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Information Sharing and Coordination Mechanisms for Managing Uncertainty in Supply Chains: A Simulation Study

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Abstract

The study aims to investigate the effectiveness of information sharing and coordination mechanisms in reducing uncertainty. Supply chains are constantly subject to unpredictable events that can adversely influence its ability to achieve performance objectives. This paper primarily aims at managing uncertainties originating from unexpectedly large demand spikes. Supply chain literature is full of effective supply chain uncertainty management practices. This paper reviews the different practices for improving management of uncertainty and proposes several combinations of information sharing and coordination mechanism for. Next, the proposed combinations are tested on the make-to-stock supply chain of a paper tissue manufacturer using an agent-based simulation approach to show how the use of different levels of information sharing and coordination can be effective in managing uncertainty under daily operations facing huge mismatch of actual and forecast demand. The findings of this research suggest that, a centralised information structure without widespread distribution of information and coordination is not effective in managing uncertainty of supply chain networks, even with increased frequency of information flow. Similarly, coordinating material flows without widespread information sharing does not improve supply chain uncertainty management. Central coordination of material flows with supply chain wide information sharing across different members is found to be essential in managing supply chains effectively under uncertainty.

Keywords supply chain, uncertainty, simulation, agent based model, information sharing, coordination

Introduction

Modern supply chains are very complex, and recent lean practices have resulted in these networks becoming more vulnerable. Kilgore (2003) and Radjou (2002) suggest that much of the supply chain management efforts in the recent past have focused on increasing the efficiency of supply chain operations. Firms increasingly depend on a complicated network of global suppliers and partners to deliver products in the right quantity and at the right place and time in increasingly volatile markets and under persistent cost pressures.

Many recent articles (Lee and Wolfe, 2003; Rice and Caniato, 2003; Starr et al, 2003; Christopher, 2004; Christopher and Lee, 2001; Kleindorfer and Saad, 2005; Sheffi and Rice, 2005; Tang, 2006) have presented recommendations for successful management of uncertainty. The literature primarily focused on a general or high level view of supply chain management under uncertainty rather than drilling down to the interplay of the different practices and evaluating the performance under uncertainty for different combinations of these recommended practices. This in turn reduces the practical utility of such studies. The paper proposes to address this gap in literature by studying different combinations of information sharing and coordination mechanisms for reducing the uncertainty in supply chains. It is well-acknowledged in supply chain literature that information sharing and physical flow coordination can lead to enhanced supply chain performance (Chen, 1998; Cachon and Fisher, 2000). Tayur et al. (1999) and Sahin and Robinson (2002) reported comprehensive surveys of the supply chain information sharing and coordination literature. Most of these works take a single-item view of the solution, consider known demand distributions, use static analytical modelling techniques with very little reference to real-world supply chains. In this paper, we expand the problem scope to consider multi-item operations in a real-world supply chain.

This paper primarily aims at reducing uncertainties originating from unexpected large demand spikes and reviews the different practices agility, flexibility, integration and information structure. The paper identifies coordination and information sharing as the basic elements for the different practices and suggests different combinations for improving performance under uncertainty. Our objective is to provide insight into the value of information sharing and coordination in managing uncertainty in supply chains, particularly focusing on make-to-stock type supply chains. Agent based simulation methodology is adopted to evaluate the different combinations of information sharing and coordination on the performance of supply chain under unpredictable demand for a paper tissue manufacturer. The entire system is modelled by replicating the rules, control procedures and strategies adopted by actual supply chain members. In the next section, several experimental scenarios are designed by incorporating the proposed combinations of different levels of information sharing and coordination mechanisms to manage uncertain demand. Finally the findings are summarised and discussed.

Management of uncertainty in supply chains – A literature review

Uncertainty

Walker et al., (2003) define uncertainty as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system". At a high level uncertainty can be considered to be derived from mismatches between demand and capacity or available resource. This occurs due to the perennial lack of ability to accurately forecast the actual demand. Uncertainties therefore can arise from various sources either internal or external to the supply chains. Focus on cost efficiency (Lee 2004), potential conflict areas, such as local versus global interests (Naish, 1994; Kahn, 1987), strong reluctance of sharing common information (McCullen and Towill, 2002; Loughman et al, 2000; O'Donnell et al, 2006) are examples of internal sources of uncertainty. Saad and Gindy (1998) classified external sources of uncertainty into demand and supply related sources. Sheffi and Rice (2005) and Jung et al (2004) point out the primary source of supply chain risks as the uncertainty in the demand for products that can give rise to over- or under-production. On top of that, there are unwarranted disruptions such as natural disasters, strikes, accidents and terrorism (Chapman et al, 2002; Mitroff and Alpasan, 2003).

