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Simulation Methods Comparison in Business Negotiation Domain

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Abstract
Roman Šperka: **Simulation Methods Comparison in Business Negotiation Domain**

The main goal of this paper is to compare the results of an agent-based and Monte Carlo simulation experiments in business process negotiation between sellers and customers of a simple trading commodity. The motivation of the presented research is to find suitable method for predicting key performance indicators of a business company. The intention is to develop a software module in the future which might help the management of business companies to support their decisions. Microeconomic demand functions were used as a core element in the negotiation. Specifically, Marshallian demand function and Cobb-Douglas utility functions is introduced. The paper firstly presents some of the principles of agent-based and Monte Carlo simulation techniques, and demand function theory. Secondly, we present a conceptual model of a business company in terms of a simulation framework. Thirdly, a formalization of demand functions and their implementation in a seller-to-customer negotiation is introduced. Lastly, we discuss some of the simulation results in one year of selling commodities. The results obtained show that agent-based method is more suitable than Monte Carlo in the presented domain, and the demand functions could be used to predict the trading results of a company in some metrics.

Key words

simulation, agent-based, Monte Carlo, trading, price negotiation, commodity, key performance indicators

JEL: C63, C99, L21, M21

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Introduction

Business process management and simulation (BPMS) is often viewed as one of the technologies, which might help to rationalize the traditional execution of business processes in contemporary fluctuant business environment. The aim of BPMS is to lower the resources (financial, personal, time, etc.) needed for the day-to-day business praxis of companies. Regardless of the area, which is company active in, it is used to find some reserves and to lower the costs. One of the possibilities to use BPMS is an automated way to execute the business processes – Workflow Management Systems (Suchánek, 2011). On one hand, there are many rigorous approaches which deal with the logical way of executing pre-modeled business processes (Weske, 2007). On the other hand, when we focus on business processes which encounter vendors and customers, we are confronted with many factors, which cannot be covered by classical methods. We focused on consumer behavior in the presented research. These factors are difficult to grasp, however, consumers behavior depends on them. We mean specifically the social factors (Cole and Maurer, 2013; Takahashi, 2014).

We have already presented the core of our research in Šperka and Spišák, KES 2014 (2014a). We have proposed an experimental business management software framework to cover a seller-to-customer price negotiation in an agent-based simulation. The simulations were based on a multi-agent system serving as a simulation platform for the negotiation experiments in a business company. The main idea was concentrated around the negotiated price establishment. We used microeconomic demand functions to base the price negotiation on.

The overall scenario comes from the research of Barnett (2003). He proposed the integration of real information system modules with the decision support modules to work together in a real-time. The real information system (e.g., ERP – Enterprise Resource Planning system) outputs proceed to the decision support system (simulation framework in our case) to be used to investigate and to predict important company's metrics (KPIs – Key Performance Indicators). Actual and simulated metrics are compared and evaluated in a management module, which identifies the steps to take to respond in a manner that drives the system metrics towards their desired values. We used a generic model of a business company and implemented a multi-agent simulation framework, which represents the decision support system. This task was rather complex, therefore we implemented only a part of the model – trading processes and the seller-to-customer negotiation concerning the price of commodities. Implemented simulation framework will be a basic part of a future business management system simulating business metrics of a real company's system.

Previously, we presented partial research results using the decision function; e.g., Šperka et al. (2013a, 2013b), Šperka and Vymětal (2013); to simulate the trading of a business company, consisting of thousands customers and sellers. In this paper we compare the aforementioned approach with the newly implemented Monte Carlo simulation to reveal the fact which of the implemented methods is more suitable to simulate trading processes using microeconomic demand functions.

The paper is structured as follows. Section 1 introduces basic features of agent-based and Monte Carlo simulation methods. Demand functions and a conceptual model is also introduced in section 1. A seller-to-customer negotiation process is formally presented in section 2. The simulation results and discussion are presented in section 3.

