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Customer Behavior in Trading Processes: A Simulation Based Approach

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Abstract—**The aim of this paper is to propose an innovative simulation approach involving 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. Our motivation is to use the framework as a basic part of a management system, operating as an integrated component of a real system implemented within a company (e.g. ERP system) so as to investigate and to predict the chosen business metrics of a company. With such a system serving to enable the management of a company to support their decision-making processes. The paper firstly presents some of the existing theories on consumer behavior and the types of factors which influence it. Secondly, the paper characterizes the multi-agent model of a virtual company, the agents participating in the trading negotiation, and the decision-making function. The decision-making function is used to count the product price during the negotiation process. Lastly, the simulation results and their comparison with real data, and verification possibilities of the simulation model are described. It will be demonstrated, that the proposed approach to customer behavior in an agent-based simulation model could properly contribute to better a decision-making process.**

Keywords—system modeling; multi-agent systems; agent negotiation; decision support; customer behavior

I. INTRODUCTION

In the contemporary, dynamic, global and competitive market environment, consumer behavior depends on many different types of factors, which are difficult to grasp. Personal and social factors are dealt with by e.g. Enis [1]. Physical factors are dealt with by e.g. McCarthy [2]. Amore complex view on social, economic, geography and cultural factors has been provided by Keagan et al. [3]. Schiffman [4] brought marketing mix and environment into the types of factors mentioned herein above. Another approach to customer behavior stems from the micro-economy theory of preferences. However, due to the complexities mentioned in the cited works, it is difficult to find an analytical solution which describes customer behavior that can be applied to the basis of a model for the support of the management decision-making process by means of e.g. simulation.

Agent-based modeling and simulation (ABMS) provides some opportunities and benefits resulting from the use of multi-agent systems as a platform for simulations with the aim of investigating consumer behavior. They are characterized by a distributed control and data organization, which enables the representation of complex decision-making processes with only a few specifications. Many scientific works devoted to the area of ABMS have been published in the recent past. They concern the analysis of company positioning and the impact on consumer behavior (e.g. [5-7]). The reception of the product by the market has been discussed in [8, 9]. More general deliberations on ABMS in the investigation of consumer behavior are shown in e.g. [10-12]. The main advantage of the ABMS models is that no complete analytical solution is needed to model sales processes, this is possible by virtue of basic agent properties such as pro-activeness, autonomy and social behavior.

The motivation of this paper is to present customer behavior within the sales part of a multi-agent based model of a virtual trading company developed by the authors. The broader purpose of the research presented is to define a model which could be used as a simulation platform aimed at supporting management decisions. The general idea comes from the research of Barnett [13]. He proposed the integration of real system models with management models working together in real-time. The real system (e.g. ERP system) outputs proceed to the management system (e.g. simulation framework) from where they are used to investigate and predict important company results (metrics). Actual and simulated metrics are compared and evaluated in a management model that identifies the steps required to respond in a manner that drives the system metrics towards their desired values. Many other researchers e.g. [14-16] use similar approach to support management decisions. In our case ewe used a generic control loop model of a company [17] and implemented a multi-agent simulation framework, which represents the sales and management parts of the system, namely the trading processes and the negotiation between sales and customers. The simulation runs are based on the real data of an active trading company.

The paper is structured as follows. In Section 1 the multi-agent model of a virtual company is described. Section 2 describes the sales-customer negotiation and its formalization. The core of this section is the derivation of the customer decision-making function. The simulation results and their comparison with real data are presented in Section 3. Section 4 concentrates on the outline of the verification possibilities.

II. MULTI-AGENT MODEL

The multi-agent model (the simulation framework) is based on a generic virtual trading company model presented by Fig.1.The sales representatives of the company are modeled by the seller agents, within the controlled subsystem “sales”. The results of the sales (controlled key performance indicators - KPIs such as revenue, gross profit, etc.) are measured by the measuring element – the ERP system, then compared with the target values and presented to management – the manager agent. The manager agent determines the company strategies such as price limits, marketing campaigns etc. The manager agent is supported by the informative agent supplying the information on the market situation such as market shares and market volumes of the products etc. A similar agent structure models the purchase part of company operations (the controlled subsystem “purchase”). The market is represented by customer agents sending randomly generated quotation requests and negotiating the price with the seller agents. This interaction between the sales and customer agents is based on the FIPA contract-net protocol [18]. The customer decision process and reasoning about the prices is described in the next section.

