<http://www.diva-portal.org>

Postprint

This is the accepted version of a paper presented at *International KES Symposium on Agent and Multi-agent Systems - Technologies and Applications, Uppsala, 3-5 June, 2009..*

Citation for the original published paper:

Hilletoft, P., Lättilä, L., Hilmola, O-P. (2009)

Agent-based decision support in manufacturing supply chain.

In: Hakansson, Anne, Hartung, Ronald (ed.), *Proceedings of the 3rd International KES Symposium on Agent and Multi-agent Systems: Technologies and Applications* (pp. 677-686).

Springer

N.B. When citing this work, cite the original published paper.

Permanent link to this version:

<http://urn.kb.se/resolve?urn=urn:nbn:se:hj:diva-20842>

Agent Based Decision Support in Manufacturing Supply Chain

Per Hilletoft¹, Lauri Lättilä², and Olli-Pekka Hilmola²

¹ School of Technology and Society, University of Skövde, P.O. Box 408, SE-541 28 Skövde, Sweden, Fax: +46 500 44 87 99, per.hilletoft@his.se

² Lappeenranta University of Technology, Kouvola Research Unit, Prikaatintie 9, FIN-45100 Kouvola, Finland, lauri.lattila@lut.fi, olli-pekka.hilmola@lut.fi

Abstract. Supply Chain Management (SCM) is becoming increasingly complex and an intensified competition in the end-markets has started to create a situation where co-operation requirements between companies in a Supply Chain (SC) are increasing. The old mechanistic operations management solutions are becoming obsolete and advanced decision support is increasingly needed to realize efficient and effective management of complex SCs. The objective of this research is to contribute to the understanding of how Agent Based Modeling (ABM) can advance decision making and to discuss why ABM should be regarded as method to realize Information Fusion (IF). In this research work an agent based model of SCM has been implemented in a simulation platform to provide an approach for evaluation of decision and management alternatives. Research shows that this kind of decision support system is based on IF, since it collects and fuses information from different sources into a situation image that provides effective support for human decision making

Keywords: Supply chains, multi-agent systems, information fusion, simulation.

1 Introduction

Supply Chain Management (SCM) can be defined as a set of approaches utilized to efficiently integrate and coordinate the materials, information and financial flows across the Supply Chain (SC), so that merchandise is supplied, produced and distributed at the right quantities, to the right locations, and at the right time, in the most cost-efficient way, while satisfying customer requirements [1]. SCM is becoming increasingly complex due to several developments in the marketplace [2-3]. In addition the difficulties in controlling and coordinating logistics operations within and among firms (i.e. across the SC) are expected to increase, since the interdependence among cooperating firms is intensifying [4]. There are several factors contributing to an increased complexity of SCM, for instance, SCs nowadays need to satisfy more demanding customers and operate on international markets [5]. In order to realize efficient and effective management of complex SCs in this environment, managers, or decision makers, continuously need correct and updated information

from different sources. They also need to be able to predict the outcome of their decisions, and how their decisions affect the whole SC. To realize this advanced decision support is needed.

One way to improve decision making is to generate business intelligence by fusing large amounts of data from various sources, i.e. Information Fusion (IF). The purpose of IF is typically to extract relevant information from several sources with known certainty to make better decisions than if fusion was not used. It can be defined as “the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making” [6]. One method to realize IF in complex SCs, which normally is not highlighted as an IF method, is Agent Based Modeling (ABM). It is related to IF in the way that information from different sources are collected and fused in a synergistic manner into a representation that provides effective support for human decision making. Empirical studies have shown that managers aided by agent based models can benefit in several ways [7]. For instance, agent based models can help managers to find the highest leverage among improvement alternatives, guide managers instinct and increase managers understanding of the impact of unscheduled factors. ABM is also expected to have comprehensive effects on the way that businesses use computers to support decision making.

In this research work an agent based model of SCM has been implemented in a simulation platform to provide a pragmatic approach for evaluation of decision and management alternatives. The agent model has been developed and described in an earlier paper [8]. The agent model was based on a case company, Alpha, a Swedish manufacturer operating on international basis in the white goods industry. In the simulation model, the SC processes are managed by a set of agents that are responsible for one or more activities; the simulation model is inspired by an actual case-study but additional data has been used to allow the simulation model to be developed. The model has been implemented through a leading agent based simulation software called Anylogic.