1. Scientific background and conceptual model

This paper presents two types of simulation experiments. The first one is an agent-based implementation. 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 and its impact on the KPIs of a business company. Agent-based models are able to integrate individually differentiated types of consumer behavior. They are characterized by a distributed control and data organization, which enables to represent complex decision processes with only a 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), and Casti (1997). Often discussed is the reception of the product by the market; e.g., Goldenberg et al. (2010), and Heath et al. (2009); and innovation diffusion; e.g., Rahmandad and Sterman (2008), Shaikh et al. (2005), Toubia et al. (2008), and Kuwata et al. (2012). More general deliberations on the ABMS in the investigating of consumer behavior show e.g., Adjali et al. (2005), Ben et al. (2002), and Collings et al. (1999).

The second presented type of a simulation is a Monte Carlo simulation. Monte Carlo simulation methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results; typically one runs simulations many times over in order to obtain the distribution of an unknown probabilistic entity. The mathematical problem we dealt with was the use of some predefined functions from economic theory. We built our experimental research on a demand functions. In microeconomics, a consumer's Marshallian demand function (named after Alfred Marshall) specifies what the consumer would buy in each price and wealth situation (Marshall, 1920), assuming it perfectly solves the utility maximization problem. Given the consumer's income, m, and prices, p_x and p_y, the consumer's problem is to choose the affordable bundle that maximizes his utility. The feasible set (budget set): total expenditure cannot exceed income, so we have

$$p_x x + p_y y \leq m \text{ and } x \geq 0, y \geq 0 \tag{1}$$

Marshallian demand is sometimes called Walrasian demand (named after Léon Walras) or uncompensated demand function instead, because the original Marshallian analysis ignored wealth effects (Pollak, 1969; Varian, 1992). We also used a Cobb-Douglas utility function and preferences saying that the quantity demanded for each commodity does not depend on income, in fact quantity demanded for each commodity is proportional to the income (Challet and Krause, 2006).

We based the seller-to-customer negotiation in our simulations on these two functions. The conceptual model considered for the simulation implementation consists of the following types of agents: sales representative agents (representing sellers, seller agents), customer agents, informative agent (measures time, informs agents about period passing), and manager agent (manages the seller agents, calculates KPIs). After a design phase a software framework, based on the business model was implemented and used to trigger the simulation experiments to ensure the outputs of trading processes simulations. The model covers processes supporting the selling of commodities by company sales representatives to the customers – seller-to-customer negotiation (Fig. 1). All the agent types were developed according to the multi-agent approach. The interaction between agents is based on the FIPA (2002) contract-net protocol.

