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Is there a Need for Agent-based Modelling and Simulation in Business Process Management?

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Background and Purpose: Agent-based modelling and simulation (ABS) is growing in many areas like, e.g., management, social and computer sciences. However, the similar trend does not seem to occur within the field of business process management (BPM), even though simulation approaches like discrete event simulation or system dynamics are well established and widely used. Thus, in our paper we investigate the advantages and disadvantages of agent-based modelling and simulation in the field of BPM in simulation experiments.
Design/Methodology/Approach: In our research, we investigate if there is a necessity for ABS in the field of BPM with our own simulation experiments to compare traditional and ABS models. For this purpose, we use simulation framework MAREA, which is a simulation environment with integrated ERP system. Our model is a complex system of a trading company selling computer cables. For the verification of our model, we use automated process discovery techniques.
Results: In our simulations, we investigated the impact of changes in resources' behavior on the outcome of company's order to cash process (O2C). Simulations experiments demonstrated that even small changes might have statistically significant effect on outcomes of the processes and decisions based on such outcomes. Simulation experiments also demonstrated that the impact of randomly distributed fluctuations of well-being have a diminishing tendency with the increasing number of sales representatives involved in the process.
Conclusions: Our research revealed several advantages and disadvantages of using ABS in business process modelling. However, as we show, many of them were at least partially addressed in the recent years. Thus, we believe that ABS will get more attention in the field of BPM similarly to other fields like, e.g., social sciences. We suggested areas in BPM simulations, e.g., modelling of resources, be it human or technological resources, where there is a need for ABS.

Keywords: *Agent-based modelling and simulation; business processes; business process management; process mining*

1 Introduction

In the past, business process management was considered to be more of the art than the actual science. Only a limited number of experts worldwide were able to implement the ideas behind the BPM concept successfully. In addition, many of the companies, that were trying to implement the process-oriented thinking without the supervision of such experts failed miserably. Many times, due to inability to foresee the impact of changes and newly implemented processes. However, over the last decade BPM matured and is considered well-established research area with significant overlap into business practices, where the process oriented thinking is nowadays very common in the most of organizations – even though there still exist a certain gap between BPM research and practice. This has been achieved through the well-defined set of principles, methods and

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tools that combine knowledge from information technology, management sciences and industrial engineering with the purpose of improving business processes (Aalst, La Rosa & Santoro, 2016; 1, Aalst, 2013, 1).

There are many ways, in which BPM is trying to improve business processes with respect to established KPIs (Key Performance Indicators) on operational, tactical and strategic management level. The examples are statistical and other mathematical techniques, queuing theory, optimization, etc. Simulation is one of those techniques that aims at improving organization's KPIs through improvement of business processes. In our paper, we focus on ABS approach and its position in the area of BPM. We investigate the question of neediness of ABS approach within BPM modelling and simulation, as the ABS approach is far from being standard in this area. While doing so, we search for the advantages of the ABS approach and its disadvantages that might be causing low level of attention in ABS approach in the field of BPM. Based on the aim of the paper, we establish following research questions:

- RQ1: Is there a need for ABS approach in the area of BPM modelling and simulation?
- RQ2: What are the advantages and disadvantages of application of ABS approach in the field of BPM?

To demonstrate some of the advantages of ABS in BPM modelling and simulation, we investigate the impact of negative within-person well-being on the BPM simulation results concerning two different simulation methodologies. Thus, we establish third research question:

- RQ3: What is the impact of negative fluctuations of well-being of resources on outcome of organization's O2C process?

The reasoning behind the paper is that ABS approach seems to be gaining on popularity in many areas like social, managerial and computer sciences, etc., which are all in the core of BPM. However, it is not similar in the field of BPM, where the use of ABS is minimal. On the contrary, simulation in general is well-accepted techniques supported by many BPM tools.

In the next section, we introduce simulation modelling in the field of BPM with particular subsection dedicated to general use of simulation and modelling; traditional approaches towards simulation modelling; ABS state-of-the-art, its advantages and disadvantages. In the third section, we describe the methodology used in this paper and simulation experiment in the form of proof of concept. The fourth section presents results of simulation experiments. To conclude, we summarize and discuss our results.

2 Simulation and modelling in the field of BPM

Modelling and simulation helps us to understand the real-world through the imitation of real world systems on different levels of abstraction. Simulation has become very common research methodology similarly to other steady methodologies like, e.g., deduction or induction. Axelrod (1997, 16) states that one of the reasons, why is simulation such highly valued is the diversity of the purposes that it can be used to, like, e.g., prediction, performance, discovery, etc. Purposes that are highly valuable for businesses and the improvement of business processes from the means of understanding the behavior of the business processes, evaluating different strategies for decision-making, re-engineering of existing processes or designing new processes.

If the processes were poorly designed or contain errors, then such processes would lead to unsatisfied customers and poor performances like, e.g., long response times, low service levels, etc. That is why it is important to analyze, understand and design the processes not only before their implementation but also after. This is reinforced by the fact that in general, organization's business processes are not the same throughout the time, but are constantly changing to fulfill the needs of the continuously developing markets worldwide. To fulfill these new needs, organization´s management often has to make the decisions and choices about the processes without any idea of what will the outcomes look like. For that and many other reasons, simulation if it's done properly, can be very useful and versatile tool for not only BPM practitioners, but also managers, responsible for the organization processes. Particularly for the organizations that believe in the concept of continuous improvements. Thus, the advantages of use of simulation in BPM can be summarized as follows (Doomun and Vunka Jungum, 2008, 840; Hlupić and Vukšić, 2004, 2): simulation allows modelling of process dynamics, possibility of investigation of influence of random variables, quantitative and qualitative view on re-engineering and design effect, process visualization and animation. Similarly to other areas, one can identify three main requirements related to business process simulations (Jansen and Vullers, 2006, 79; Martin, Depaire and Caric, 2016, 4; Aalst et al., 2010, 319):

- Process control flow – there are two types of process model analysis verification and performance analysis (Aalst, 2013, 21). Verification focuses on the logical correctness of the model while performance analysis focuses on process improvement. However, to be able to acquire credible results through performance analysis, it is necessary to come out from adequate process workflow (like, e.g., process behavior, sequence flow, gateways) that faithfully describes modelled business process.

- Data flow – describes the decisions made within the process, the relation to decisions and the objects appearing in the process.
- Organization – business processes are not isolated entities, but are highly dependent on the environment, in which they occur and with which they interact. Thus, it is necessary for business process simulation tools to be able to incorporate these interactions (like, e.g., arrival times of new cases, processing times, etc.) and resources performing activities contained in the given process.

If workflow management or similar information system is involved, Rozinat et al. (2009, 838) mention historic information and state information as additional requirements. The historic information means ability to construct the history of the processes, involved with the use of so-called event logs. In addition, in the latter case, state information means the ability to use the current state of the process as an initial state of the process.

2.1 Discrete event simulation and system dynamics

Discrete event simulation (DES) and system dynamics (SD) are considered to be classical approaches towards business process simulation. DES is a modelling approach, based on the concept of entities, resources and block charts describing entity flow and resource sharing (Borshchev and Filippov, 2004, 6). Entities (e.g., people, documents, tasks, etc.) are passive objects traveling through flowchart blocks. These entities can stay in queues, be processed, be delayed, etc. As one can see, DES is based on the queuing theory. The main differences with respect to ABS is the focus on system details and macro behavior of the modelled system, top-down modelling approach and centralization (Siebers et al., 2010, 207). While DES does not focus on entities, those are rather simple, reactive and limited in capabilities (Chan, Son and Macal, 2010, 136).

