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Agent Based Decision Support in the Supply Chain Context

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Abstract

Purpose: The purpose of this paper is to investigate the benefits and the barriers of agent based decision support (ABDS) systems in the supply chain context.

Design/methodology/approach: Two ABDS systems have been developed and evaluated. The first system concerns a manufacturing supply chain while the second concerns a service supply chain. The systems are based on actual case companies.

Findings: This research shows that the benefits of ABDS systems in the supply chain context include the possibility to increase versatility of system architecture, to improve supply chain visibility, to conduct experiments and what-if analyses, to improve the understanding of the real system, and the possibility to improve communication within and between organizations in the supply chain. The barriers of ABDS systems in the supply chain context include the difficulty to access data from partners in the supply chain, the difficulty to access data on a higher level of granularity, and the difficulty to retrieve data from other information systems.

Research limitations/implications: The research is explorative in nature therefore empirical data from similar and other research settings should be gathered to reinforce the validity of the findings.

Practical implications: This research provides knowledge and insights on how ABDS systems may be developed and used in the supply chain context and demonstrates its main benefits and barriers.

Originality/value: This research expands the current research of benefits of ABDS systems to the supply chain domain and also addresses the barriers of ABDS systems to a larger extent than previous research. Comparisons to other simulation based decision support systems are also given.

Keywords: Supply chain management, decision support system, agent based modeling and simulation.

Paper type: Case study

1. Introduction

The supply chain and its management, is of highest importance in many industries (Christopher, 2005). At an overall level, supply chain management concerns collection and analysis of data in order to provide a better basis for logistics decision-making (Lummus and Vokurka, 1999). This is a very complex task since the supply chain span within and across multiple firms on many levels (Gimenez and Ventura, 2005). The intensified globalization has also further increased the complexity because facilities and firms now tend to be geographically separated with a number of barriers between them (Meixell and Gargeya, 2005). Therefore, there is a great demand for advanced decision support in the supply chain context (Hilletofth, 2009). Decision support systems can be created in several ways (e.g., Power, 2002). However, to make them efficient and effective in the supply chain context (i.e., in dynamic and complex environments) they must provide decision-makers with suitable and accurate information as well as be able to predict the outcome of their decisions and how these affect the whole supply chain (Hilletofth et al., 2010a).

One type of decision support systems, which currently is receiving a lot of attention in the literature, is simulation based decision support systems (e.g., Petering, 2011; Acar et al., 2010; Fröhling et al., 2010). This decision support system implies that the real system of interest is modeled and implemented in simulation software. The simulation model is then used to support the decision-making of the real system through repeated simulations. Different modeling and simulation approaches may be used. However, one of the most promising, from a supply chain perspective, is agent based modeling and simulation. This is a quite new modeling and simulation paradigm, especially suited for dynamic and complex systems distributed in time and space (Lim and Zhang, 2003), such as supply chains.

Agent based decision support (ABDS) systems provide a pragmatic approach to the evaluation of management alternatives (Swaminathan et al., 1998). Empirical studies have shown that this type of support system can aid managers in several ways (e.g., Frayret et al., 2007; Hilletofth et al., 2010a; Hilletofth et al., 2010b; Nilsson, and Darley, 2006). For example, they can support managers to find the highest leverage among improvement alternatives, guide managers' instinct through emergent pattern, and enhance managers' understanding of the impact of unscheduled factors (Nilsson, and Darley, 2006). These systems may also sometimes improve predictability (Frayret et al., 2007) and their reconfiguration ability is very high (Seilonen et al. 2009).

Even if several benefits of ABDS systems have been reported in the literature, the issue is in need of further attention from a supply chain perspective. An issue in need of even more attention is the barriers of ABDS systems. It may be argued that the benefits are more discussed compared to the barriers. Very few comparisons to other approaches have also been reported in the literature. Thus, the aim of this research is to enhance the current knowledge of ABDS systems. The specific research questions are: "What are the main benefits of ABDS systems in the supply chain context?" and "What are the main barriers of ABDS systems in the supply chain context. These issues have been investigated through the development and evaluation of two ABDS systems. The first support system concerns a manufacturing supply chain while the second concerns a service supply chain. Actual case companies have inspired the simulation models (called

Alpha and Beta for anonymity), however, additional data have been used to allow the simulation models to be developed. The simulation models have been built in a simulation software called Anylogic.

The remainder of this paper is structured as follow: To begin with, the concept of ABDS is described in more detail in Section 2. Alternative modeling and simulation approaches are also described in this section. Thereafter, a literature review concerning the benefits and the barriers of ABDS systems is presented in Section 3. It is shown that the benefits are more deeply discussed compared to the barriers. After that, the two developed ABDS systems are described in Section 4 and 5. It is shown how the support systems are designed and what knowledge that may be derived from them. Thereafter, the research findings are presented and discussed in Section 6. In essence, the identified benefits and barriers of ABDS systems are discussed. However, we also discuss what benefits ABDS systems have in comparison to other simulation based decision support systems. Finally, the research is concluded and further research avenues are proposed in Section 7.

2. An agent based decision support system

ABDS systems represent a relatively new class of decision support systems. This kind of decision support system implies that the real system of interest is modeled and implemented in simulation software using agent based modeling and simulation principles (Hilletofth et al., 2010a). Agent principles mean that the real system is modeled as a set of interacting agents in a defined environment (Jennings et al., 1998). The agents are presumed to be acting in what they perceive as their own interests, such as economic benefit (they have individual missions), and their knowledge regarding the entire system is limited (Macal and North, 2006). The most important feature is the agents' ability to interact with each other and with the environment to achieve common goals (Cicirello and Smith, 2004). By sharing information, knowledge, and tasks among the agents in the system, collective intelligence may emerge that cannot be derived from the internal mechanism of an individual agent. The ability to coordinate also makes it possible for agents to coordinate their actions.

The simulation model is used to support the decision-making of the real system through repeated simulations (Figure 1). It consists of some agents that perform the functions and some performance and risk indicators that show the performance. The simulation model allows the decision maker to iteratively set parameters, run simulations, and evaluate the results (e.g., performance and threats). Based on the retrieved information and knowledge the decision maker can make decisions regarding how to operate the real system. The data utilized in the model can be collected from databases, observations, interviews, or documents in the real system. This implies that an ABDS system fuses information from different sources in a synergistic manner into a situation image that provides effective support for human decision-making (Hilletofth et al., 2010a).