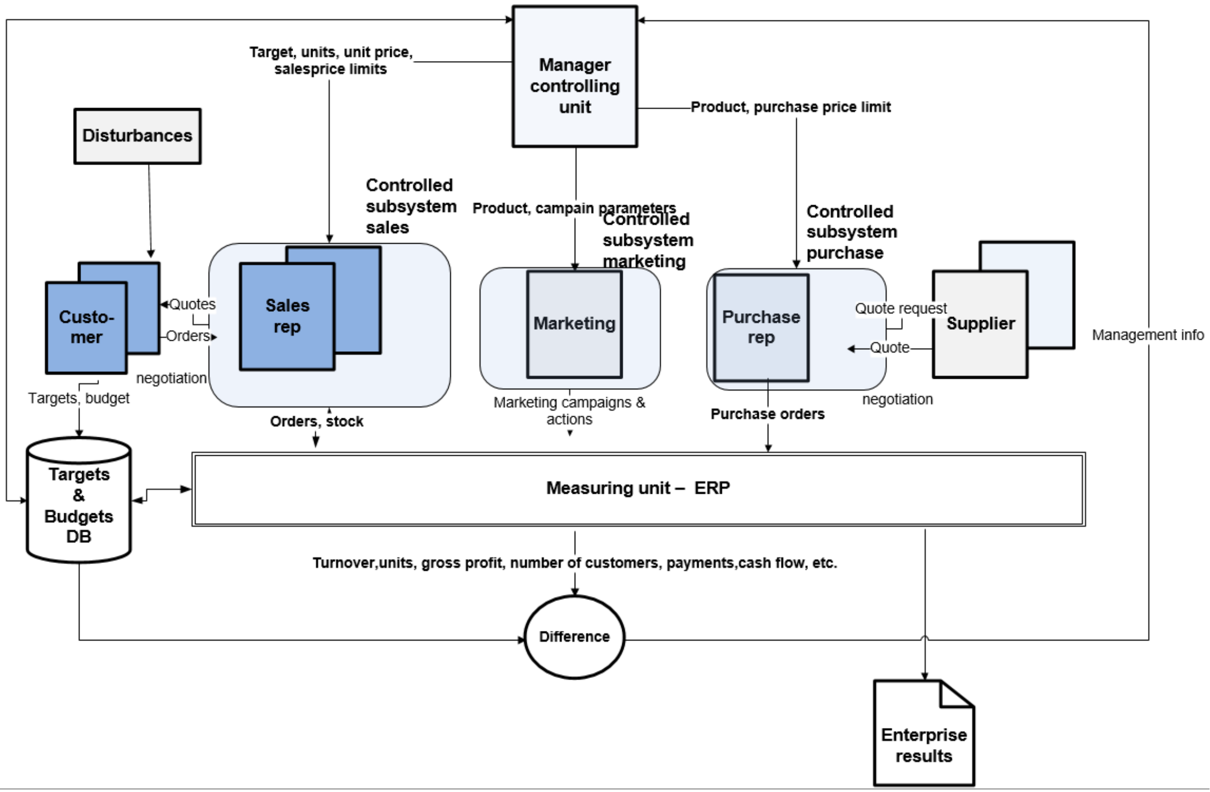

Fig. 1: Conceptual model of a company

(Source: adapted from Šperka et al. (2013b))

The number of customer agents is significantly higher than the number of seller agents in the model because the situation on the real market is the same. The behavior of agents is influenced by two randomly generated parameters: an amount of requested commodities using binomial distribution, and a sellers' ability to sell the commodities using normal distribution. In the lack of real information about the business company, there is a possibility to randomly generate more parameters (e.g., utility ratio of the current commodity, or an income of the customer). The influence of randomly generated parameters on the simulation outputs while using different types of distributions was previously described in Vymětal et al. (2012).

2. Negotiation formalization

In this section, the seller-to-customer negotiation workflow is described and the definition of the Marshallian demand function is proposed. The formalization is common for both types of conducted simulation experiments: agent-based and Monte Carlo. Only a part of the company's generic structure, defined earlier, was implemented. This part consists of the sellers and the customers trading with commodities (e.g. tables, chairs, etc.). One stock item simplification is used in the implementation. Participants of the contracting 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 by the Marshallian demand function based on the Cobb-Douglas utility function. Marshallian demand 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.

In our previous experiments; e.g., Šperka and Spišák (2014b); disturbance agent was used to correct the input data, based on the percentage calculation of the real data. Currently, after a change of a distribution for the quantity, disturbance agent is not used. 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 is generated using binomial distribution. The seller agent answers with a proposal message (a specific 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 demand function by calculating their maximal price. The Marshallian demand function was derived from Cobb-Douglas utility function and represents the quantity of the traded commodity as the relationship between customer's income and the price of the demanded commodity. If the price quoted is lower than the customer's price obtained as a result of the demand 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.

Marshallian function specifies what would consumer buy at each specific price and income, assuming it perfectly solves utility maximization problem. For example: If there are two commodities and the specific consumer's utility function is:

$$U(x_1, x_2) = x_1^{0,5} x_2^{0,5} U(x_1, x_2) = x_1^{0,5} x_2^{0,5} \tag{2}$$

Then the Marshallian demand function is a function of income and prices of commodities:

$$x(p_1, p_2, I) = \left(\frac{1}{2p_1}, \frac{1}{2p_2} \right) \tag{3}$$

Where I represents income and p_1 and p_2 are the prices of the commodities. In general, Cobb-Douglas utility function can be defined as:

$$U(x_1, x_2) = x_1^{\alpha} x_2^{1-\alpha} \tag{4}$$

The corresponding Marshallian demand function is:

$$x(p_1, p_2, I) = \left(\frac{\alpha I}{p_1}, \frac{(1-\alpha) I}{p_2} \right) \tag{5}$$