According to Borshchev and Filippov (2004, 4), SD represents processes in terms of so called stocks (e.g., material, people, money, etc.). Flows between these stocks and information that determines the values of the flows. It has its roots in dynamic systems and control theory (Macal, 2010, 371). Thus, SD abstracts from single events and entities and takes an aggregate view concentrating on policies. Similarly, to DES, SD also considers a top-down approach. It is shown that well defined SD has an equivalent in ABS, despite its deterministic nature. Therefore, it is possible to model any SD model using ABS, but not vice versa.

2.2 Agent-based modelling and simulation

ABS approach arrived in the early 1990s. Compared to other simulation approaches ABS is still relatively young discipline. Unlike discrete event simulation (DES) and system dynamics (SD), which have relatively abstract nature, with ABS, one is able to focus in much more detail on particular elements of modelled system (Kelly et al., 2013, 159). Active elements of the modelled system are represented by software agents. These agents are specific in a way that they are programmed to follow some behavioral rules and autonomously interact with each other and make their own decisions, which replicates the complexity of the system (Macal and North, 2008, 101). Agents may represent plethora of entities like, e.g., products, organizations, departments, people, etc. Thus, through the use of ABS we are able to simulate complex systems and repeatedly study its behavior on either macro or micro level (Macal and North, 2010, 151). This is usually hard to achieve by other techniques and many times even impossible, especially if we find ourselves in areas like, e.g., social sciences.

As is showed by Abar et al. (2017, 13), ABS approach is applied diversely across countless application domains such as climate change, ecology, biology, economics, sociology, social sciences, agriculture and many others, while still supported by many ABS simulation tools. While Abar et al. (2017, 13) mention particular domains of use of ABS, there are also applications that are of interest to BPM researches and practitioners like, e.g., manufacturing, automation, logistics, operational and management science, market simulation, etc. ABS approach is experiencing synergic effect in relation with all the new technologies that are being integrated into business domain. One of such technologies is cloud computing, where MAS find their use for allocation of limited amount of resources (Gasior and Seredyński, 2015, 403; Khalil et al., 2017, 11). Similarly, Internet of Things (IoT) is another concept within which ABS experience success in recent years as suitable and effective modelling, programming and simulation paradigm for complex heterogeneous systems (Savaglio et al., 2017, 307).

One of the key features of IoT are Smart Objects, which are expected to be intelligent, context-aware and autonomous. These ideas are pushed even further by the concept of Industry 4.0 adopted across the world, e.g., in EU, USA, China, Japanese, SEA, etc. Industry 4.0 is expected to bring significant socio-economic changes, which will be projected into business sphere. Fortunately, the ABS approach has promising results across many business areas that are being transformed like, e.g. smart manufacturing (Bannat et al., 2011, 148), smart products (Savaglio et al., 2017, 307), vertical integration across value chain (Hsieh, 2015, 252). Leitão et al. (2016, 1086) did deep analysis of integration of ABS and Cyber-Physical Systems (CPS).

One of the general problems of simulations and discouragement of their use is inability to find optimal solution, however according to Kamdar, Paliwal and Kumar (2018, 1), ABS were successfully used with several optimization techniques.

ABS have several other features useful in BPM modelling and simulation. One of such features is self-organization. Self-organization enables agents of MAS to change their behavior without external control based on changes in its operating conditions and its environment (Boes and Migeon, 2017, 12; Axtell, 2016, 806). Thus, ABS systems are able to meet the set threshold, achieve set value or minimize or maximize a value. All three possibilities are heavily emphasized in business domain. The digitization and automation of businesses require more sophisticated robot-human and robot-robot interactions (Pomarlan and Bateman, 2018). ABS are naturally suited for modelling and simulation of such interactions. To achieve autonomy and self-organization, the agents of ABS has to be able to coordinate their actions (Claes, Oliehoek, Baier, and Tuyls, 2017, 492; Amador Nelke and Zivan, 2017, 1082), to be able to learn, etc.

Our argumentation for incorporation of ABS into BPM modelling and simulation and mainly our simulation experiment might give an impression, that our research is based on the principles of subject-oriented BPM (S-BPM). However, this is not the case. We do not make subjects a center pieces of BPM as the S- BPM does (Fleischmann, Schmidt and Stary, 2013, 295). Moreover, we do not argue for modelling business processes from stakeholder perspective (Aitenbichler, Borgert and Mühlhäuser, 2011, 19). We argue that some modelled and simulated systems benefit from implementation in terms of ABS approach. However, it is not based on focus and general nature of the subject as it is in the case of S-BPM. On the contrary, it is based on very specific properties of the subjects itself. Many research papers that cover ABS in area of S-BPM seem to be pushing the narrative of perfect complementarity between ASB and S-BPM due to the nature of S-BPM, as it separates the internal behavior of the subjects from communication and thus, focus mainly on the integration of ABS and S-BPM (Fleischmann, Kannengiesser, Schmidt and Stary, 2013, 138). We do not push this narrative, as we acknowledge there are many situations, where the classical approaches towards BPM modelling and simulation are better. In addition, the decision to implement the modelled system based on ABS does not have to be done based on property of subject of the process, but also object of the process or the predicate of the process, where ABS implementation enhances the simulation of the system.

2.2.1 Disadvantages of ABS

One of the major problematic areas of ABS that attracts attention of many researchers is the validation and verification of the model (Vanhaverbeke & Macharis, 2011, 186). This is caused mainly by the fact that it becomes harder to manage it with more complex models. However, as mentioned in Siebers et al. (2010, 209), system dynamics approach, unlike discrete event simulation, faced similar problem that has not proved to be a substantial barrier. Besides that, thanks to the recent development, process mining is able to partially solve this problem, which will be demonstrated in the last section of this paper.

Second drawback is the need of the modeler to be familiar with principles of object-oriented programming and programming language (e.g., Java). Even though this is also partially addressed by use of graphical approach in the form of drag and drop technique and others. Nevertheless, atypical software agents and their behavior will still have to be done mostly using specialized tools, toolkits or development environments (Macal and North, 2010, 151).

The objective of business process modelling is to provide a notation that is readily understandable by all business users and other users interested in modelling and later implementation of business processes (Gamoura, Buzon and Derrouiche, 2015, 481). However, there is no modelling notation determined for ABS. Even though as showed by Onggo and Karpat (2011, 671), it is possible to use existing notations like BPMN. Problematic is also a time dimension, since the modelling using ABS and thus also deliverable time of the simulation is much more time consuming than it is in the case of both discrete event simulation or systems dynamics. This is also related to the lack of a general framework that would guide both academics and practitioners during the modelling and simulation process. On the other hand, once the model is set, ABS becomes very flexible and reusable (Gomez-Cruz, Saa and Hurtado, 2017, 323).

The last major obstacle is on the side of managers themselves, as they are lot of the times not willing to use new techniques, unless it is absolutely necessary. On top of that, as we said earlier, ABS requires some special skills that managers usually do not possess. However, because of the data, the modern data-oriented approaches influence organizations all over the world. And managers are pushed to continually improve their informatics literacy. As one can see, ABS has several disadvantages and obstacles, but basically, all of them are being gradually solved or at least their negative impact is being reduced.

2.2.2 Advantages of ABS

The enthusiasm around the ABS was not for nothing, as it has many advantages. As we already mentioned, one of ABS' advantages is its ability to model very complex sys-

tems (Terano, 2008, 175) at a much lower level of abstraction. That is something that traditional BPM simulation approaches struggle with. Not to mention the increasing complexity of today organizations' processes due to present trends like, e.g., globalization, horizontal integration, etc. It is safe to say that vast majority of organizations entail uncertainty and complexity going beyond intuition and traditional analytical methods (Gomez-Cruz, Saa and Hurtado, 2017, 314).