The overall purpose of this research is to contribute to the understanding of how ABM can advance decision making by an increased understanding of the problem domain and also generate a basis for decision making, thus improving the performance of the SC. Moreover, this paper aims to discuss why ABM should be regarded as method to realize IF by investigating where IF could be incorporated in agent based systems. The remainder of this paper is structured as follows: In Section 2, the concept of ABM is presented and discussed through existing literature. Thereafter, in Section 3 we introduce our agent based simulation model, which is based partially in our earlier case study results from the white goods manufacturer. Modeling logic in agent based systems is more complex, but scalability (e.g. adding more products, suppliers, and wholesalers etc.) is easier to complete. We illustrate this with the initial simulation results from two products with different demand characteristics through delivery capability as well as inventory development implications. In the final Section 4 we conclude our research work and propose avenues for further research.

2 Agent Based Modeling

ABM is a new modeling paradigm especially suited for complex and dynamic systems distributed in time and space [9]. It is expected to have comprehensive effects on the way that businesses use computers to support decision making. For instance, it provides a pragmatic approach for the evaluation of management alternatives [10]. Moreover, it is considered important for developing industrial applications in complex environments [11]. ABM implies that a real (observed) system is modeled in form of a couple of interacting agents within a certain environment (Fig. 1). The agent model is later implemented through different platforms, e.g. simulation or system development. This implies that an agent system consists of a couple of individual agents with specified relationships to one another within a certain environment. The agents are presumed to be acting in what they perceive as their own interests, such as economic benefit (i.e. they have individual missions), and their knowledge regarding the entire system (i.e. other agents and environment) is limited [12]. Still, the most important feature in an agent system is the agents' ability to collaborate, coordinate and interact with each other as well as with the environment to achieve common goals. By sharing information, knowledge, and tasks among the agents in the system, collective intelligence may emerge that can not be derived from the internal mechanism of an individual agent. Furthermore, the ability to coordinate makes it possible for agents to coordinate their actions among themselves, i.e. taking the effect of another agent's actions into account when making a decision about what to do. The term Multi-Agent System (MAS) is commonly used for agent systems including several interacting and collaborating agents.

Fig. 1. The process of agent based modeling

An agent based model implemented through simulation can be used to simulate the actions and interactions of autonomous agents in an agent system to evaluate the agents' effects on the system as a whole as well as to evaluate the system in general (Fig. 2). The implemented model basically consists of the interacting agents and some performance and risk indicators. The utilized data in the model can be collected from databases or from sensors within the real system. Managers, or decision makers, can set parameters in the simulation model, run the simulation and evaluate the results. Based on the retrieved information/knowledge they can make decisions regarding how to handle the real system. They could also continually alter different parameters and simulate again to evaluate different management alternative, or perhaps initiated a

re-modeling of the real system. This implies that ABM basically collects and fuses information from different sources in a synergistic manner into a representation that provides effective support for human decision making. Therefore, it could be regarded as an IF method.

Fig. 2. Agent based decision support system.

Nilsson and Darley [7] conclude in their empirical study that managers aided by agent based models and simulations can benefit in several ways. Firstly, they acquire an increased understanding of the impact of unscheduled factors such as breakdowns, accidents and changes of demands. Such factors are often found in reality, but usually reduced or even ignored when transferred to most traditional models. This implies that the optimized solutions from these traditional models mislead managers into believing in future scenarios, which do not reflect reality. Secondly, ABM based simulations can guide managers instinct, since interactive agents generate an emergent pattern, which can be explained and understood and therefore beneficial for the improvement of decision making in companies. Thirdly, ABM can help managers to find where the highest leverage is to be gained among improvement alternatives. This is based on the fact that ABM allows models to encompass several business functions and how they affect each other. Finally, there are sometimes even opportunities to improve predictability based on the scenarios generated.

There is a growing interest in using ABM in several business related areas, such as manufacturing, maintenance, and SCM [8]. Macal and North [12] have discussed a couple of reasons to the increased utilization of ABM. Firstly, the observed systems are becoming more complex in terms of their interdependencies which imply that traditional approaches no longer are as applicable as they once were. Secondly, some systems have earlier been too complex to model, but now possible to model through ABM. Thirdly, data are becoming organized into databases at finer levels of granularity. Micro-data can now support micro simulations. Finally, but most importantly, computational power is advancing rapidly. Even if the interest in implementing ABM in various types of business is increasing, is it currently a quite