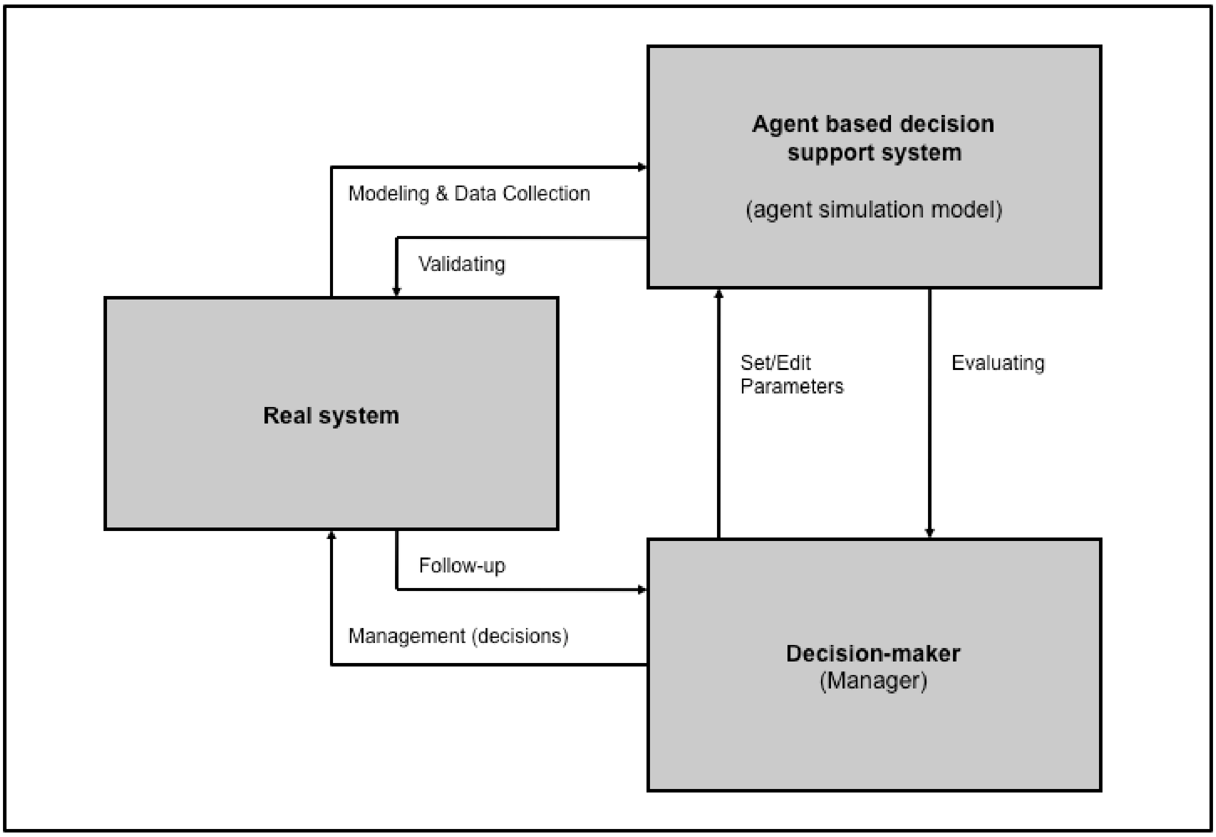

Figure 1. Agent based decision support system (Hilletofth et al., 2010a)

Different modeling and simulation approaches may be used to develop a simulation based decision support system. In addition to agent based modeling and simulation, system dynamics, discrete event simulation, or hybrid models may be used (Jahangirian et al., 2010). System dynamics concentrates on dynamic complexity instead of detailed complexity (Sterman 2000). In detailed complexity there is a large set of potential solutions, while in dynamic complexity the area of interest is in the changes which occur during different time periods. These changes are analyzed with the help of stock-and-flow diagrams. Stocks represent different kinds of accumulations (for instance, amount of goods in warehouse) while flows move the elements between the stocks. Discrete event simulation, on the other hand, focuses on individual events. Usually these events are analyzed with the help of queues and servers (Banks et al. 2005). Entities enter the system and wait in queues to be served by servers. The servers have different capacities and delays, and it is possible to create more realistic systems by incorporating intelligence to the servers as well as the entities (Jenkins and Rice 2009). Hybrid models simply combine multiple approaches in one model (e.g. Lättilä et al., 2010). Both system dynamics and discrete event simulation are frequently used to develop decision support systems (e.g., Acar et al., 2010; Mahdavi et al., 2010; Petering, 2011; Marguez and Blanchar, 2006; Hao et al. ,2008).

3. Benefits and barriers of agent based decision support systems

ABDS systems can support decision-makers in several ways (Table 1). However, there are also many barriers that might make it difficult to develop an ABDS system and that hinder the usability (Table 2). As can be noted in the tables, more benefits than barriers have been reported in the literature. It may be possible that researchers tend to ignore the barriers (or not report them) since their research often focuses on the advantages of ABDS systems. However, it is interesting to note that a majority of the barriers are also connected to the benefits.

The difficulty to access data from partners in the supply chain has been reported as a critical barrier when developing an ABDS system (Liang and Huang 2006). At the same time, the possibility to increase versatility of system architecture is considered as a main benefit of ABDS systems (Chatfield et al. 2006; Balbo and Pinson 2010; Giannakis and Louis 2011). The barrier is connected to the potential benefit since the advantage from a versatile structure will be restricted if it is not possible to share information between organizations. The difficulty to develop agent rules that generates the wanted behavior is another reported barrier of ABDS systems (Behdani et al. 2010). Simultaneously, the possibility to convert manager experience into agents is regarded as a critical benefit of ABDS systems (Liang and Huang 2006; Giannakis and Louis 2011). Again the barrier and the potential benefit are connected. If it is not possible to create good rules for the agents, the experience of the manager will not show up in the system.

Another important benefit of ABDS systems reported in the literature is the possibility to find the highest leverage points of the real system (Nilsson and Darley 2006; Behdani et al. 2010). This allows managers to make improvements in the real system by focusing on the leverage points. However, as noticed by Valluri et al. (2009), the algorithms used in an ABDS system have a big impact on the results. If the “wrong” algorithm is used, it might generate wrong agent behavior. Simulation models are normally validated with historical data but if the model is used as a normative system (i.e., giving instructions to the decision-makers instead of providing overall understanding of system), it might give suggestions that are far from optimal. Liang and Huang (2006) and Tan et al. (2012) regard ABDS systems as a method to reach global optimization. As such, the algorithms are of very high importance when the model is developed.