In relation to complexity of simulated systems, ABS allows to analyze the behavior of complex systems from two different viewpoints – macro and micro level (Siebers et al., 2008, 959). While the macro level viewpoint is well applicable for the strategic and tactical decision making, the micro level viewpoint is more suitable for the operational decision making. It makes very appealing to be able to cover all three stages of managerial decision making under the cover of one methodology. Another advantage is its ability to make the simulated models more realistic (Twomey and Cadman, 2002, 56). The significant factor here is the ability of ABS to model people's behavior and interactions like communication, cooperation or coordination and thus better capture the behavior of human resource within the process.

Not only we are able to model the behavior, but ABS also introduces high level of heterogeneity into the modelled system. We can think about heterogeneity in several ways. For instance, as the ability of ABS to work with many different classes of agents, but also in all the new possibilities of defining the behavior of the agents with use of, e.g., machine learning and artificial intelligence, etc. As business processes always interacts with the environment, in which the organization is located, another advantage is that besides modelling the interaction between agents it is also possible to model interaction with the environment. On top of that, the software agents naturally represent entities involved in organizational processes.

3 Methodology

In the following subsections, we introduce the remaining concepts and tools needed for simulation experiment and describe the experiment itself. In our proof of concept experiment we deal with a complex model of trading company. The model is composed from autonomous interacting agents.

3.1 MAREA

We use modelling and simulation framework called MAREA (Vymětal, Spišák and Šperka, 2012, 342) for our experiments. It consists of the simulation of multi-agent system and ERP system based on the principles of REA ontology (**R**esource-**E**vent-**A**gent). Simulation designer is used for simulation design. The ERP system stores data, keeps track of KPIs (**K**ey **P**erformance **I**ndicator) and provide a possibility to read and insert data. The main KPIs are cash level, turnover, profit, but it is possible to define additional KPIs relevant to the simulation like, e.g., costs, etc. The cash level is calculated as a total of all transactions that change it including initial cash – payments for purchases, income from sales, payment of bonuses, etc. Turnover and gross profit is calculated as a total of gross profits and turnovers of specific product types (Šperka and Halaška, 2017, 8). The framework model is based on two fundamental business processes, namely purchase to pay (P2P) and order to cash (O2C). In the core of the P2P process is the supplier-to-purchase representative negotiation. The P2P process covers the activities related to requesting, purchasing, paying for and accounting for the purchased goods and services. The O2C process covers the activities related to ordering, getting paid for and accounting for the sold goods and services. The negotiation between customers and sales representatives is based on the mathematical decision function below (Vymětal and Ježek, 2014, 3). The function is derived from the fundamental economic concepts that are Marshallian demand function, Cobb-Dougles preferences and utility function, where they assume the sold goods to be normal goods, as we do in our simulation. Decision function for *i*-th customer determines the quantity that *i*-th customer accepts. If x_i < quantity demanded by customer, the customer realizes that according to his preferences and budget, offered quantity is not enough, he rejects sales quote.

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

x_i^m 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.

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 of goods). As one can see, in our setup software agents represent people and company departments. All agents are developed according to multi-agent approach and the interaction between agents is based on the FIPA contract-net protocol (Sandita and Popirlan, 2015, 480). For the general structure of the

company, agents involved in the company and relations between agents see Figure 1.

The negotiation between customer agent and sales representative agent is as follows: customer agent sends product requests randomly during the simulation run. After the sales representative agent receives the request, it sends quote with the price for goods to the customer agent. Based on Equation (1), customer agent either accepts the price for quoted amount of goods or not. If the customer agent accepts the quote, the negotiation is over. If the customer does not accept the quote, the message is sent to the sales representative, the negotiation continues, and if possible, sales representative resends quote with different price for the good. If the negotiation takes longer than 10 days, the negotiation ends. Every agent class has a set of its own properties (the properties relevant for our experiments will be discussed below). Besides properties specific for agent classes, simulation has so called global properties (e.g., duration of simulation run; number of customers, suppliers, vendors, sales representatives; average income of customer agents, limit sales price, etc.). Each group of customer agents is served by concrete sales representatives (which is responsible to manager agent), and none of them can change the counterpart.

MAREA was built as a trading company simulation tool, not a business process simulation tool. Thus, its main focus is on trading, but because its unique implementation as message MAS, trading is modelled and simulated with

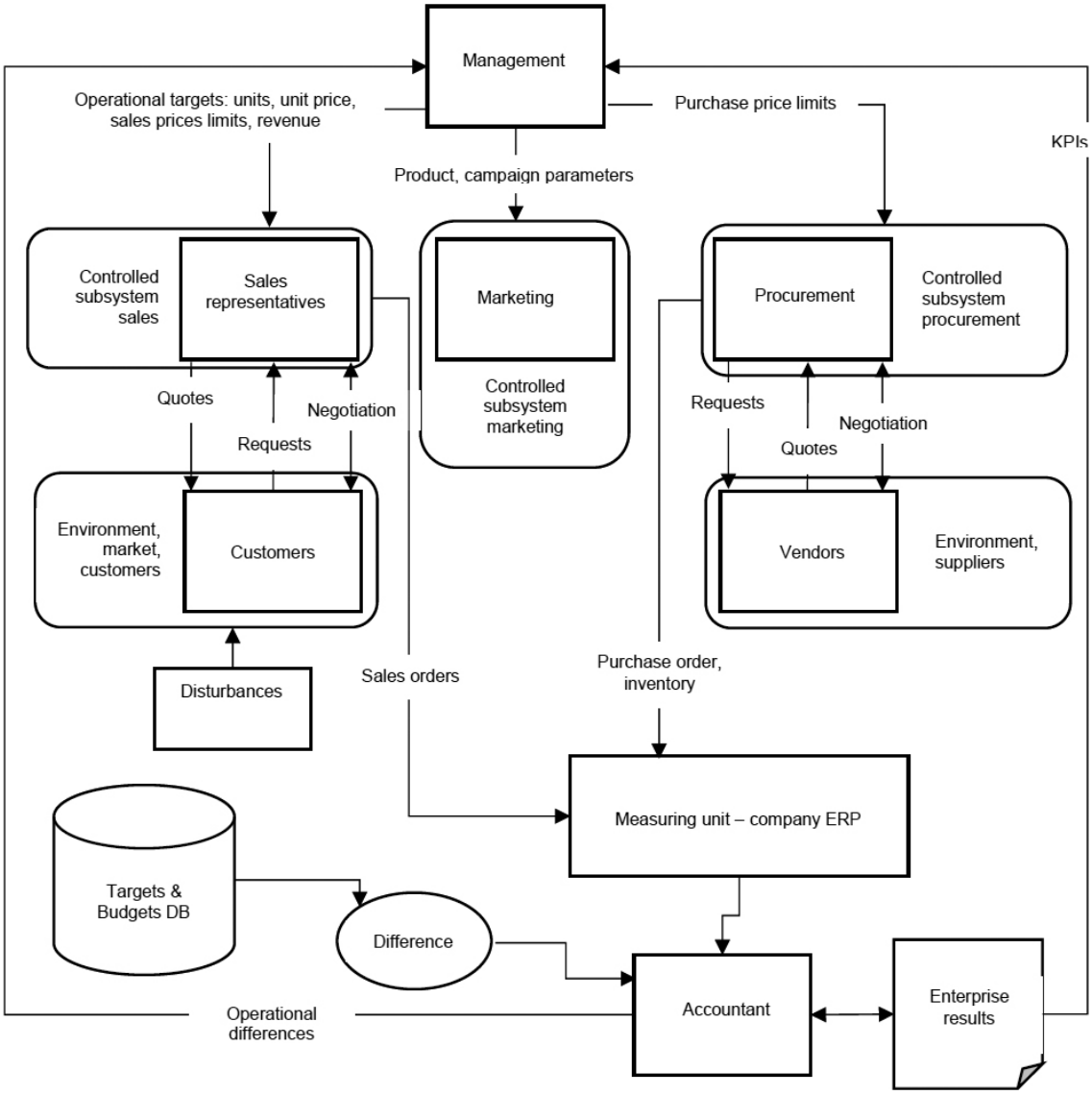

Figure 1: Generic model of a business company. Source: Vymětal, Šperka and Spišák (2012, 342)

use of business processes. Nevertheless, it misses some features of typical BPM simulation tool from the process perspective as they were not necessary for modelling trading company. However, it is well suited for the purpose of this paper. If we go back to simulation requirements from section 2. It enables to model process control flow due to its unique implementation as a message multi-agent system (in which all actions are messages among agents). It enables to model data flow due to its ABS character. Historical data and state information are enabled due to implementation of ERP system. Only organization is not fully supported. This is related mainly to inability to directly work with time dimension, e.g., waiting times, arrival times. We are able to record, analyze and monitor time dimension. However, we are not able to directly setup waiting times nor arrival times in the current version. Nevertheless, we are able to influence them indirectly through other global and local parameters. The limited possibilities in organization dimension are irrelevant, as we do not directly focus on time dimension.