Only one commodity is calculated in the model (which is traded by the simulated company). In this case – using the Marshallian demand function there are two commodity baskets. The first one is represented by a commodity, which is traded by a company. The second one represents all alternative commodities that customer can buy. So only x_1 is used, supposing that utility ratio α is known and that for the rest of commodities the utility ratio is (1-α). Therefore the demand function looks like this:

$$x = S \frac{\alpha I}{p} \tag{6}$$

Where X represents the amount of the commodity, α is utility ratio, I is income and p is the price of the commodity. Customer's decision is described by retrieving the price from the demand function. We also include the ability of the seller for increasing/decreasing the price according to his skills:

$$p = S\frac{\alpha I}{x} \quad (7)$$

This is the core formula, by which the customer decides if the quote is acceptable. The aforementioned parameters represent global simulation parameters, which are set for each simulation experiment. The remaining global simulation parameters are:

- I – customer's income – it's normal distributed value generated at the beginning and not being changed during the generation;
- α – utility ratio – normal distributed value, which is generated for each customer each turn (week, while customers' preferences can change rapidly);
- p – commodity price;
- S – seller skills (ability to change price);
- x – amount of commodity – binomially distributed value generated, when customer decides to buy something.

Customer agents are organized in groups and each group is being served by a specific 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 as a result of simulations 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 provided by the informative agent. This agent is also responsible for the turn management and represents outside or controllable phenomena from the agents' perspective.

In case of Monte Carlo experiments the process of a generation begins for the customer. For each week he is going to decide: to buy something or not; this is uniformly distributed vector of 52 values (between 0 and 1). If the value is >= 0.5, the customer decides to buy something according to the price decision; otherwise doesn't buy anything. After that the vectors of quantities (customer needs to decide the quantity), prices (quotes), customer incomes, customer utility ratios, and seller abilities are generated. All these numbers are derived from normal distribution with given mean and standard deviation.

3. Experimental results

Two simulation sessions were conducted and their results are presented in this section. Firstly, an agent-based simulation session took part in the simulation framework. Secondly, a Monte Carlo method was implemented in Matlab software.

The agent platform JADE was chosen for the implementation of agent-based model. JADE is a real tool for rapid agent development. It contains not only communication language, but the whole platform for agents' deployment. This includes runtime environment, where agents exist, libraries to write them and also graphical tools to administrate them and monitor their state. Wooldridge (2009) says that it is best-known and the most widely used. At the start of simulation experiments phase some parameters were set. Agent count and their parameterization are listed in Table 1. This simulation session works with multi-agent system.

Tab. 1: Multi-agent simulation parameterization

AGENT TYPE	AGENT COUNT	PARAMETER NAME	PARAMETER VALUE
Customer	500	Maximum Discussion Turns	10
		Mean Quantity	40 m
		Quantity Standard Deviation	32
		Mean Income	600 EUR
		Income Standard Deviation	10
		Mean Utility Ratio	1.15
		Utility St. Deviation	0.2
Seller	25	Mean Ability	1
		Ability St. Deviation	0.03
		Minimal Price	0.36 EUR
Manager	1	Purchase Price	0.17 EUR
Market info	1	Iterations count	52 weeks

Source: own

For the Monte Carlo simulation the Matlab software from the Math-Works, Inc. was used. Matlab is very sufficient mathematical tool for numerical computation, visualization and for programing. In this case its ability to work with matrix and especially vectors was used. Main process of a generation for each customer is based on few vectors containing 52 values – representing 52 weeks of the year. The complex Monte Carlo parameterization is listed in Table 2 for the second simulation session. The purpose of these experiments was to compare the simulation results for the agent-based and the Monte Carlo simulation method. Nevertheless, we also aim to prove if the demand functions could serve as a core element in the seller-to-customer negotiation.