Supply Chain Practices to Manage Uncertainty

Several supply chain practices to manage uncertainty are listed in literature and these are discussed below.

Agility

Supply chain agility is the capability to respond to uncertain consumer demand more quickly (Faisal et al, 2006). Christopher (2000) mentioned, a truly agile supply chain is obtained through market sensitivity and technology. Sheffi (2005) focuses on monitoring and detecting weakest signals to create demand-responsive agile supply chains. Yusuf et al. (2004) found high degree of cooperation, information based integration as the key agile supply chain capabilities. An essential element in achieving agility in supply chains is visibility (Christopher & Peck 2004).

Supply Chain Information Structure

Supply chain structures have been found to be a deciding factor in managing uncertainty (Christopher & Peck 2004, Craighead et al 2007). Samaddar et al (2006) investigated the relationship between supply network structure design and information sharing. Coordination mechanism based on global information is found to influence the nature of inter-organisational information sharing in specific supply network designs. Anand and Mendelson (1997) refer to the use of local and global information, or a hybrid of the two, for decision-making purposes within a supply network with different configurations. In a decentralised supply network structure firms are able to respond quickly to changes at their individual location. The centralised structure is more appropriate when the decision maker needs to take actions that benefit the total network.

Integration

Supply chain integration can be defined as synchronization among multiple autonomous business entities represented in it. Improved coordination within and between various supply-chain members and alignment of interdependent decision-making processes constitute an integral part of integration (Chandra and Kumar, 2001) and this reduces uncertainty (Geary et al 2002, Hoyt and Huq 2000). In order to manage uncertainty effectively in a supply chain, organisations are moving to adopt closer relationships with each other (Giunipero and Eltantawy, 2004).

Flexibility

Flexibility entails creating capabilities to respond when needed and designing production systems accommodating multiple products and real time changes (Rice and Caniato, 2003). In the supply chain literature, flexibility is seen as a reaction to environmental uncertainty (Giunipero et al, 2005). Rupp and Ristic (2000) find that lack of coordination and inaccurate information flows lead to inflexible production planning and control. In tackling uncertainty, flexible planning and re-planning requires seamless information flow across the supply chains (Christopher & Lee 2001).

Information Sharing and Coordination Mechanisms

The common elements of all the above supply chain uncertainty management strategies are coordination and information sharing mechanisms. Literature has studied the impact of information sharing and coordination mechanisms in detail for quite a long period of time. Information sharing between the buyer and vendor in supply chain has been considered as useful strategies to remedy bullwhip effects and supply chain performance (Lee et al., 1997; Metters, 1997; Lee and Whang, 1999; Lee and Tang, 2000). Nassimbeni (1998) identified different coordination mechanisms for different supply chain network structures. Simatupang et al. (2002) used four different modes of coordination to supply chain performance. More recently supply chain coordination literature focuses on revenue sharing (Giannoccaro and Pontrandolfo, 2004; Cachon and Larriviere, 2005), decision support models (Wang and Benaroch, 2004; Boyaci and Gallego, 2004) and attributes (Xu and Beamon, 2006). Lee (2002) mapped the uncertainties in supply and demand processes and provided information sharing and coordination as measures for reduction. Literature suggests two interrelated forms of coordination mechanisms. The first type involves coordinating the upstream and downstream product flows (Cooper et al., 1997; Perry et al., 1999). The second type involves the coordination of information among partners (Christopher, 1998; Handfield and Nichols, 1999). This refers to the sharing of information among members of the supply chain to synchronize their activities

(Lee, 2002; Zeng & Pathak, 2003). Supply chain collaboration is often defined as two or more chain members working through sharing information and making joint decisions (Simatupang and Sridharan, 2002). Though literature has identified the two aspects of coordination and considered information sharing as an important element of coordination mechanism but there has been no mention of the mechanism of product or information flow coordination. For example, the product flow can be controlled by a single member in the supply chain (centralised structure) or it can be coordinated jointly by several interacting members (decentralised structure). Also the decisions taken by each entity can be based on local information (involving own and immediate upstream/downstream member) or supply chain wide global information.