In our simulation experiments, we work with a model of complex system of trading company composed of above mentioned agents (see Figure 1). For simplicity, company sells only one product in form of computer cables. As one can see, our simulation model resembles the real company. Similarly, in our simulation setup we use significantly higher number of customer agents than agents representing the employees of the company. Four dimensions, so called Devil's Quadrangle, can characterize the focus of BPM in the real companies: time, cost, quality, and flexibility. In our experiments, we focus on the cost and quality dimension due to the nature of the simulation experiment and MAREA tool. However, it is not to say that in case of flexibility and time use of ABS cannot add useful features. In most BPM simulation tools the time dimension is treated with use of different probability distributions of arrival times, working times, etc. However, if the planning or scheduling activities are important for the model and simulation itself, classical modelling and simulation BPM tools do not provide easy solution. With respect to flexibility, due to development of the state-of-the-art in ABS provides high degree of flexibility towards BPM simulations.

In our research, we are interested in how specific behavior of company's resources that is the qualitative dimension of the business process, influence the outcomes of the process. The outcomes of the processes represent the cost dimension of the business process. The influence of the outcome of the process is measured through the company's profit at the end of the reference period. As we show in section 4, even small changes in resources' behavior may have statistically significant impact on the outcome of the business process, especially if the resources are human actors or other autonomous agents (like, e.g., robotics, advanced machinery, etc.). The resources are usually modelled in a very simplistic way that is far from the reality. In DES and SD, the class of resources is treated as one. On the other hand, ABS allows us to work with resources individually at the particular agent instances level. This applies to entities involved in the process in general. In our simulations, we experiment with short-term, within-person fluctuations in well-being (Xanthopoulou, Bakker and Ilies, 2012, 1051). The work-related well-being concerns the evaluations employees make about their working life experiences.

In the past, well-being was mainly investigated as a static phenomenon on between-person level. However, research from recent years show that it is important to consider more dynamic within-person approach too (Dalal et al., 2009, 1051; Ceja and Navarro, 2011, 627; Dimotakis, Scott and Koopman, 2011, 572). The well-being on this level can fluctuate on a daily basis towards positive or negative effect. The studies show that there is a correlation between psychological well-being and job performance (Wright, Cropanzano and Bonett, 2007, 93; Wright and Cropanzano, 2000, 84). Thus, transient fluctuations of well-being with negative effect can negatively affect employee's performance (Beal et al., 2005, 1054). In our simulation, we link employee's performance to the quality of service provided to the customer. As research show, quality of service is related to customer loyalty and retention (Salanova, Agut and Peiró, 2005, 1217). Where one of the aspects that customer loyalty usually contributes to is the willingness to pay established prices. Thus, in our simulation experiments if the customer agent negotiates with sales representative, when sales representative agent is experiencing the effect of negative within-person well-being, the customer is less willing to pay higher prices for the goods. This is eventually related to the organization's profit.

3.2 Simulation experiments

In our simulations, we work with two different scenarios based on the number of resources, concretely sales representatives involved in the process. In the case of basic scenario, sales representatives are modelled as it is typical for DES or SD approach. Thus, we compare implementation of simulation of modelled system with respect to DES approach in case of basic scenario and with respect to ABS approach in case of experimental scenario. The difference is that in the case of experimental scenario, each sales representative can get into the state of negative within-person well-being caused by within-person fluctuations in well-being. These fluctuations affect negatively their job performance that is lowering quality of sales service provided to the customers. Customers are then much less likely to buy the product, unless the product is cheaper. For simplification, the coefficient quality of service is the same for every sales representative agent, no matter the reason or strength of the effect of the negative well-being. However, different customers are affected differently, be-

Table 1: Part of the simplified event log of the process. Source: authors

	Basic scenario_1	Experimental scenario_1	Basic scenario_3	Experimental scenario_3	Basic scenario_6	Experimental scenario_6
Number of customers	500	500	500	500	500	500
Number of sales representatives	1	1	3	3	6	6
Probability of negative well-being fluctuation	0,1	0,1	0,1	0,1	0,1	0,1

Table 2: Simulation parameters. Source: authors

Case ID	Activity	Complete Timestamp	Resource
12209	Sales request revoked	2016/10/17 10:08:24.000	Customer 123
12197	Sales request	2016/10/06 10:41:34.000	Customer 155
12209	Sales quote	2016/10/07 02:10:14.000	Peter Hanson
12204	Sales quote rejection	2016/10/07 10:41:34.000	Customer 165
12204	Sales request	2016/10/08 02:10:14.000	Peter Hanson
12190	Sales quote acceptance	2016/10/08 10:41:34.000	Customer 175
12193	Material request	2016/10/09 02:10:14.000	Peter Hanson
12194	Production request	2016/10/09 02:10:14.000	Peter Hanson
12190	Sales order	2016/10/09 02:10:14.000	Peter Hanson
12190	Bonus payment	2016/10/09 02:10:14.000	Peter Hanson
12190	Production ready	2016/10/09 02:26:49.000	Production line manager 1
12190	Stock level	2016/10/09 02:26:49.000	Production line manager 1

cause they have different randomly distributed preferences towards goods. If the sales representative agent does not experience negative within-person well-being fluctuation, the coefficient quality of service is equal to 1. In the opposite case, the coefficient is equal to 0,85. Each sales representative can get into the state of negative within-person well-being on random days during the simulation run. If the sales representative gets into this negative state, he stays in it until the end of the working day. The frequency of these negative states during the simulation run is determined based on the "Probability of negative well-being fluctuation" parameter. Probability of negative well-being fluctuation means that each working day, each sales representative has a 10 % chance to experience negative within-person well-being fluctuation. We use normal probability distribution. Negative within-person well-being fluctuations are caused, e.g., by interaction of sales representative with angry and unpleasant customer, conflicts in the company, stress, etc. Each simulation has 365 days long simulation run and we made 15 simulation runs for each scenario.

The parameters relevant for our simulation experiments are in Table 2, even though our model contains much more parameters. The numbers at the end of each scenario's label indicates the number of resources involved in each simulation run, e.g., "Experimental scenario_6" means that 6 sales representatives were involved in the process simulations. For simplicity, we consider the effect of lower quality service on each customer to be the same. However, these parameters are under the ceteris paribus assumption. The probability of customer creating sales request is equal to 20 % across all scenarios. Similarly, the probability of negative well-being fluctuation are also the same across all scenarios.