Table 1. Benefits of agent based decision support systems

Benefits	References
Improved understanding of the real system	Nilsson and Darley (2006); Hilletofth et al. (2010a)
Ability to conduct experiments and what-if analyses	Julka et al. (2002); Gao et al. (2009); van Dam et al. (2009); Hilletofth et al. (2010a)
Ability to find the highest leverage points of the real system	Nilsson and Darley (2006); Behdani et al. (2010)
Improved operations in the real system	Frayret et al. (2006)
Ability to convert manager experience into agents	Liang and Huang (2006); Giannakis and Louis (2011)
Ability to find global optimization avenues in the real system	Liang and Huang (2006); Tan et al. (2012)
Increased predictability of operations in the real system	Nilsson and Darley (2006); Balbo and Pinson (2010)
Ability to re-use part of or whole models for other purposes	Tan et al. (2012); Sun et al. (2012)
Increased versatility of system architecture	Chatfield et al. (2006); Balbo and Pinson (2010); Giannakis and Louis (2011); Seilonen et al. (2009)

Table 2. Barriers of agent based decision support systems

Barriers	References
The difficulty to access data from partners in the supply chain	Liang and Huang (2006)
The issue with long development and validation time	Frayret et al. (2007); Hilletofth et al. (2010a)
The issue with long learning time	Valluri et al. (2009)
The difficulty to develop agent rules that generates the wanted behavior	Behdani et al. (2010)
The issue that selected algorithms have a big impact on results	Valluri et al. (2009)

Another important barrier of ABDS systems reported in the literature is the issue with long learning time. Valluri et al. (2009) have concluded that some times ABDS systems might not be able to learn quickly enough how to operate in the real system. This is a problem, if the system is supposed to learn while it is in use. If the purpose is to improve operations in the real system (Frayret et al. 2006), the ABDS system needs to be able to learn quickly or it is of no use to the decision-makers. A final barrier of ABDS system is the issue with long development and validation time (Frayret et al. 2007; Hilletofth et al. 2010a). This does not contradict any of the benefits but the decision-makers need to be aware that the actual simulation project might take a long time before the decision support system is operational.

4. Agent based decision support in a manufacturing supply chain

4.1 Methodology

The ABDS system for the manufacturing supply chain is based on a Swedish company from the appliance industry (called Alpha for anonymity). Alpha is one of the largest producers in Sweden. Recently, it has experienced difficulties in managing the supply chain, especially matching supply with demand. Therefore, Alpha wanted to develop a decision support system that could help it to understand how the supply chain operates in different conditions. Since the case company was interested in understanding the dynamics of its supply chain, simulation was chosen as the appropriate approach as it tries to explain how the supply chain works rather than giving normative results. Agent based modeling and simulation was chosen, as it would allow a higher amount of flexibility than system dynamics. Most of the used data was gained from the case company but additional data have been added to allow the simulation model to be developed. The required data was collected during 2006 using sources such as databases, interviews, and documents.

4.2 Model

In this model, the manufacturing planning and control process of the case company is managed by a set of agents that are responsible for one or more activities. As the company follows a traditional logic, the agent also represents this view. Inside the company, different agents are responsible for demand management (DM), master production scheduling (MPS), and material requirement planning (MRP). Outside the company, other agents handle wholesaler and supplier activities. The agents' work according to their own local information and the whole supply chain emerge through collaboration between the agents. The DM agent communicates with the wholesaler agents and the MPS agent. The MPS agent further communicates with the MRP agent, which in turn also communicates with the supplier agents.

Wholesalers compare a 12-week forecast, based on exponential smoothing, against current inventory levels. Using a safety stock of 100 units and a delivery batch size of 20 units, the wholesalers create a delivery plan. As soon as the DM agent has received all of the delivery plans from the wholesalers, it checks the amount of end item inventory at the plant and aggregates the total demand for the MPS agent.

With this information, the MPS agent starts to work on the production planning. The DM agent also sends the aggregated demand to the suppliers, so they more easily can manage their own raw material purchases. The MPS has a production batch size of thirty units, a lead time of two weeks, and the plant does not want to hold any excess end item inventory. During the MPS run, a rough-cut capacity calculation also is done to ensure that sufficient capacity exists for the plan.

The current production plan is then sent to the MRP agent, who checks the amount of raw materials available at the manufacturing unit. The lead-time for all of the raw materials is four weeks, safety stock is set at 1000 units, and the order batch size is 500 units. With this information, the MRP calculations are done and the agent modifies the production plan according to raw material availability. When the MRP agent finishes the MRP calculation, it creates raw material orders, which are sent to the suppliers. When the MRP agent finishes the production plan, the plan is sent back to the DM agent to create the confirmed deliveries for the wholesalers.

As the suppliers have access to the end item forecast, they use this information in their own MPS calculations. The suppliers have a three week long lead-time with their own suppliers and they want to have safety stock of 15000 products in raw materials and the materials are ordered with a 5000 unit batch size. The suppliers send their own purchases to their suppliers, but they have not been modeled, so it is not shown in the main view.

The current version of the simulation model contains two products. Product 1 has a life cycle demand where the demand initially increases steadily until saturation is reached. Thereafter, the demand slowly starts to decrease. Product 2 has a cyclic demand that varies steadily.

4.3 Results

Several statics are collected in the simulation model, including aggregated sales and forecasts at the wholesaler level, and amount of finished goods inventory at the factory and wholesaler level. Figure 2 shows the actual aggregated sales at wholesaler level. It also shows the forecasts created by the wholesalers, as well as the historical forecasts. The most interesting finding is the impact of the bullwhip effect on the whole supply chain. As soon as the demand for the cyclical product starts to rise again (for instance, day 200, or 450), there is a sharp decrease in total sales of both of the products (day 250, or 500). The forecast for life-cycle product does not underestimate the future demand. As there are common components shared by both products, the life-cycle product cannot be produced in large enough quantities.

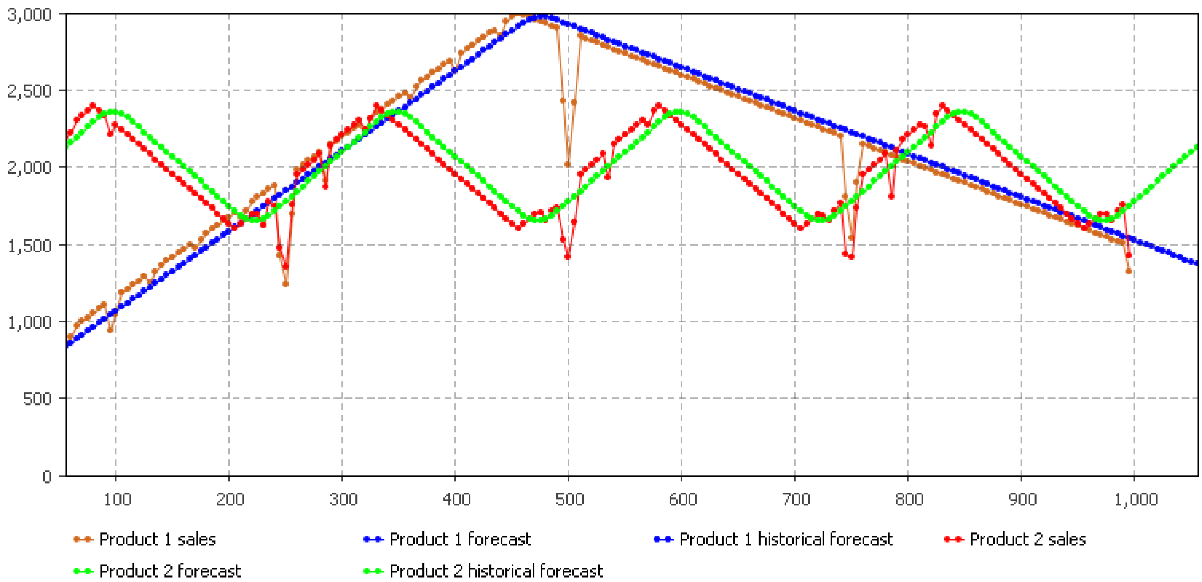

Figure 2. Aggregated sales (demand) and forecast at the wholesaler level. The x-axis represents days in the model while y-axis represents amount of units.