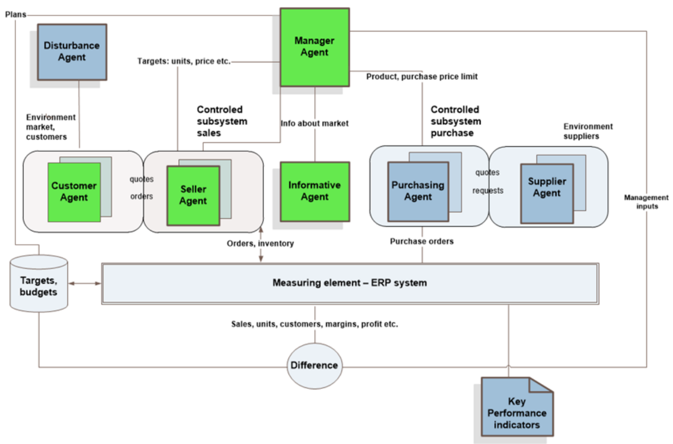

Fig. 1. Generic model of a trading company (Source: adapted from [16]).

III. CUSTOMER BEHAVIOR AND NEGOTIATION

First, let us define the concept of customer behavior used in this paper. Customer behavior here is presented as a core of the customer agent reasoning about the price proposed by the seller agent. It is obvious that this is only a part of the behavior that can generally be ascribed to the customer. But, keeping our target in mind, the simulation of the trading company results in mind, price negotiation can be seen as a basic part of the model.

There are two approaches that can be used to model the customer decision making process. The first approach can use preferences and budget constraints. We can define the consumer basket consisting of the product and money at disposal. The customer preferences regarding the product (typically represented by indifference curves) and the budget constraint can be used to define the acceptable price quoted by the sales agent. This approach typically stems from microeconomics theory. (see e.g.[19, 20]. Let us call this approach, the customer view perspective. However, we are modeling the customer decision process from the company point of view. Therefore we leave customer perspective out of the scope of this paper and use the following approach based on the balance of the product on the market as follows. (see also e.g. [21, 22])

From the company point of view, the balance of the product sold by the company on the market is represented by the equation:

$$\gamma_n \cdot c_n = \tau_n \cdot T_n \tag{1}$$

Where

γ_n - quantity of n-th product sold in a simulation period (e.g. one year – units),

c_n - price of the n-th product achieved in a simulation period (e.g. EUR/piece),

τ_n - company market share of the n-th product,

T_n - market volume of the n-th product in a simulation period (e.g. EUR).

The quantity sold is calculated as:

$$\gamma_n = O \cdot v_n \tag{2}$$

Where

O - number of sales orders for the simulated time,

v_n - average quantity of the n-th product, ordered by sales orders.

The price accepted by the customer can be modeled based in this balance, but it obviously depends on the ability of a sales representative to sell (to persuade the customer). Let ρ_m - m-th sales representative ability to sell. Then the accepted price can be calculated from (1) and (2) as follows

$$c_n^m = \frac{\tau_n T_n \rho_m}{O v_n} \tag{3}$$

In the real world, market fluctuations can come into play, which adversely affect the acceptation of price as well. Let γ - competition coefficient, lowering the success of the sale $0 < \gamma \le 1$. Then the final decision formula of the accepted price (the customer decision function) is defined as:

$$c_n^m = \frac{\tau_n T_n \gamma \rho_m}{O v_n} \quad (4)$$

As shown in Fig. 1, we do not use the market disturbances at present. Therefore, the coefficient of competition in equation 3 equals 1 in all simulation steps. However, it can be easily included by means of randomly generated values.

Example: The accepted price for 1m of computer cable is summed up in the Table 1.

TABLE I. EXAMPLE OF ACCEPTED PRICE CALCULATION.

Market Volume EUR	Market Share	Sales rep. Ability	Coefficient of Competition	Mean Quantity Sold	Number of Orders	Accepted Price EUR
800000	0,15	1	1	5	52000	0,307

There can exist a case, when the number of orders is not known. The model uses the following approximation in order to solve this challenge:

$$O = ZIp \quad (5)$$

Where

Z - number of simulated customers in a simulation run,

I - number of iterations in a simulation run,

p - mean sales request probability in one iteration.

In this case, equation 3 is modified using equation 4.