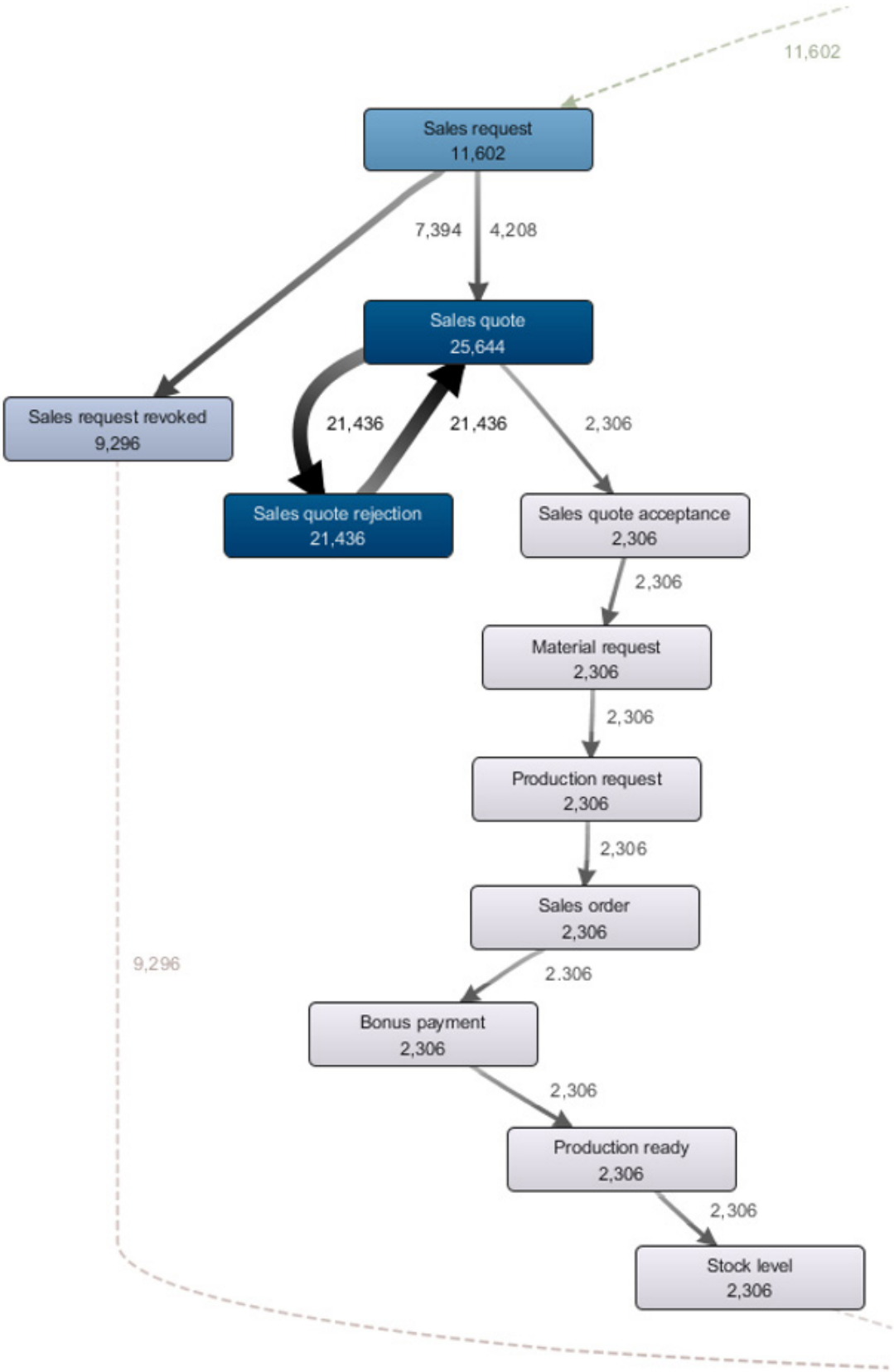

Figure 2: Process model of O2C subprocess consisting of 10 simulation runs. Source: authors

3.3 Process mining

Process mining is relatively young discipline filling the gap between process-centric approach of BPM and data-centric approach of data sciences. Process mining is a set of techniques used for discovery, monitoring and improvement of processes based on knowledge extracted from today's information systems (Aalst et al., 2011, 171). Process mining consists of three main areas: (1) automated process discovery, (2) conformance checking, (3) enhancement, and several recent areas like, e.g., operational support and deviance analysis.

The main goal of process discovery is to find patterns in the data and based on this information to construct the process model. Nowadays, there exist many automated discovery techniques presented by, e.g., Aalst, Weijters and Maruster (2004, 1128), Leemans, Fahland and Aalst (2013, 311), Medeiros, Weijters and Aalst (2005, 203). The data, so called event logs, are recorded by company's information systems and extracted from different sources, e.g., databases, data warehouses, etc. In Table 2, one can see simplified excerpt from event log used for construction of process model in Figure 2. The log shows only required and the most common characteristics of event logs, even though it may contain much more attributes. The log produced by MAREA and used for process mining analysis is in the XES standard officially published by IEEE. XES is a standard for event logs among process mining tools (Verbeek et al., 2010, 60).

Table 3: Profit statistics (Profit is measured in EUR). Source: authors

	Basic scenario_1	Experimental scenario_1	Basic scenario_3	Experimental scenario_3	Basic scenario_6	Experimental scenario_6
Mean profit	29155,97	21838,05	30980,65	27326,73	29925,87	28270,06
Std. Dev.	3310,32	2146,55	2209,22	2502,37	3221,73	2561,53