Figure 3 represents the amount of finished goods inventory at the factory. The demand patterns can be clearly seen from the finished goods inventory. Due to the planning delays the warehouse lags the actual demand. The bullwhip effect can be seen clearly in the inventory levels of both products, even though it is due to the demand pattern of the cyclical product. The warehouses at wholesaler level are presented in Figure 4.

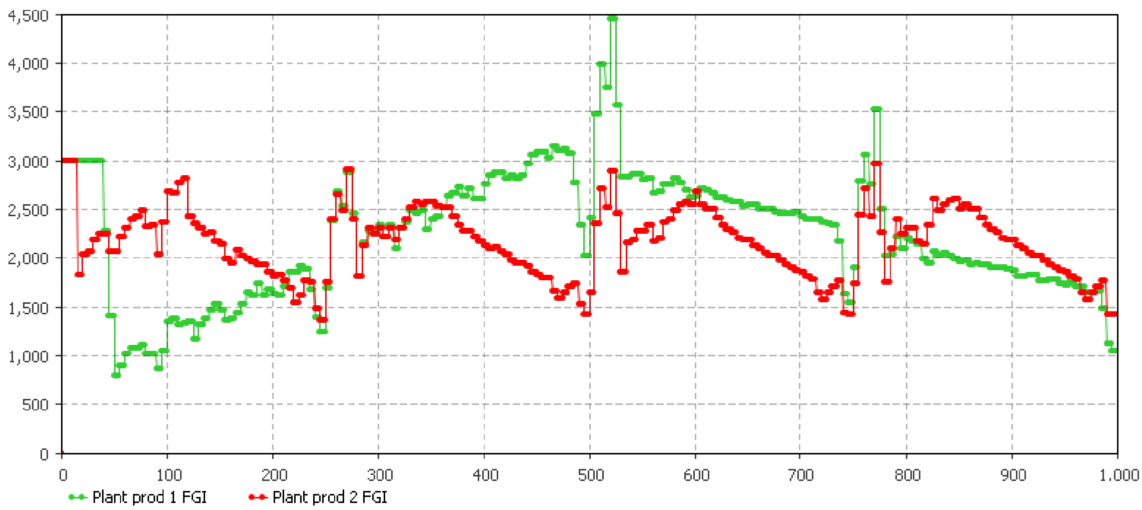

Figure 3. Inventory level at the factory. The x-axis represents days in the model while y-axis represents amount of units.

The warehouse level for the life-cycle product oscillates as the demand for the product is increasing. There are some stock-outs, which can also be seen in Figure 3 as minor "bumps" in the demand. When the demand starts to decrease, the warehouse reaches a stable level. Finally, when the demand for the cyclical product increases, there is a clear bullwhip effect with both products.

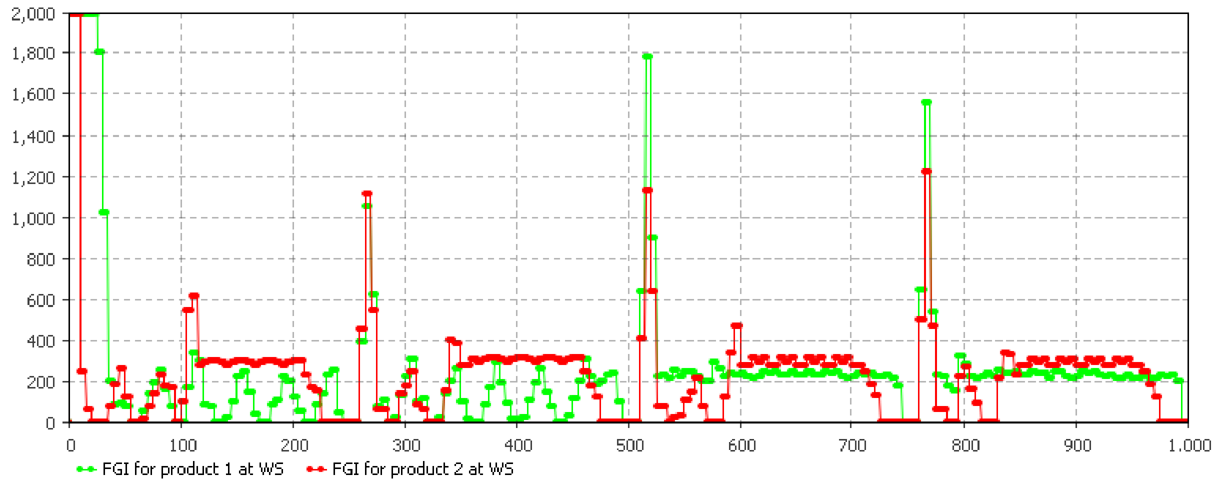

Figure 4. Inventory level at the wholesalers. The x-axis represents days in the model while y-axis represents amount of units.

In this simulation model, the user can modify the used parameters without the modeler being present and investigate how it impacts the results. For example, the production manager could investigate how an implementation of new production technology, that allows faster production with lower inventories, would impact overall supply chain performance. Let us assume that the new production technology allow the factory to produce the goods in one week instead of two weeks. Figure 2 shows the performance of the supply chain with a two-week delay while Figure 5 shows the same issue with a one-week delay.