Tab. 2: Monte Carlo simulation parameterization

PARAMETER NAME	PARAMETER VALUE
Number of Customers	10000
Mean Quantity	50 m
Quantity Standard Deviation	29
Mean Income	600 EUR
Income Standard Deviation	10
Mean Utility Ratio	0.15
Utility St. Deviation	0.2
Mean Ability	1
Ability St. Deviation	0.03
Mean Sell Price	3.15 EUR
Sell Price St. Dev.	3.00 EUR
Purchase Price	0.17 EUR
Iterations count	52 weeks

Source: own

Agents were simulating one year – 52 weeks of interactions. As mentioned above, the manager agent calculates the KPIs. The simulation was done for each customer in the case of a Monte Carlo method. The results were counted in four categories that are frequently used to describe the company's trading balance. The categories are: sold amount, income, costs, and gross profit. We unveil some gross profit values in the graphs bellow.

The commodity to be traded with was a UTP (unshielded twisted pair) cable. Indeed, companies are dealing with a whole portfolio of products. In our simplification we concentrated only on one product and this was the UTP cable. Further, total gross profit was chosen as a representative KPI. Figure 2 contains the month sums of average gross profit for real and generated data for the agent-based simulation. Figure 3 represents the Monte Carlo simulation results for the same category. As can be seen from these figures, the result of simulations represents trend, which is quite similar to the real data.

Real data was delivered by a Slovak anonymous company trading with PC components and supplies. The company was established in 1999 as a local shop in the city near Polish and Czech border with 4 employees. It has extended in the recent years and currently operates in 3 Slovak cities with 4 branches and 25 employees. Except from PC components the company develops own economic software and acts also as a software distributor. The time series was discovered for the 2012 and the parameters of the simulations were set to mirror the situation on the market of the company in that time.

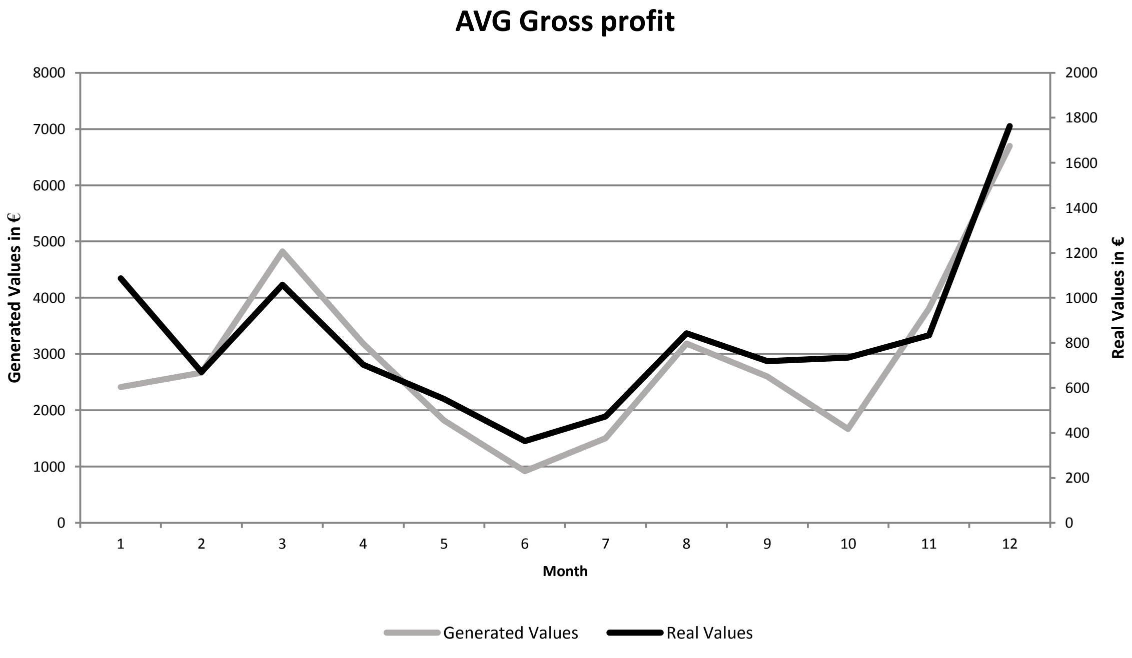

Fig. 2: Multi-agent simulation. The generation values graph (AVG Gross Profit) – monthly
(Source: own)