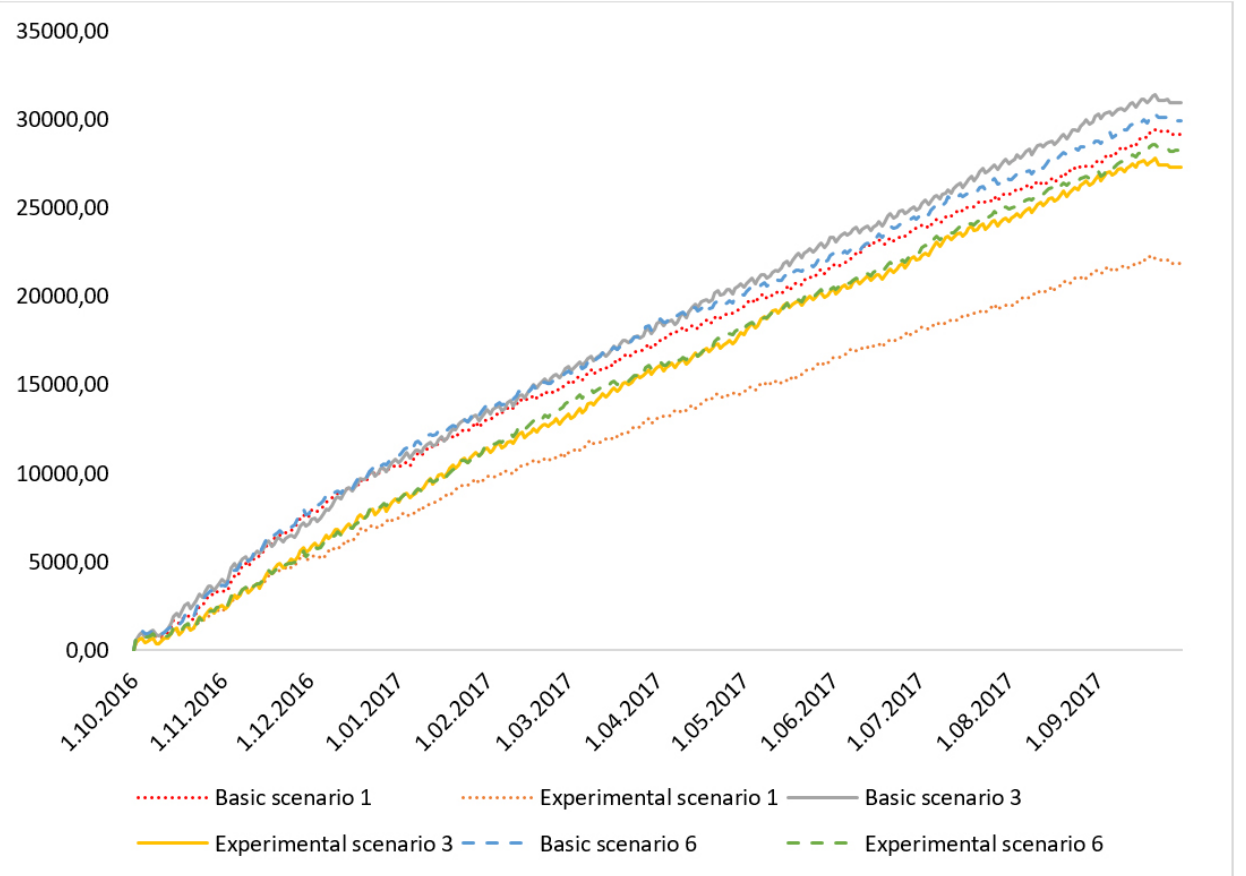

Figure 3: Development of profits for each scenario. Source: authors

4 Simulation experiments and results – proof of concept

Because of the unique implementation of MAREA as a message multi-agent system and development of new techniques in the field of BPM, namely, process mining we are able to visualize the ongoing process (Figure 2). Based on the visualization of the company's processes we can validate that the simulation model corresponds to the proposal and does not contain errors, etc. Figure 2 shows the O2C subprocess. The overall model consists of two more subprocesses: P2P and management subprocess. Due to the size of particular subprocesses, we are not able to present the overall process.

In our simulations, we analyze how micro level fluctuations of performance affects macro level outcomes of O2C process in form of profits. The implementation of sales representatives as software agents is necessary. With use of classical approaches like DES and SD we would not be able to exploit performance fluctuations caused by negative within-person fluctuations of well-being as we would not be able to implement behavioral patterns to the agents. Nor would we be able to exploit the impact of performance fluctuations in the collective of sales representative agents. In our simulation experiment, we consider the differences in achieved profits to be the costs related to the process (see Table 3). Figure 3 shows the development of profits for each scenario. Each time series is calculated as an average of each simulation run respective to each scenario. The values of KPIs are aggregated on a daily basis that means in case of economic quantities we are not able to access lower level of abstraction (e.g., track changes in profits hourly).

As one can see from Figure 3 and Table 3, there are differences in simulation outcomes. Rather small changes in resources' behavior have statistically significant impact on the outcomes of business process simulations. The profits acquired by the company are statistically significantly higher in simulation experiments with 1 or 3 sales representative agents modelled according to the classical simulation methodologies. Moreover, according to simulation experiments based on DES methodology, the company achieves on average highest profits in case it employs 3 sales representative (see Figure 4). On the contrary, according to simulation experiments based on ABS methodology it would be best for the company to employ 6 sales representatives. Thus, in our case, decisions about organization's processes based on DES or SD approach would be significantly different from decisions based on ABS approach. Thus, if the management of the company would base its decision about number of sales representatives on basic scenario, the best option is to employ 3 sales representatives. On the other hand, in case of experimental scenario, the best option is to employ 6 sales representatives. To this decision are related implicit costs of value 2 710,59 EUR as the difference between profits in Basic scenario_3 and Experimental scenario_6.

Table 4 presents the results of ANOVA and size of

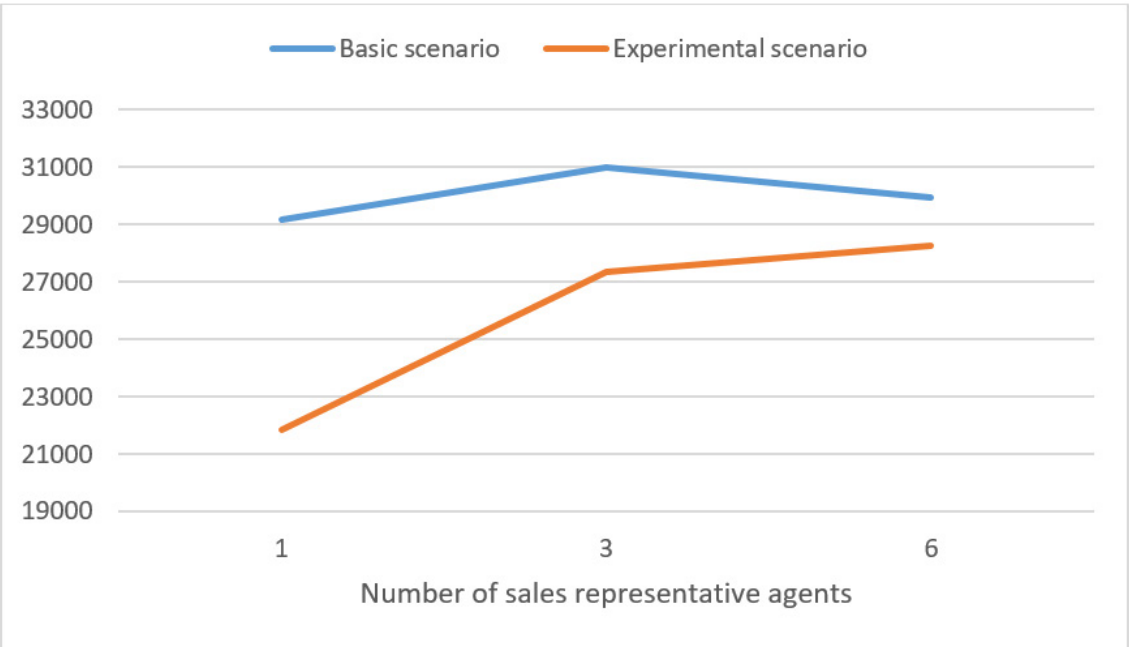

Figure 4: Development of the profit of the company with respect to particular scenarios based on number of sales representatives. Source: authors

omega-squared effect for each factor that is the number of sales representatives involved in the O2C process. According to ANOVA, factor number of sales representatives is statistically significantly different considering the factor number of sales representatives for scenarios with 1 or 3 sales representatives involved, and with omega-squared effect being equal to 0,6278 and 0,3613 respectively. But, in case of 6 sales representatives, factor number of sales representatives is not statistically significant anymore. Moreover, the gap in profits between basic and experimental scenario has a tendency diminish with increasing number of sales representatives involved in the process (see Figure 4). This means that the performance fluctuations induced by randomly occurring negative states of within-person well-being have a tendency to diminish with increasing number of resources. This fact is not trivially deductible and expectable. One would expect the differences between basic and experimental scenario to stay the same or go in other of direction that is the gap between profits basic and experimental scenario to raise.

For organizations, where there is an interaction between resources and customers part of the organization's core process, the ability to model the behavior of its resources in a more sophisticated way is crucial to obtain relevant results. As we show, even small changes in resources' behavior might have significant impact on the outcomes of process simulations and on decisions based on such simulations. Modelling resources in the field of BPM simulations with use of DES or SD is insufficient in many cases. Moreover, this need can be generalized to other entities involved in business process. Even though, ABS approach is not the best for every problem, which BPM faces, one cannot argue that it is valuable addition and complementary tool to already well-established approaches.

5 Discussion and conclusions

The paper presents main advantages and disadvantages of ABS approach in the field of BPM. We compare it to more classical and well-established approaches like discrete event simulations and system dynamics in the field. We established that the main disadvantages and possible obstacles in engagement of ABS are connected to complexity and robustness of the approach and required skills for its successful application. Perhaps the most difficult disadvantage to overcome is the lack of guidelines that would help to manage its own complexity. However, as we show, most of the disadvantages were, at least partially, successfully addressed in the recent years. In addition, many of the disadvantages we mention are overflowing to other application domains as well, but there it does not seem to be such a problem. Thus, we believe that the problem so far is the specificity of the companies and situational nature of ABS that in combination with time-consuming process of ABS model development prevents higher degree of utilization of ABS specifically in BPM domain.