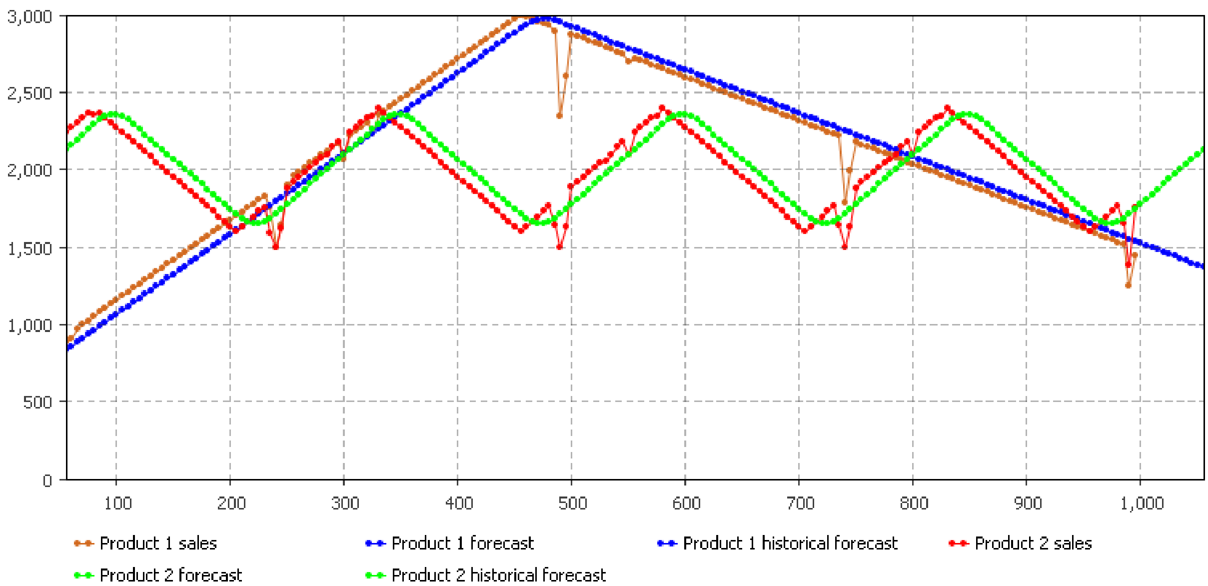

Figure 5. Aggregated sales (demand) and forecast at the wholesaler level with a one week production delay. The x-axis represents days in the model while y-axis represents amount of units.

As can be noted in Figures 2 and 5, the supply chain is able to have higher sales when the delay is shorter. This is because the bullwhip effect is not that intense as the supply chain is able to produce the desired goods faster.

5. Agent based decision support in a service supply chain

5.1 Methodology

The ABDS system for the service supply chain is based on a Swedish company from the third party maintenance industry (called Beta for anonymity). Beta operates through a centralized service structure and provides services to many customers in different locations. Recently, Beta has experienced difficulties with regard to capacity utilization. Therefore, Beta wanted to develop a decision support system that could help it to understand the dynamics behind its service operations. Since the case company was interested in investigating how a centralized and decentralized service structure would impact capacity utilization, simulation was chosen as the appropriate approach. Agent based modeling and simulation was chosen, since the number of locations and combinations of parameters was too large for system dynamics and since the scalability would be an issue in discrete event simulation. Most of the used data was gained from the case company (e.g. estimates are gained from service times, travel times, demand types and operating structure) but additional data have been added to allow the simulation model to be developed. The required data was collected during 2008 using sources such as databases, interviews, and documents.

5.2 Model

In this model, the service fulfillment process of the case company is managed by a set of agents that are responsible for one or more activities. The service network in the model is complex, including more than 50 customer factories with one common machine to be served. The model contains two types of agents: engineers and tasks. Each task requires a certain time to be completed and engineers work on these tasks. There are two types of engineers in the model: mechanical and electrical. Each type of engineers can only work on a certain type of tasks. Two types of tasks exist in the model: corrective and planned. The planned tasks can be seen to be preventive maintenance; they occur on a specific time and the engineers can be well scheduled for the tasks. The corrective tasks occur immediately and cannot be properly estimated.

Each engineer has four different states: waiting at depot, heading for a task, working on a task, and heading home. The engineers start at their home location and wait for a task to arrive; when it does they will change their state to "heading for a task". As soon as the engineer reaches its target, it will change its state to "working on a task". At the same time the engineer will send a message to the task to inform that it is being worked on. The engineer will work on the task until it receives a message from the task. When the message arrives, the state changes to "heading to depot" and it will further change to "waiting at depot" as soon as the engineer arrives to the depot. The tasks (both corrective and planned) have only three states. The first one, "corrective situation", only initiates the agent. Immediately after this the state changes to "Backlog" which is used to calculate the time waited for service. As soon as the first engineer arrives, the state is changed to "being worked on".

The locations of the tasks have been predefined and there are 57 different customer locations where they can occur. These locations are based on current customer locations. The corrective tasks occur all of a sudden while the planned tasks are planned well ahead of their occurrence. The share between corrective and planned tasks was extracted from real task data. The task lengths and frequency of occurrence are however estimations. The time interval between corrective tasks is 4 to 12 hours, while the interval with planned tasks is 10 to 30 hours. When a task has been generated, a uniform distribution is used to create the next occurrence. The corrective tasks contain only one sub-task. The duration of the visit is normally distributed with a mean value of 8 hours and a standard deviation of 5.2 hours. 75% of the corrective tasks require a mechanical engineer.

Unlike the corrective tasks, planned tasks can have anything between one to three sub-tasks, and the length for each sub-task comes from a normal distribution with a mean value of 10 and a standard deviation of 5. There will always be at least one task, but there is a 50% chance to have a second sub-task. If there is a second sub-task, a third one will also have a 50% chance of occurring. A planned task will also have a randomized preferred starting date.

In planned tasks each engineer has a schedule for two weeks. When a new planned task is generated, the total length of the task is used to fit the task to a free time-slot. The time-slots will be checked one at a time for each engineer so the actual starting date will not be minimized, e.g. it will first check the whole time table for engineer one, then engineer two, and so on. If a planned task cannot be fitted to any of the engineers, the task will be fitted at a later time (each hour in the model). If there is more than one unscheduled planned task, the shorter one will "steal" a time-slot from the longer one. This is, because there will be a free slot earlier for a smaller task. This does not necessarily reflect reality, but it is one solution to the scheduling problem.

5.3 Results

Several statistics are collected in the simulation model, including engineer waiting time, kilometers driven and task waiting time, overall and at individual customer locations. Figure 6 shows the engineer waiting time. On average the engineers have to wait for work 76% of their time. It should however be noted that the time engineers spend waiting is not translatable to idle time; in reality this time is spent on other tasks at the service provider, but potentially with a lower billable hourly rate. Only 15% of their total working time is used on the actual value adding time of servicing at customer locations, while 10% is spent on moving between locations.