conceptual concept. Based on literature reviews Davidsson et al. [13] and Cantamessa [14] conclude that very few field experiments and developed systems can be reported to be found in the academic literature. Davidsson et al. [13] reviewed the maturity of agent approaches presented in the literature and used following four main levels: (i) conceptual proposal, (ii) simulation experiment, (iii) field experiment, and (iv) deployed system. In their sample of 56 journal articles published between 1992 and 2005, it was only identified one level 4 and three level 3 research works. A more recent literature review confirms that this situation still exists. In Hilletoft et al. [8] sample of 33 journal articles published between 2000 and mid 2008 only one paper included empirically verified results after the implementation of ABM. Furthermore, the literature review showed that very few agent based frameworks were developed based on empirical information and most of the articles only included developed prototype systems.

3 Simulation Model and Initial Results

In this section the structure of the developed simulation model is described as well as some initial results.

3.1 Structure of the simulation model

The current simulation model contains five different kinds of agents: wholesalers, order management, production planning, requirements planning and suppliers. The wholesalers communicate only with order management. Order management also communicates with production planning, while production planning can further communicate with requirements planning. The requirements planning agent is connected to the final agents, the suppliers. This current logic is shown in Fig. 3.

Fig. 3. Agent connectedness in the simulation model.

In the simulation model only two products is modeled. One of the products has a cyclical demand while the other one has a life-cycle demand. By life-cycle demand we mean that the product will have an increasing amount of sales before the markets become saturated. After this point the demand for the product will start to slowly decrease.

Wholesalers create a 12 week long forecast with the help of exponential smoothing. This forecast is then used with the item inventory to create a delivery plan. The wholesalers want to have a safety stock of 100 units and use a delivery batch size of 20 units. As soon as the order management agent has received all of the delivery plans from the wholesalers the agent checks the amount of end item inventory at the plant and aggregates the total demand for the production planning agent. After these procedures the information is sent to production planning agent who can then start to work on the Material Requirements Planning. The order management agent also sends the aggregated demand to the suppliers, so they can more easily manage their own raw material purchases. Production has a two week long lead time, which is also used in the MRP calculations. MRP has a production batch size of thirty units and the plant does not want to hold any excess end item inventory. During the MRP run a rough cut capacity calculation is also done to ensure that sufficient capacity exists for the plan. When the production planning agent finishes the MRP calculations, it sends the current production plan to requirements planning. Requirement planning checks the amount of raw materials at the manufacturing unit. The lead time for all of the raw materials is four weeks, the manufacturing unit wants to have a safety stock of 1000 units and the order batch is 500 units. With this information it is possible to do mrp calculations and requirements planning agent modifies the production plan according to the raw material availability. When the requirements planning agent finishes the mrp calculation, it will have the raw material orders, which are sent to the suppliers. Requirements planning finishes the production plan, which is sent to order management in order 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 MRP 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.

There is an actual case behind the simulation model but some of the data has not been gathered from the case-company. The bill-of-material and batch-sizing rules (and their respective suppliers) have been made-up as it was not available for the researchers when the simulation model was constructed. However, data regarding delays corresponds to actual delays and the company also uses 12 week long forecasts, which are used in this simulation model.

As highlighted above each one of the agents performs different sorts of tasks. This implies that every agent in the model has its own internal mechanisms and also a specific mission. When the agents collaborate, coordinate and interact with each other a collective intelligence may emerges that can not be derived from the internal mechanism of an individual agent. This implies that IF occurs at several places in the model. Firstly, it takes place within an agent to decide actions in order to achieve the agent specific goals. However, it also takes place on a holistic level when the agents generates a situation image by communicate and interact with each other to achieve system overall goal. Each agent's specific tasks and information usage is presented in Table 1, while all of the communicated information is presented in Table 2.

Table 1. Agent framework environment description.

Agent	Tasks	Information (source)
Wholesaler	Receive Orders	Demand (system generated)
	Create/Edit Forecast	Previous Demand (database/variable)
	Create/Edit Delivery Plan	Safety Stock Size (database/variable) Delivery Batch Size (database/variable) Confirmed Delivers (order management)
Order management	Create/Edit Aggregated Delivery Plan	Delivery Plans (wholesalers)
	Confirm Deliveries	Finished Inventory (database/variable) Confirmed Production Plan (requirement planning)
Production planning	Create/Edit Production Plan	Aggregated Delivery Plan (order management)
	Perform Capacity Planning	Lead Time (database/variable) Batch Size (database/variable)
Requirement planning	Create/Edit Purchase Orders	Production Plan (production planning)
	Confirm Production Plan	Raw Material Inventory (database/variable) Bill Of Materials (database/variable) Lead Time (database/variable) Batch Size (database/variable) Safety Stock Size (database/variable)
Supplier	Create/Edit Production Plan	Aggregated Delivery Plan (order management)
	Create/Edit Purchase Orders	Lead Time (database/variable)
	Confirm Purchase Orders	Batch Size (database/variable) Safety Stock Size (database/variable)

Table 2. Information flows between agents in the simulation model.