There has been a growing trend in literature to study the information sharing-coordination continuum in managing supply chain performance. Sahin and Robinson (2002) proposed a systematic framework for organising the two major dimensions of supply chain integration at operational level. The researchers identified different levels of information sharing and coordination. One extreme is represented by no information sharing and no physical flow coordination between supply chain members. Under such situation, each member operates in self-interest using local information. The other end of the spectrum is fully coordinated decision-making and physical flow control approach, in which all information and decisions are used together to attain global system objectives. Within these two extremes, multiple scenarios exist based on different levels of information sharing (e.g., production plans, stock levels, actual demands, forecasts, product portfolio etc.) and decision-making coordination (i.e., replenishment orders (Lagodimos 1992), risk pooling (Schwarz 1989)). According to Sahin and Robinson (2002, 2005), there is an emerging trend in literature to examine the impact of these alternatives but it is slow and does not study the interaction of these two important dimensions in reducing uncertainties in supply chains. Li and Wang (2007) found most studies in supply chain coordination do not aim to find out the most effective mechanism under uncertainty. Majority of the papers in the survey conducted by Sahin and Robinson (2002) are found to adopt simple analytical models to study the effects of information sharing and coordination. Only in 2005, Sahin and Robinson applied simulation to study make-to-order supply chains. The scope of current literature needs to be expanded to include multiple products, more complex network structures (both physical and information) and more realistic demand structures. This research on studying the impact of different combinations of information sharing and coordination mechanisms on the performance of complex real-life supply chain under real demand data including multiple products is well-justified and addresses an important gap in literature.

This paper aims to consider different coordination and information sharing techniques in order to understand which combination is the most effective in managing uncertainty. Several different coordination and information sharing mechanisms investigated in this paper are supported by literature.

Joint decision making and material flow control

Joint decision making has helped Toyota group recover fast from a fire at one of its plants (Nishiguchi and Beuder, 1998). Arshinder et al (2007) studied the impact of joint decision making by supply chain members on a real-life supply chain. Holweg et al (2005) have mentioned joint inventory and production control by suppliers and retailers are beneficial for the supply chain performance. Zhao et al (2002) state that, under certain conditions, total supply chain cost savings may be even 60% due to ordering coordination. Although postponement is an effective strategy for joint material flow control but it is typically viewed from the manufacturer's point-of-view in literature (Van Hoek, 2001; Pagh and Cooper, 1998). However, in joint decision making and material flow control sense, we refer to the offering of downstream supply chain members to delay or withhold their orders for the overall benefit of the supply chain, particularly under uncertainty. The members in case of scarcity can decide to coordinate the best order volume to be placed on upstream members to minimise disruption. This has not been considered in literature as an effective coordination mechanism.

Centrally coordinated material flow and decentralised decision making

Adler (1995) and Bailetti et al. (1998) state that in highly uncertain situations like new product development, concept of responsibility interdependence is more useful for coordination. By this they mean to say, coordination occurs through sharing the responsibility among different partners. Lee and Billington (1993) mentioned that due to difficulties in complete centralised control of material flows , supply chain inventory decisions are most often decentralised and inter-dependent. Holweg et al

(2005) found for products that are supplied centrally or regionally from a focused manufacturing plant, the benefits of joint decision making are reduced. They suggested decentralised decision making based on actual customer consumption patterns in each local market combined with centrally controlled material flow to be the best option. Piplani and Fu (2005) developed a coordination framework aligning centrally the inventory decisions (safety stock and order-up-to levels) in decentralised supply chains and applied the same to a real-life supply chain. Jones and Riley (1989) supported the same argument stating, where inventory is to be held at a number of locations, the stock decisions must be taken by each echelon in a decentralised manner. This paper uses this as a different coordination mechanism to understand its impact on supply chain performance under uncertainty. In this mechanism, we have assumed a central facility allocates materials to the downstream members based on fair share rationing discussed by Eppen and Schrage (1981). All ordering decisions are taken by the members close to the markets without coordinating with each other.

Centrally coordinated material flow and decision making

Most researchers argue that organizational barriers and restricted information flows in supply chains render complete centralised control of material flows and decision making virtually impossible (Piplani and Fu, 2005). However, several studies have presented somewhat differing results. Chen (1998), for example, finds that by centralised decision making, supply chain costs can be lowered on average by 1.75%. Chen et al (2000) showed that bullwhip effect could be reduced, but not completely eliminated, by centralising demand information. Based on these studies, in this paper we have introduced a coordination mechanism where all decision rights rest with a central facility.