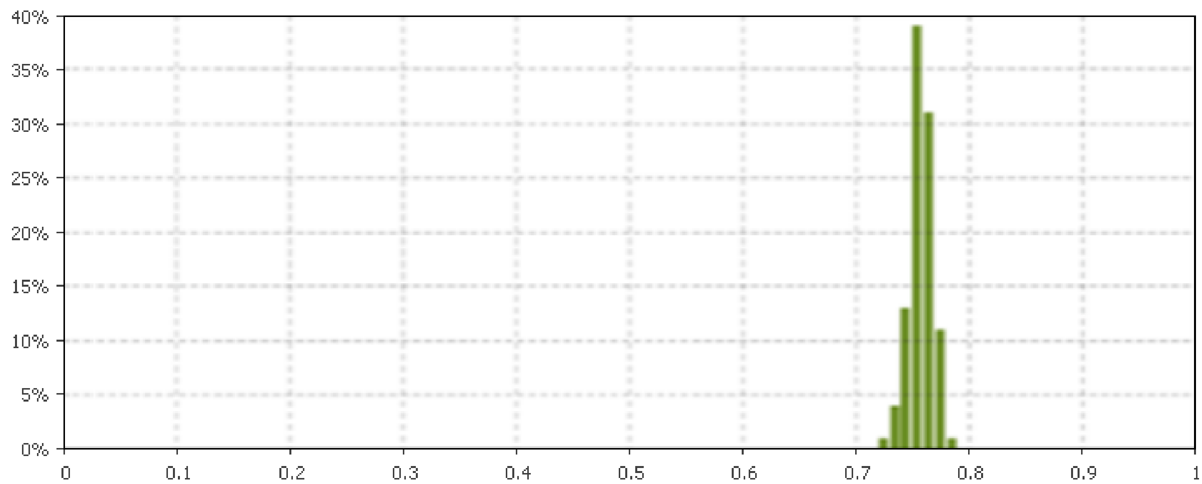

Figure 6. Histogram for engineer waiting time. The x-axis shows how large a share of their total time the engineers have to wait at the depot while the y-axis shows the share of these waiting times.

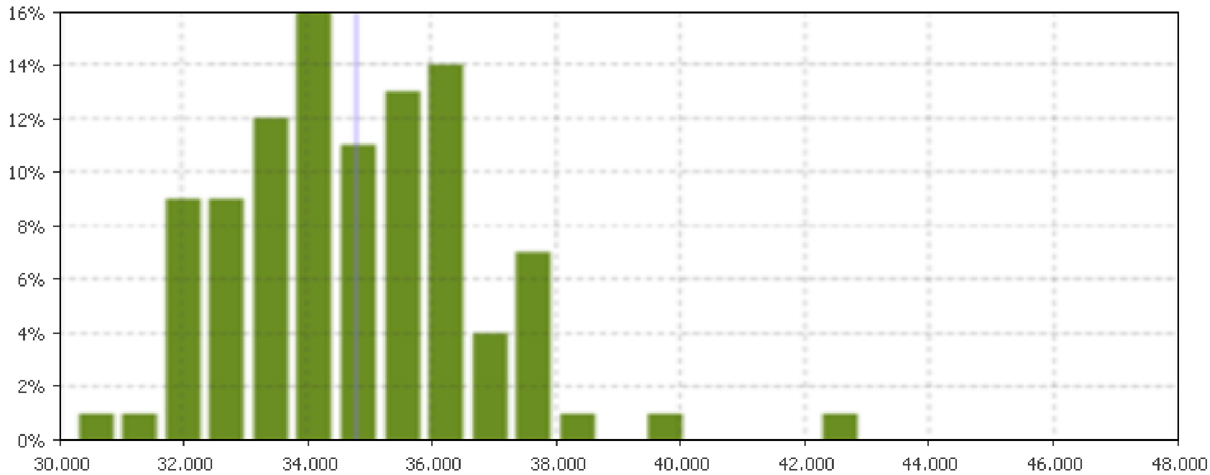

Figure 7. Histogram for kilometers driven. The x-axis shows average the number of kilometers driven in different simulation runs while the y-axis shows the relative frequency of these distances.

Figure 7 shows the histogram for the kilometers driven in different simulation runs. The mean value is 34 804 kilometers and the standard deviation is 1 957 kilometers. As the engineers have to spend a lot of time traveling between locations, the kilometers driven has a strong impact on the profitability of individual customers.

Figure 8 shows overall corrective task waiting time. The waiting time does not depend solely on the location, but also on the availability of engineers. The availability of engineers is affected by the location of the previous tasks and their length. Also, if the wrong engineer is sent to a corrective task, this uses a lot of engineer time.

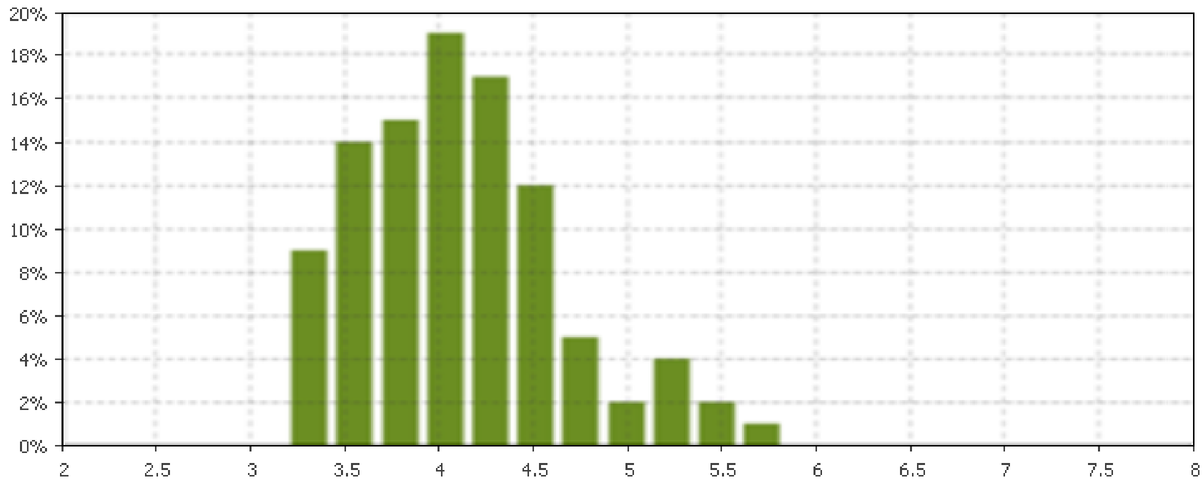

Figure 8. Histogram for corrective task waiting time. The x-axis shows average waiting time in different simulation runs while the y-axis shows the relative share of these times.

Figure 9 shows average task waiting time at individual locations. As can be noted the average waiting time on individual locations differs much. The individual location average waiting times vary between 2 to 7 hours. If a similar contract is offered to customers in different cities, the firm will either pay fines for a delayed service or lose customers by offering a slow response time.