Sender	Receiver	Information
Wholesaler	Order Management	Delivery plan
Order management	Wholesaler	Confirmed deliveries
Order management	Supplier	Aggregated delivery plan
Order management	Production planning	Aggregated delivery plan
Order management	Production planning	Finished inventory
Production planning	Requirements planning	Production plan
Requirements planning	Order management	Confirmed production plan
Requirements planning	Suppliers	Purchase orders

As a lot of information is communicated between the agents, there is a need to have a numerous variables to store this information in different agents. Most of the information in the model is stored in matrixes (e.g. multiple products, agents, and time). The information is communicated between the agents using ports and these ports can deliver different kinds of information (e.g. matrixes, individual values, text).

3.2 Results

Fig. 4a shows the sales generated by the wholesalers. It also shows the final forecasts and current forecasts. During the simulation it is possible to show how the forecast changes during the simulation. As there is sufficient capacity in the manufacturing system, the whole SC can relatively well meet the market's demand. From Fig. 4a it is possible to notice how the whole SC has difficulties when the demand for the cyclical product starts to rise again. This is due to the lags in the SC. As the forecast is lower than the actual demand, there is insufficient amount of raw materials in the factory, when the up-turn starts again. The sales for the life-cycle product are also impacted as many raw materials are used by both products. As the manufacturing unit cannot cope with the demand, there is going to be a huge backlog at the plant. As soon as the

manufacturing unit receives a sufficient amount of raw materials, it can manufacture the backlogged units. This can be seen from Fig. 4b.

Fig. 4. Statistics from simulation analysis

Fig. 4b shows the finished product inventory at the manufacturing unit before the deliveries to the wholesalers. The amount of finished product inventory clearly shows what kind of demand is behind both products. The manufacturing overshoots, when the demand for the cyclical product changes and the reaction is very intensive for the life-cycle product during its peak demand. The overreactions are similar to the Forrester effect [15], even though information is shared very openly in the 4c. Fig. 4c shows the finished goods inventory at the suppliers.

The suppliers cannot reach their desired finished goods inventory level of 20000 and it fluctuates very heavily. Even though the order batch size for the manufacturing unit is 500 units, the average purchase is a lot larger. The supplier in Fig. 4c is supplying parts, which are only used in the life-cycle product, but the supplier's finished goods inventory clearly reacts to the cyclical product's demand: they seem to have a negative correlation. As the demand for the cyclical product is low, the end item inventory is a lot higher at the supplier. This indicates that the whole supply-network reacts as a whole to changes in one part of the chain.

4 Discussion and Conclusions

To realize efficient and effective management of complex SCs, decision makers, continuously require correct and up to date information. The possibility to predict the outcome of their decisions is beneficial, also what effect these decisions will have on the SC operations. This research shows that an effective decision support system can be developed through Agent Based Modeling (ABM). This implies that the real system of interest is modeled using agent principles and implemented in simulation software, this model consists of interacting agents and some performance and risk indicators. In this agent based decision support system, decision makers, can set parameters, run the simulation and evaluate the results, iteratively and to evaluate different management alternatives. Based on the retrieved information/knowledge they can make decisions regarding how to handle the real system. This implies that an agent based decision support system collects and fuses information from different sources in a synergistic manner into a representation (situation image) that provides effective support for human decision-making.

In this research work a decision support system has been developed for planning of SC operations using ABM. This research shows that this kind of decision support system is based on IF since it collects and fuses information from different sources into a situation image that provides effective support for human decision making. The information comes from databases and from various messages generated by different agents. Fusion may occur on agent or system level, and the result of this fusion is a collective intelligence that cannot be derived from the internal mechanism of an individual agent.