For 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. The seller agent answers with a proposal message (a certain quote starting with his maximal price: *limit price * 1.25* – a generally observed practice in business operations). This quote can be accepted by the customer agent or not. The customer agents evaluate the quotes according to the decision function. The decision function is used to model the customer behavior. If the price quoted is lower than the customer's price obtained as a result of the decision function, the quote is accepted. In the opposite case, the customer rejects the quote and negotiation is started. The seller agent decreases the price (several strategies can be defined in the model) and re-sends the quote back to the customer. The message exchange repeats until there is an agreement, or a minimal price defined by the company manager is reached or a reserved time passes.

The parameters used in equations 1-5 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.

Customer agents are organized into groups with each group served by a concrete sales agent. Their relationship is given; none of them can change the counterpart. The sales agent is responsible to the manager agent. With each turn, the manager agent gathers data from all sales agents and stores the KPIs of the company. The data is the result of the simulation and serves to understand the company behavior in a specific period of 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 turn management and represents outside or controllable phenomena from the agents' perspective.

IV. SIMULATION RESULTS

The parameterization of the model and the obtained simulation results are introduced in this section. The decision-making function (4) is the engine of the simulation. Based on it, the customer agents decide to buy or not. One year of sales and purchasing processes was simulated. Each turn represents one week. Five simulation experiments were done. Each purchase of the product type was registered. In order to include randomly generated inputs, two important agents' attributes were chosen to be generated by a pseudo random generator. Firstly, the seller agent's ability, and secondly the customer agent's decision about the quantity for the purchase were applied.

The parameterization of the MAS is listed in Table 2. The table represents the parameters listed by the name and the value of each type of an agent (customer, sales representative). It also shows the number of agent type instances (how many of a particular agent type is present in the system).

TABLE II. LIST OF AGENTS' PARAMETERS.

Agent Type	Agent Count	Parameter Name	Parameter Value
Customer	500	Maximum Discussion Dialog Switch Minimal Quantity for Turn Maximal Quantity for Turn	10 0 50 first, 5 seconds
Seller	25	Mean Ability Ability Standard Deviation Minimal Price	1 0,03 0,35 EUR
Manager	1	Purchase Price	0,17 EUR
Information	1	Item Market Share Item Market Volume	15,37% 1033535 EUR

The results of the simulation are the number of product units sold (amount, pieces), income (*amount x item price*, EUR), costs (EUR), and revenues (EUR) obtained for selling these products. We name these result categories as the KPIs. The parameters of the simulation were set up according to a real company trading with UTP cable. Therefore, the units traded are the meters (m). In Figure 2, the generated weekly KPIs are depicted. The volatility of the curves shows a stable position of the company on the UTP cable market. The trends of KPIs point to balanced selling during the whole year (except for a dip in May).

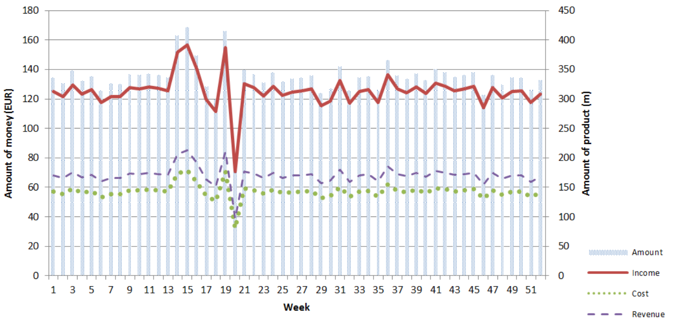

Fig. 2. Generation values graph – weekly (Source: own).

Implemented MAS provides necessary results in the form of KPIs for every week during one year of trading. The obtained KPIs could be compared from one simulation experiment to another. This could be used to analyze different simulation parameterizations and the impact on company performance.

Simulation results were compared with the real data from an anonymous computer retail company with 30 employees (from Slovakia). The real data was taken from the company's accounting information system. For the comparison of generated and real data, monthly averages were used. Another view of the simulation results is represented by the sold items price (Fig. 3) and sold items count (Fig. 4). The generated price trend is almost stabile with only a few slight fluctuations. On the other hand, the real price fluctuates with a few sharp peaks. Nevertheless, the real and the generated time series have similar development in this time. All curves are located in the range from EUR 0.355 up to EUR 0.38. A similar situation can be seen in Figure 4. It is obvious, that if we are able to properly simulate item price and the item count, then we might also simulate KPIs in the same way. KPIs are derived from the price and count. This shows that this simulation approach could be used to properly simulate real business processes.