Information Sharing

Although there have been a number of articles published on coordination, there has been very little work that explicitly takes into account uncertainty (Soroor and Tarokh, 2006). On the other hand, there has been a considerable amount of work on role of information sharing in reducing supply chain vulnerability (Christopher and Lee, 2001; Lee, 2002; Geary et al., 2002). Gavirneni et al. (1999) found that suppliers' costs can be lowered by 1-35% by sharing customer inventory information. Yu et al (2001) conclude that both expected inventory and associated costs can be reduced through information sharing. Angulo et al. (2004) indicated that forecasting information sharing between retailer and supplier can significantly increase the order fulfilment ratio under uncertain demand. Shared information provides visibility into supply chain processes used to coordinate the material flow (Soroor et al., 2009). This shared information may include customer needs, customer demand, product related data, costs related data, process related data and performance metrics (Karaesman et al., 2003; Ozer, 2003). According to Zha and Ding (2005), for an effective coordination not all, but some of the private information could be shared among partners in supply chain. Some types of information that could be shared are inventory information, sales data, sales forecasting, order information, new product information. It is a key issue to make sure what the accurate information that should be shared is when coordination takes place. In this research we have used different levels of information sharing, ranging from full to no information sharing between the partners. By full information sharing in this paper, we mean information on stock levels, demand shared across multiple echelons (production and distribution). Partial sharing of information implies sharing the information in one echelon (only distribution). This is discussed in the section describing the model configurations. Also how often such information can be shared is a prime matter of consideration for effective coordination and this paper discusses the impact of sharing information on weekly, monthly and daily basis.

While, literature views information sharing and physical flow coordination as essential for effective supply chain integration necessary for effective management of uncertainty, several gaps exist in identifying the magnitude of benefits of different information sharing and coordination mechanisms in real-life supply chain with multiple products, capacity constraints and uncertain lumpy demand situations. Also the above information sharing and coordination mechanisms are studied in isolated manner without attempts to study the combined effects on managing uncertainty in real-world supply chains. This research addresses this gap by considering the supply chain of a paper tissue manufacturer subject to high demand-forecast mismatch. The paper industry is considered important for understanding the research gap due to the uniqueness of the paper tissue supply chain characterised by highly interdependent and time sensitive work processes, lack of visibility of end-customer demand and long transit lead times (Carlsson et al., 2006).

Methodology

Most of the research in studying the impact of information sharing and/or coordination has employed analytical techniques. However, simulation is essential for understanding the effects of these combinations on the supply chain performance over time. The explicit modelling of decision making infrastructure, the linkages between different levels of decision making, the systems responsible for control, their activities and their mutual attuning with time to adapt to changes are essential for this research and considered as intrinsic weakness of existing models. Agent based modelling (ABM) is most suitable for addressing the research question. ABM provides a method of integrating the entire supply chain as a network system of independent echelons; different entities employ different decision making procedures in most cases (Gjerdrum et al, 2001).

Use of ABM in supply chain management research is quite recent. Swaminathan, et al (1998) use the notion of agents to propose a flexible modelling framework to enable rapid development and customised decision support tools for supply chain management. Fox et al (2000) investigate and present solutions for the construction of an agent-oriented software architecture. Their work incorporates the three levels of decision making, strategic, tactical and operational. In a parallel study, Chen et al (1999) studied the negotiation methods using agents in supply chain management. In a similar way, Lin and Pai (2000) show how Swarm, a multi-agent simulation platform, may be used for studying supply chain networks. Parunak et al (1998) explore the capability of equation and agent based models in the problem domain of manufacturing supply networks. Chang and Harrington (2000) modelled a retail chain as a multi-agent adaptive system to study the effects of centralisation versus decentralisation on innovations. Ahn et al (2003) proposed a flexible agent system, which is adaptable to the dynamic changes of transactions in the supply chains.