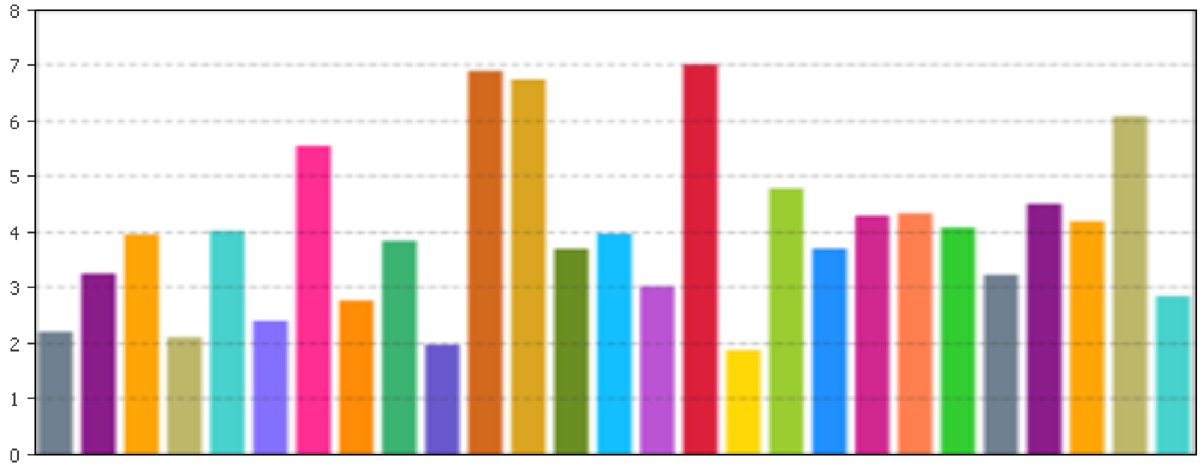

Figure 9. Average waiting times at individual locations. The x-axis shows different cites in the model while the y-axis shows the average waiting time in hours.

Also in this simulation model, the user can alter all the used parameters without the modeler being present and investigate how it impacts the results. An example of this is presented in Figure 10. By having a different amount of engineers, it is possible to analyze how the whole system works and how long customers have to wait for service. As can be noted in the figure, there is a big difference in waiting times if the amount of corrective mechanical engineers is increased from two to three. However, there is only a slight change from three to four engineers. Also, the changes in the amount of corrective electrical engineers are not that important for the customer waiting times.

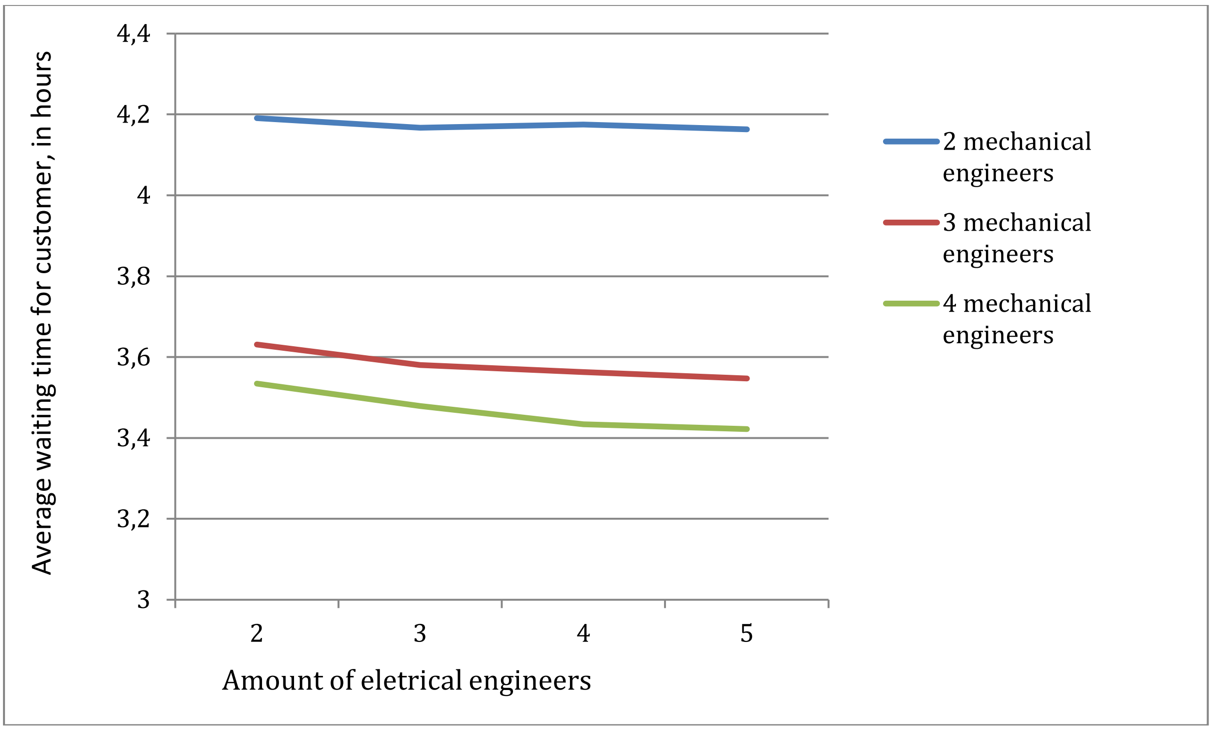

Figure 10. Waiting time for customers with different amounts of engineers

In addition to making changes to the amount of engineers in different locations, it is possible to analyze the impact of changes in the demand. The user can modify the locations, in order to understand how the system would work if the services would be expanded to new regions without expanding the engineer network.

6. Discussion

Our research shows that ABDS systems offer similar benefits in the supply chain context as it does in other contexts (Table 3). To begin with, ABDS systems are very versatile when it comes to the system architecture (Chatfield et al., 2006; Balbo and Pinson, 2010; Giannakis and Louis, 2011). At the same time, the models can cover many different kinds of aspects through the agents. Since the model parameters and even structure can come from different databases, it is possible to have a high amount of versatility in the model (Chatfield et al. 2006; Seilonen et al. 2009, Hilletofth et al. 2010a). A well designed ABDS system is able to use data from various sources and fuse them into a coherent view on the supply chain (Hilletofth et al., 2010a). This is in line with the need to have advanced decision support systems that integrate data to appropriately estimate complex supply chains (Hilletofth, 2009).

ABDS systems also make it possible to better understand how a decision maker's actions impact the whole supply chain. In essence, simulation allows the studying of individual entities on a detailed level, which can be regarded as a visible supply chain (Francis, 2008). This means that ABDS systems provide improved supply chain visibility. For instance, the decision maker in the Alpha case could investigate how its decisions would impact also the warehouses of the suppliers. The decision maker in the Beta case could instead analyze how long individual customers need to wait for service. This would be difficult to estimate using other methods.