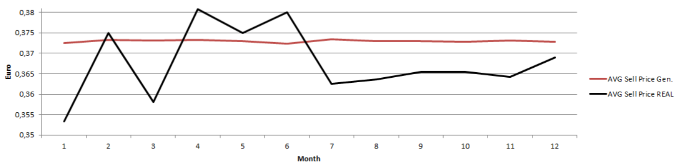

Fig. 3. Sold items price – monthly (Source: own).

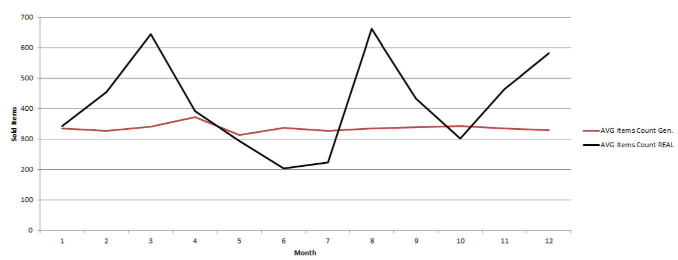

Fig. 4. Sold items count – monthly (Source: own).

On the other hand, we used statistics to support our assertions. Nevertheless, it is obvious even from the visual that t-test of student and X^2 test do not prove tight correlation between real and generated sold items price resp. real and generated sold items count. Although the trends show similar evolution. In our contemporary research we add a "disturbance agent" to the simulation model to enhance the KPIs evolution according to the sharp peaks in real data. We assume better results in statistical tests after that.

To sum up, the results presented herein above visualize the real possibilities of the method proposed for use in real business process simulation. In the next section, the possibilities of the simulation model verification will be introduced.

V. Verification Possibilities

One of the verification possibilities could be the analysis of agents' behavior during the simulation according to the parameterization of the MAS. The analysis can reveal behavioral patterns of agents and can discover groups of agents with similar behavior which can be valuable in the verification process of the simulation model, as well as for further management of ERP system.

MAS logs all the agents activities during the simulation into a log file. Therefore, the analysis of agents' behavior can be done by methods of log mining and process mining [23, 24]. Using these principles, we are able to define agents' behavior in the system (for example type of negotiation), to create agents' profiles describing their behavior, and to find behavioral patterns (this enables a better understanding of agents' behavior during the simulation). By comparing agents' profiles, we are able to divide them into groups and to provide the transparent visualization of latent ties between them.

The visualization of agent groups with relations between them is presented in Fig. 5. The groups of agents with similar behavior were found by clustering agent profiles using methods of artificial intelligence (in this case Self organizing maps, SOM). The colored groups were obtained using spectral clustering. A detailed description of this process was published in our previous work [25, 26].

Fig. 5. Visualization of agents' groups with similar behavior (Source: own).

Each agent in Fig. 5 is described by its unique ID. Nodes represent groups of agents with similar behavior obtained from SOM and ties represent similarity between them. Various colors indicate that even the groups of agents obtained from SOM may be similar and may create smaller groups. Two approaches for comparing agents' profiles were tested to create the agents' network, vector space model and SOM. The experiments in our previous work mentioned before found that the most promising could be the presented result in Fig. 5. Of course, the obtained groups of agents can be described in details, as well as the behavior of agents in the found groups.

VI. Conclusion

The simulation experiment in the form of MAS was introduced in this paper. The proposed simulation model was implemented in order to simulate the business process participants and their negotiation in a virtual company. The overall methodology is based on the company's generic structure. The simulation provides useful information about core business processes. The comparison of the generated results with real data outlines the validity of the simulation model and led us to the idea of using the disturbance agent to disperse the item price and item count in future research. The verification possibilities introduced might be a promising way to analyze the agents' behavior and to confirm the correctness of the proposed approach.

The next steps of our research concentrate on the statistical test of the validation, and the formal definition of the algorithm implemented. However, the customer behavior in negotiations was based on the proposed decision function and did not take budget constraints and customer preferences into consideration. This will be the topic of further research. As the agent framework proposed uses the negotiation base as a behavior module of the customer, any customer preference changes might be easy to implement. To conclude, using MAS implemented as a decision support tool for the management of a company will be a leading idea in the future.

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