The main benefit of an agent based decision support system for the decision maker comes mainly from the ability to see how different situations flow through the company. Normally a decision maker can only observe his own small decision making node while the simulation model allows the decision maker to see how decisions are generated and how different situations will show up in different parts of the organization. For instance, the supplier for the life-cycle product will be impacted by the demand for the cyclical product. This kind of behavior would be impossible to analyze without proper IF as the supplier would assume that the fluctuations are due to demand cycles in the life-cycle product. It would also be possible to see what happens if some of the information would be distorted and how it would escalate in the decision making chain.

The proposed system is still a simple one; only showing the necessary information flows in an organization that uses a MRP-system. Thus, the model only has a low amount of total IF possible. However, the model can easily be expanded to include more information flows and if the manufacturing unit would also be modeled, it would be possible to connect the simulation model to be part of the decision support system. Most of the information for the simulation model could directly come from the real databases of the company and from real information flows. This is a clear advantage for an agent based simulation model as there would be no need to gather any additional information from the organization. Also, situation awareness of individual decision makers would improve as they could see how the same initial information is used in different parts of the organization.

Initial simulation results seem to be promising and we will continue in pursuing to have more strategic and tactic decision making completed from this environment. Also real-life demand data among lead time, capacity addition, production lead times, and change over times etc. are planned to be gathered in the future to establish real-life simulation platform, from where management could make better decisions, and possibly apply agent based logic in operative decisions. We need also to evaluate in the future with past data, what kind of decisions simulation model has proposed, and how case company has actually in traditional mechanistic manner completed these.

References

1. Gibson, B.J., Mentzer, J.T., Cook, R.L.: Supply Chain Management: The Pursuit of a Consensus Definition", *Journal of Business Logistics*, Vol. 26, No. 2, 17--25 (2005)
2. Christopher, M.C.: The agile supply chain: competing in volatile markets. *Industrial Marketing Management*, Vol. 29, No. 1, 37--44 (2000)
3. Nilsson, F.: Logistics management in practice - towards theories of complex logistics. *International Journal of Logistics Management*, Vol. 17, No. 1, 38--54 (2006)
4. Prater, E., Biehl, M., Smith, M.A.: International supply chain agility – tradeoffs between flexibility and uncertainty. *International Journal of Operations & Production Management*, Vol. 21, No. 5/6, 823--39 (2001)
5. Christopher, M., Lowson, R., Peck H.: Creating agile supply chains in the fashion industry. *International Journal of Retail and Distribution Management*, Vol. 32, No. 8, 367--376 (2004)
6. Boström, H., Andler, S.F., Brohede, M., Johansson, R., Karlsson, A., van Laere, J., Niklasson, L., Nilsson, M., Persson, A., Ziemke, T.: On the Definition of Information Fusion as a Field of Research. Technical report, University of Skövde (2007)
7. Nilsson, F., Darley, V.: On complex adaptive systems and agent-based modeling for improving decision-making in manufacturing and logistics settings. *International Journal of Operations & Production Management*, Vol. 26, No. 12, 1351--1373 (2006)
8. Hilteofth, P., Aslam, T., Hilmola, O.-P.: Multi-agent based supply chain management: Case-study of requisites. *International Journal of Networking and Virtual Organisations* (accepted, forthcoming).
9. Lim, M.K., Zhang, Z.: A multi-agent based manufacturing control strategy for responsive manufacturing. *Journal of Materials Processing Technology*, Vol. 139, No. 1/3, 379--384 (2003)
10. Swaminathan, J.M., Smith, S.F., Sadeh, N.M.: Modeling supply chain dynamics: a multiagent approach. *Decision Sciences*, Vol. 29, No. 3, 607--632 (1998)
11. Davidsson, P., Wernstedt, F.: A multi-agent system architecture for coordination of just-in-time production and distribution. *The Knowledge Engineering Review*, Vol. 17, No. 4, 317--329 (2002)
12. Macal, C.M., North, M.J.: Tutorial on Agent-based Modeling and Simulation Part 2: how to Model with Agents. *Proceedings of the 2006 Winter Simulation Conference* (2006)
13. Davidsson, P., Henesey, L., Ramstedt, L., Trönquist, J., Wernstedt, F.: An analysis of agent-based approaches to transport logistics. *Transportation Research Part C*, Vol. 13, No. 4, 255--271 (2005)
14. Cantamessa, M.: Agent-based modelling and management of manufacturing systems. *Computers in Industry*, Vol. 34, No. 2, 173--186 (1997)
15. Forrester, J.W.: Industrial dynamics – a major breakthrough for decision makers. *Harvard Business Review*, Vol. 36, No. 4, 37--66 (1958)