Table 3. Identified benefits of agent based decision support systems

Benefits	Literature	Case Alpha	Case Beta
Increased versatility of system architecture	X	X	X
Improved supply chain visibility		X	
Ability to conduct experiments and what-if analyses	X	X	X
Improved understanding of the real system	X	X	X
Improved communication within and between organizations in the supply chain		X	X

ABDS systems also make it possible to conduct different experiments and what-if analyses. This is similar to earlier findings reported in the literature (Nilsson and Darley, 2006; Legato and Mazza, 2001; Guo et al. 2001; Vlachos 2007; Julka et al., 2002; Gao et al., 2009; van Dam et al., 2009; Hilletofth et al., 2010a). For instance, the decision maker in the Alpha case could investigate how the desired stock levels would impact supply chain performance. The decision maker in the Beta case could instead investigate how the level of demand, the amount of engineers or the service structure would impact supply chain performance. It may be argued that ABDS systems may provide a higher degree of versatility in what-if analyses than discrete-event or system dynamics based decision support systems since agents more easily can be scaled and are easier to make versatile.

ABDS systems also make it possible to improve the understanding of the supply chain and its problem domains. This is possible as the ABDS system provides a holistic view and awareness on how decisions affect the real system. This is in line with earlier research on simulations (Harrison, et al. 2007; Shen et al., 2004; Nilsson and Darley, 2006; Hilletofth et al., 2010a). In the Alpha case, it was noticed that the bullwhip effect might occur with unrelated products due to common components, even if information is totally shared in the supply chain. In the Beta case, it was noticed that service provider must find a proper balance between a centralized and a decentralized service structure. The decentralized solution allows faster travel times to locations, but there need to be a higher amount of engineers in the whole system due to randomness in demand.

ABDS systems also make it possible to improve the communication within and between organizations in the supply chain. This is also possible due to the holistic view provided by the decision support system since it makes it easier to discuss various topics, as the decisions are backed up by the results. For instance, the ABDS system in the Beta case was used within the organization in order to discuss pros and cons of a decentralized service structure. Later the case company changed its service structure towards a decentralized solution and the ABDS system helped to achieve this. Other authors have also seen simulations as a good way to improve communication (van der Zee and van der Worst 2005).

Our research also shows some barriers of ABDS systems in the supply chain context (Table 4). One barrier is the difficulty to access data from partners in the supply chain. Since supply chains cover multiple organizations (Gimenez and Ventura, 2005), it might be problematic to gather empirical data for models, as organizations might not be willing to share information freely (Liang and Huang, 2006). This was evident in the Alpha case as some of the parameters were estimated instead of using actual data.

Table 4. Identified barriers of agent based decision support systems

Barriers	Literature	Case Alpha	Case Beta
The difficulty to access data from partners in the supply chain	X	X	
The difficulty to access data on a higher level of granularity		X	X
The difficulty to retrieve data from other information systems		X	X

Another barrier of ABDS systems identified in this research is the difficulty to access data on a higher level of granularity. This makes the information sharing even more difficult. As agents can be very detailed, they also require more detailed data. However, as Macal and North (2006) point out, data exists on a higher level of detail today, which makes ABDS more applicable. If data is not available, the results of the model are also unreliable.

A final barrier of ABDS systems is the difficulty to retrieve data from other information systems within the organizations or across the supply chain. If the data is available in some information systems it can be retrieved from there. However, it can be difficult to directly connect an ABDS system to an external information system. In the Beta case, some of the data was available in an external database. However, in the simulation model the data was analyzed separately instead of allowing the ABDS system to directly connect with the database. However, some authors argue that ABDS systems make it possible to connect to other external information systems (Giannakis and Louis, 2011). This comes back to the structure of the model and the information system.

Our research also shows that ABDS systems have some advantages in relation to other simulation based decision support systems (Table 5). In the Alpha case, it became clear, that system dynamics would not been able to provide the same amount of versatility, as it works best when the level of aggregation is high. An ABDS system can scale much more freely than system dynamics, especially if the model can be scaled using databases. This corresponds to the findings of van Dam et al. (2009). However, constructing a similar kind of system dynamics model would have taken less time. Discrete event simulation also could not have been able to scale as well as ABDS systems are able to.

In the Beta case, the service network could have been represented with discrete event simulation but it can be argued that it would have been more difficulties with regard to scaling. Also, it would have been more difficult to estimate waiting times at individual locations. This could have been achieved if the servers and entities would have been very intelligent (Jenkins and Rice, 2009), but it can be argued that it is easier to build an ABDS system than a complex discrete event model. Location estimation would have been even more difficult for system dynamics. The Beta case was also compared against a model constructed with the help of queuing theory. It was also evident, that queuing theory could not represent the structure that well, as the structure is so complex.

Table 5. Comparison between different simulation based decision support systems

Comparison	Case Alpha	Case Beta
Decision support systems based on system dynamics or discrete event simulation are not able to provide the same amount of versatility as ABDS systems	X	
Decision support systems based on system dynamics work best when the level of aggregation is high	X	
Decision support systems based on system dynamics take less time to build	X	
Decision support systems based on discrete event simulation are more difficult to scale to the same level as ABDS systems		X
System dynamics and discrete event simulation cannot estimate individual locations that easily		X
Queuing theory gets into problems when the system becomes too complex		X

7. Conclusions

This paper aimed to investigate the benefits and the barriers of ABDS systems in the supply chain context. It can be concluded that the benefits of this decision support system include the possibility to increase versatility of system architecture, to improve supply chain visibility, to conduct experiments and what-if analyses, to improve the understanding of the real system, and the possibility to improve communication within and between organizations in the supply chain. It can also be concluded that the barriers of ABDS systems include the difficulty to access data from partners in the supply chain, the difficulty to access data on a higher level of granularity and the difficulty to retrieve data from other information systems.

This research provides knowledge and insights on how ABDS systems may be developed and used in the supply chain context. The importance of using ABDS systems in the supply chain context is stressed. It is clear that supply chain managers may benefit in several respects from using ABDS systems. For example these systems provide supply chain visibility and overall insight of the performance of the entire supply chain system. After analyzing the performance of the entire supply chain, a manager might recognize that it is more beneficial to use multiple warehouse locations instead of centralizing all warehouse activities to one location. These systems also allow the understanding of the cost structure, delays, and waste, in different types of supply chains. In addition to enhanced understanding, the possibility to conduct experiments and what-if analyses allows managers to test the implications of decisions in a safe environment. These systems may also assist to achieve consensus in organizations as it represent the whole supply chain, not only individual parts of it.

One limitation of the research is that the benefits and the barriers of ABDS systems only have been evaluated in two research settings (i.e. case companies). Thus, empirical data from similar and other research settings should be gathered to reinforce the validity of the reported findings. Another limitation is that the developed decision support systems are rather simple. For example, there was no need to gather data from supply chain partners. This might decrease the usability of ABDS in the supply chain context. These limitations should be considered when researchers later attempt to replicate or further evaluate the reported findings, and each of these limitation can be addressed by further research. Other interesting aspects for further research include the usage of the developed ABDS systems within the case companies. It is important to investigate where and how these decision support systems are useful. Another important issue for further research is how these decision support systems could be connected to other information systems within the case companies.

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