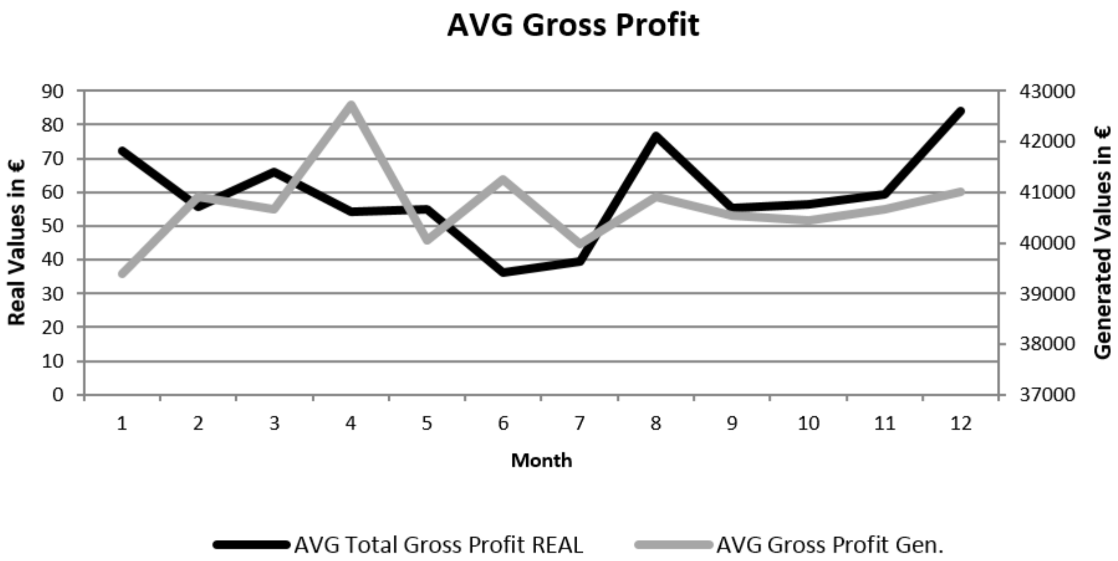

Fig. 3: Monte Carlo simulation. The generation values graph (AVG Gross Profit) – monthly
(Source: own)

To discover the correlation between the real and generated AVG month price the correlation analysis was performed. The correlation coefficient for a total gross profit amount was 0.894 in the case of the multi-agent simulation, which represents very strong correlation between real and generated data. The correlation coefficient for a total gross profit amount was 0.693 in the case of the Monte Carlo simulation, which represents strong correlation between real and generated data.

The subject of the simulation experiments is a business company. There are many parameters which should be taken into consideration when simulating the trading behavior of the company. This makes the task rather complex. In the presented research we focused only on a part of the business company (seller-to-customer negotiation) as mentioned above and we tried to prove the idea that simulation methods can be used to predict some of the KPIs of the company (in our case gross profit). Further simulation experiments with more complex parametrization and more parts of the company are needed to be able to demonstrate this approach on more KPIs. In the presented simplification the gross profit KPI was chosen as a representative KPI.

Under these circumstances the obtained results show that the agent-based method is more suitable for this type of simulation problem. Moreover the microeconomic demand functions could be used in further experiments to support the predictive purposes of decision making tools based on it.

Conclusion

The paper introduces a comparison of an agent-based and Monte Carlo simulation approach dealing with business processes within a trading company. The experiments were set to prove the idea, that microeconomic demand functions could be used as a core element in a seller-to-customer price negotiation. The overall idea is to use this approach to implement decision support models that could be connected to real management information systems in order to serve as prediction modules. We obtained successful results in some of the KPIs (gross profit) proving that the agent-based method is more suitable than Monte Carlo method. This supports our motivation to proceed with the experiments and to enhance our approach to extend the results on the rest of the KPIs. In our future research we will concentrate on the enhancement of the model.

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