Table 4. ANOVA results and omega-squared effect. Source: authors

Number of sales representatives	P-Value	ω2
1 sales representative	0,0000	0,6278
3 sales representatives	0,0002	0,3613
6 sales representatives	0,1305	0,0454

Moreover, we decided to demonstrate the need for ABS approach with our own simulation experiments. In our simulations, we investigate the impact of changes in resources' behavior on the outcome of company's order to cash process. We worked with two scenarios. In the first scenario, we modelled resources as they are typically modelled in the case of more classical DES and SD approach. We chose to experiment with resources, because of the naive and simplistic way, they are treated by DES and SD approach. In the second scenario, we implemented a specific behavior to the resource agents. Concretely, we use resources to experience randomly distributed effects of negative within-person well-being fluctuations and observed the influence of these fluctuations on the outputs of company's order to cash process. As we show, even small changes in resources' behavior might have statistically significant effect not only on outcomes of the processes but also on the decisions based on such outcomes. Our research shows that the impact of randomly distributed fluctuations of well-being has a diminishing tendency with the increasing number of sales representatives involved in the process. Nevertheless, due to digitalization, upcoming industrial revolution and utilization of new technologies in business domain, the application of ABS is raising. And in our opinion, the support of business processes by ABS will eventually raise beyond the threshold of broader application of ABS in BPM modelling and simulation as arguably, there is no better way to model and simulate ABS than with use of ABS.

In conclusion, based on our investigation, we believe that there is a need for ABS in BPM modelling and simulation. In addition, we believe that we will see the raise of utilization of ABS in BPM domain with the technological advances to come and the technological transformation of businesses. The classical approaches like DES or SD still have their strengths. However, in case of resources where the behavioral patterns play many times crucial roles as we show in simulation experiments, ABS seems to be much more appropriate and powerful tool for both researchers and businesses as we show in the study, as it resolves the criticized simplicity in modelling of resources. This role of resources will get more empowered with further automa-

tion of business process. Even though the study illustrates our case very well, there are some limitations to it. Firstly, we consider only negative within-person well-being fluctuations in our study. However, employees may also experience positive within-person well-being fluctuations that on the hand have positive effect of employee's performance. Secondly, the performance of employee is not being influenced only by ones within-person well-being. Thirdly, the effects of such fluctuations might not always be easily detectable. In the future research, we would like to explore technological resources with use of more sophisticated agents and provide them with more intelligent behavior in sense of ABS approach and its interaction with human resources that might be very useful, e.g., in concept of Industry 4.0.

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Literature

Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. P. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*, 24, 13–33. https://doi.org/10.1016/j.cosrev.2017.03.001

Aitenbichler, E., Borgert, S., Mühlhäuser, M. (2011). Distributed Execution of S-BPM Business Processes. In A. Fleischmann, W. Schmidt, R. Singer, D. Seese (Eds), *Subject-Oriented Business Process Management. S-BPM ONE 2010. Communications in Computer and Information Science* (19-35). Berlin: Springer.

Alfonso Gomez-Cruz, N., Saa, I. L., & Ortega Hurtado, F. F. (2017). Agent-based simulation in management and organizational studies: a survey. *European Journal of Management and Business Economics*, 26(3), 313–328. https://doi.org/10.1108/EJMBE-10-2017-018

Amador Nelke, S., & Zivan, R. (2017). Incentivizing Cooperation Between Heterogeneous Agents in Dynamic Task Allocation. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems* (1082–1090). Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems

Axelrod, R. (1997). Advancing the art of simulation in the social sciences. *Complexity*, *3*(2), 16–22. https://doi.org/10.1002/(SICI)1099-0526(199711/12)3:2<16::AID-CPLX4>3.0.CO;2-K

Axtell, R. L. (2016). 120 Million Agents Self-Organize into 6 Million Firms: A Model of the U.S. Private Sector. In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems* (806–816). Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems

Bannat, A., Bautze, T., Beetz, M., Blume, J., Diepold, K., Ertelt, C., … Zaeh, M. F. (2011). Artificial Cognition in Production Systems. *Ieee Transactions on Automation Science and Engineering*, 8(1), 148–174. https://doi.org/10.1109/TASE.2010.2053534

Beal, D. J., Weiss, H. M., Barros, E., & MacDermid, S. M. (2005). An episodic process model of affective influences on performance. *The Journal of Applied Psychology*, 90(6), 1054–1068. https://doi.org/10.1037/0021-9010.90.6.1054

Boes, J., & Migeon, F. (2017). Self-organizing multi-agent systems for the control of complex systems. *Journal of Systems and Software*, 134, 12–28. https://doi.org/10.1016/j.jss.2017.08.038

Borshchev, A., & Filippov, A. (2004). From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. In The 22nd International Conference of the System Dynamics Society, 25-29 July 2004. Oxford: Scientific research.

Ceja, L., & Navarro, J. (2011). Dynamic patterns of flow in the workplace: Characterizing within-individual variability using a complexity science approach. *Journal of Organizational Behavior*, 32(4), 627–651. https://doi.org/10.1002/job.747

Claes, D., Oliehoek, F., Baier, H., & Tuyls, K. (2017). Decentralised Online Planning for Multi-Robot Warehouse Commissioning. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems* (492–500). Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems

Dalal, R. s., Lam, H., Weiss, H. M., Welch, E. R., & Hulin, C. L. (2009). A Within-Person Approach to Work Behavior and Performance: Concurrent and Lagged Citizenship-Counterproductivity Associations, and Dynamic Relationships with Affect and Overall Job Performance. *Academy of Management Journal*, 52(5), 1051–1066. https://doi.org/10.5465/amj.2009.44636148

Dimotakis, N., Scott, B. A., & Koopman, J. (2011). An experience sampling investigation of workplace interactions, affective states, and employee well-being. *Journal of Organizational Behavior*, 32(4), 572–588. https://doi.org/10.1002/job.722

Doomun, R., & Vunka Jungum, N. (2008). Business process modelling, simulation and reengineering: call centres. *Business Process Management Journal*, 14(6), 838-848. https://www.emeraldinsight.com/doi/full/10.1108/14637150810916017

Fleischmann, A., Kannengiesser, U., Schmidt, W., & Stary, C. (2013). Subject-Oriented Modeling and Execution of Multi-agent Business Processes. In *2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*. Atlanta: IEEE.

Fleischmann, A., Schmidt, W., & Stary, C. (2013). Open S-BPM = Open Innovation. In H. Fischer, J. Schneeberger (Eds), *S-BPM ONE - Running Processes. S-BPM ONE 2013. Communications in Computer and Information Science* (29 –320). Berlin: Springer.

Gamoura, S., Buzon, L., & Derrouiche, R. (2015). Machine Learning Agents in the Cloud to Support Smart Business Process Management. In L. M. Camarinha-Matos, F. Benaben, & W. Picard (Eds.), *Risks and Resilience of Collaborative Networks* (479–488). Berlin: Springer-Verlag Berlin.

Gąsior, J., & Seredyński, F. (2015). A Decentralized Multi-agent Approach to Job Scheduling in Cloud Environment. In P. Angelov et al. (Eds), *Intelligent Systems'2014. Advances in Intelligent Systems and Computing* (403-414). Cham: Springer.

Hlupić, V., & Vukšić, V. B. (2004). Business Process Modelling Using SIMUL8. In Proceedings of 16th European Simulation Symposium, 17-20 October 2004 (191-196). Budapest: SCS Publishing.

Hsieh, F.-S. (2015). Scheduling Sustainable Supply Chains based on Multi-agent Systems and Workflow Models. In *2015 10th International Conference on Intelligent Systems and Knowledge Engineering (iske*) (252–259). New York: Ieee.

