlative relation between them and Chi-Square Test for Independence to show the similarity of distribution for both data series.

Correlation coeficient for total gross profit amount was 0.857, which represents very strong correlation between real and generated data.

Also the Chi-Square Test for Independence has proven that the distribution of real and generated values is very similar. In figure 3, there is a frequency histogram of gross profit for real and generated values.

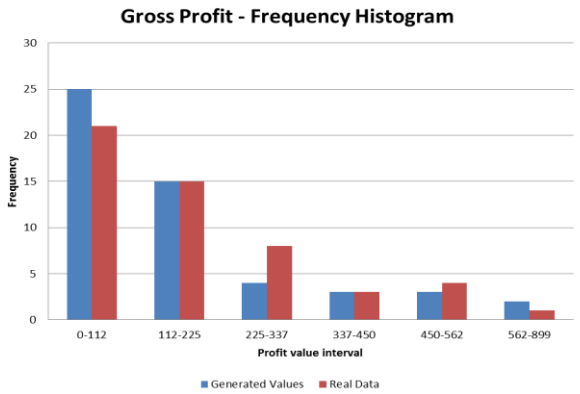

Figure 3: Gross Profit Frequency Histogram (Source: own).

CONCLUSION

Introduction of disturbance agent has caused closer distribution similarity between real and generated data. By its influence on the amounts sold in every turn (even if the price remained as a result of negotiation between seller and customer agent) very strong correlation between reality and generation has risen.

For the future experiments – two improvements shall be made – implement the disturbance agent more sophisticated in history analyzing and also each customer agent shall be more individualistic – have its own targets, beliefs, desires – not only to follow the production function.

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