Chan, W. K. V., Son, Y. J., & Macal, C. M. (2010). Agent--based simulation tutorial - simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation. In Proceedings of the 2010 Winter Simulation Conference, 5-8 December 2010 (135–150). Maryland: IEEE

Kamdar, R., Paliwal, P., & Kumar, Y. (2018). A State of Art Review on Various Aspects of Multi-Agent System. *Journal of Circuits Systems and Computers*, 27(11), 1830006. https://doi.org/10.1142/S0218126618300064

Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., … Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software*, 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005

Khalil, K., Abdel-Aziz, M., Nazmy, T., & Salem, A. (2017). Multi-Agent Model for Job Scheduling in Cloud Computing. *International Journal of Computers*, 11, 11-17.

Leemans, S. J. J., Fahland, D., & Aalst, W. M. P. van der. (2013). Discovering Block-Structured Process Models from Event Logs - A Constructive Approach. In J.-M. Colom & J. Desel (Eds.), *Application and Theory of Petri Nets and Concurrency* (311–329). Berlin: Springer.

Leitão, P., Karnouskos, S., Ribeiro, L., Lee, J., Strasser, T., & Colombo, A. W. (2016). Smart Agents in Industrial Cyber–Physical Systems. *Proceedings of the IEEE*, 104(5), 1086–1101. https://doi.org/10.1109/JPROC.2016.2521931

Macal, C. M. (2010). To Agent-based Simulation from System Dynamics. In *Proceedings of the Winter Simulation Conference* (371–382). Baltimore, Maryland: Winter Simulation Conference.

Macal, C. M., & North, M. J. (2008). Agent-based Modeling and Simulation: ABMS Examples. In *Proceedings of the 40th Conference on Winter Simulation* (101–112). Miami, Florida: Winter Simulation Conference.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3), 151–162. https://doi.org/10.1057/jos.2010.3

Martin, N., Depaire, B., & Caris, A. (2016). The Use of Process Mining in Business Process Simulation Model Construction. *Business & Information Systems Engineering*, 58(1), 73–87. https://doi.org/10.1007/s12599-015-0410-4

Medeiros, A. K. A. de, Weijters, A. J. M. M., & Aalst, W. M. P. van der. (2005). Genetic Process Mining: A Basic Approach and Its Challenges. In C. J. Bussler & A. Haller (Eds.), *Business Process Management Workshops* (203–215). Berlin: Springer.

Onggo, B. S. S., & Karpat, O. (2011). Agent-Based Conceptual Model Representation Using Bpmn. In S. Jain, R. Creasey, & J. Himmelspach (Eds.), *Proceedings of the 2011 Winter Simulation Conference (wsc)* (671–682). New York: IEEE.

Pomarlan, M., & Bateman, J. (2018). Robot Program Construction via Grounded Natural Language Semantics & Simulation. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems* (857–864). Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems

Rozinat, A., Wynn, M. T., van der Aalst, W. M. P., ter Hofstede, A. H. M., & Fidge, C. J. (2009). Workflow simulation for operational decision support. *Data & Knowledge Engineering*, 68(9), 834–850. https://doi.org/10.1016/j.datak.2009.02.014

Salanova, M., Agut, S., & Peiró, J. M. (2005). Linking Organizational Resources and Work Engagement to Employee Performance and Customer Loyalty: The Mediation of Service Climate. *Journal of Applied Psychology*, 90(6), 1217–1227. https://doi.org/10.1037/0021-9010.90.6.1217

Sandita, A. V., & Popirlan, C. I. (2015). Developing A Multi-Agent System in JADE for Information Management in Educational Competence Domains. *Procedia Economics and Finance*, 23, 478–486. https://doi.org/10.1016/S2212-5671(15)00404-9

Savaglio, C., Fortino, G., Ganzha, M., Paprzycki, M., Bădică, C., & Ivanović, M. (2018). Agent-Based Computing in the Internet of Things: A Survey. In M. Ivanović, C. Bădică, J. Dix, Z. Jovanović, M. Malgeri, & M. Savić (Eds.), *Intelligent Distributed Computing XI* (307–320). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-66379-1_27

Siebers, P.-O., Aickelin, U., Celia, H., & Clegg, C. (2008). A Multi-Agent Simulation of Retail Management Practices. In Proceedings of the Summer Computer Simulation Conference, 9-12 July 2017 (959-966). Bellevue, WA, USA: ACM DL.

Šperka, R., & Halaška, M. (2017). The impact of sales service in MAREA trading simulation under changing environment circumstances. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 12*(2), 355–371. 10.24136/eq.v12i1.19

Terano, T. (2008). Beyond the KISS Principle for Agent--Based Social Simulation. *Journal of socio-informatics*, 1(1), 175–187.

Twomey, P., & Cadman, R. (2002). Agent-based modelling of customer behaviour in the telecoms and media markets. *Info*, 4(1), 56–63. https://doi.org/10.1108/14636690210426640.

van der Aalst, V. D., & P, W. M. (2013). Business Process Management: A Comprehensive Survey. *ISRN Software Engineering*, 1-37. https://doi.org/10.1155/2013/507984

van der Aalst, W. M. P., Nakatumba, J., Rozinat, A., & Russell, N. C. (2008). Business process simulation : how to get it right? Retrieved May 27, 2018, from http://www.win.tue.nl/~jnakatum/publications/Simulation-Paper.pdf

van der Aalst, W. M. P., Rosa, M. L., & Santoro, F. M. (2016). Business Process Management. *Business & Information Systems Engineering*, *58*(1), 1–6. https://doi.org/10.1007/s12599-015-0409-x

van der Aalst, W. M. P., Weijters, T., & Maruster, L. (2004). Workflow mining: discovering process models from event logs. *IEEE Transactions on Knowledge and Data Engineering*, 16(9), 1128–1142. https://doi.org/10.1109/TKDE.2004.47

van der Aalst, W., Adriansyah, A., Medeiros, A. K. A. de, Arcieri, F., Baier, T., Blickle, T., … Wynn, M. (2011). Process Mining Manifesto. In *Business Process Management Workshops* (169–194). Springer, Berlin, Heidelberg.

Vanhaverbeke, L., & Macharis, C. (2011). An agent-based model of consumer mobility in a retail environment. *Procedia - Social and Behavioral Sciences*, 20, 186–196. https://doi.org/10.1016/j.sbspro.2011.08.024.

Verbeek, H.M.W., Buijs, J.C.A.M., van Dongen, B.F., & van der Aalst W.M.P. (2011) XES, XESame, and ProM 6. In: Soffer P., Proper E. (Eds.), *Information Systems Evolution. CAiSE Forum 2010. Lecture Notes in Business Information Processing, vol 72* (60-75).Berlin: Springer.

Vymětal D., Spišák M., Šperka R. (2012) An Influence of Random Number Generation Function to Multiagent Systems. In: Jezic G., Kusek M., Nguyen NT., Howlett R.J., Jain L.C. (Eds), *Agent and Multi-Agent Systems. Technologies and Applications. KES-AMSTA 2012. Lecture Notes in Computer Science, vol 7327*. Berlin: Springer.

Vymětal, D. & Ježek, F. (2014). Demand function and its role in a business simulator. Retreived May 27, 2018, from https://mpra.ub.uni-muenchen.de/54716/1/MPRA_paper_54716.pdf

Wright, T. A., & Cropanzano, R. (2000). Psychological well-being and job satisfaction as predictors of job performance. *Journal of Occupational Health Psychology*, 5(1), 84–94.

Wright, T. A., Cropanzano, R., & Bonett, D. G. (2007). The moderating role of employee positive well being on the relation between job satisfaction and job performance. *Journal of Occupational Health Psychology*, 12(2), 93–104. https://doi.org/10.1037/1076-8998.12.2.93

Xanthopoulou, D., Bakker, A. B., & Ilies, R. (2012). Everyday working life: Explaining within-person fluctuations in employee well-being. *Human Relations*, 65(9), 1051–1069. https://doi.org/10.1177/0018726712451283

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