Although there have been many uses of ABM in supply chain management but application of ABM in studying management of supply chain uncertainty or studying the impact of combination of information sharing and coordination is very limited. Lin and Shaw (1998) studied the impacts of different order fulfilment process improvement strategies in different supply chain networks using multi-agent information systems approach. However, the researchers did not consider real-world supply chain systems. Another criticism of their work is the use of swarm simulation platform. In words of Bonabeau and Meyer (2001, p114) *'Many people have great difficulty understanding how swarm intelligence can work, mainly because they are unfamiliar with self-organising systems … critics often object that insects and people cannot – and should not – be described with the same mathematical frameworks'*. Also the strategies adopted were not validated against literature or real-world. The paper thus falls short in describing the decision rules in depth for each of the strategies and the research is very difficult to be validated against real-world. Cavalieri et al. (2003) described a multi-agent model for coordinated distribution chain planning focusing mainly on the distribution part of a real-world supply chain. Lee and Kim (2008) reviewed use of multi-agent modelling techniques and simulations in the context of supply chain management. Although they found some papers dealing with supply chain uncertainty, however some are limited to conceptual framework development and hence of limited practical value (Allwood and Lee, 2005; Huang and Nof, 2000), while one (Moyaux et al., 2003) focuses on bullwhip effects only. Very few work have been done recently using ABM for managing uncertainty (Mele et al, 2007), improving agility (Forget et al, 2007) but those have mostly focused on make-to-order hypothetical supply chains. Datta et al. (2007) present an agent-based framework for studying multi-product, multi-country supply chain subject to demand variability, production, and distribution capacity constraints, with the aim of improving supply chain resilience. The model developed by the authors shows the advantages of using a decentralized information structure and flexible decision rules, monitoring key performance indicators at regular intervals, and sharing information across members of the supply chain network. Some key limitations of this study are that, it did not consider the variation of different strategies to study the impact on the supply chain performance; it is dependent on one set of demand data and checks the performance of the system for one set of strategies to compare with the actual data. The agent-based model proposed in this paper to study the impact of different combinations of information sharing and coordination (described in previous section) in a real-world supply chain's performance under different sets of uncertain demand is of immense value in both ABM and supply chain literature and practice.

A justification of using ABM in comparison to tested and established methods for addressing the current research question is provided in Table 1. [Table 1 here]

Case Example

[Figure 1 here]

Figure 1 shows the material flow in the supply network of a paper tissue manufacturer to be used as a case study in this research. This is a make-to-stock supply chain and has its own bottlenecks of operations. First of all, half of the company's customers are distributors and not real customers. So the company has to depend on history based forecasts. Sales-forecast mismatch (Table 2) is an obvious consequence. Planning is done based on aggregate forecasts, but in reality the forecasts at country level are often wrong (the deviations of actual sales from the forecast are more pronounced for low volume products, *X6* or new products, *X2* as is evident in Germany, Table 2). Consequently the network is plagued with huge stocks in locations where it might not be required or less stock where there might be a surge in demand.

[Table 2, Figure 1a here]

Studying the supply chain for years 2003 and 2004, except for products *X1, X11* and *X12* all the other products are introduced in 2003 or 2004 (Figure 2). So there is a problem of relatively uncertain sales of most of its products that gives rise to production and inventory planning problems.

[Figure 2 here]

Figure 1a above shows the map of different disturbances faced by the organisation. The disturbance characteristics and their impact on performance of the entire supply network are plotted in Figure 1a. The chart axes rated the characteristics from high to low. From the left hand side of the figure, it can be seen that disturbances due to sales-forecast deviations are most frequent, more pronounced but short-lived. Among the other forms of disturbances, production planning related disturbance are found to be infrequent but occurs for longer duration. The level of disturbance is moderate. Raw material variability and human error in deployment are low level disturbances. Over-all the most severe form of disturbance is the demand-forecast deviation and hence is considered the most worthy of attention in this paper.

Description of the ABM

Each member is modelled as an independent agent with autonomous decision-making ability. The converting facility is represented by a factory agent. The distribution centre agents replicate the regional sales manager's decisions. This is done to capture the decision making of each entity and allow implementation of different combinations of the proposed coordination and information sharing techniques for improving management of uncertainty. The daily sales history and forecast figures of the different products in each country for one year. The company provided initial stock levels at the beginning of the year for all stock-points. Daily orders and production amounts were obtained for each country and product combination. The lead times for transport, the production constraints are also obtained.

Baseline Model

All the agents are designed to follow the exact rules, control procedures followed by the members in the actual supply network and the informational flow structure (Figure 3). The assumptions are: 1) Raw material variability is not considered and infinite raw material stock is assumed in all the models, 2) All customer orders are due on the day of placement, 3) No transport constraints are present, 4) No materials are stored in the factory and there is no delay in transit from the factory to the store, 5) Fixed yearly maintenance period is assumed.

Central Planning Agent – The central planning agent has full visibility of all the operations in the network and generates monthly production plans for each product. Every month, the central planner has information on that month's budgeted production days set by the operations group (APD), the stock levels of each product at the central warehouse, the next month's total forecasted sales in each product throughout the entire network. The central planning decides an ad-hoc target aggregate inventory cover for central warehouse and obtains the days of production needed. If the number of days' production is less than 1 in any product, the central planning normally decides to produce for one day. If the sum of total number of production days (TotPD) and maximum changeover time is greater than APD, the central planning agent scales down the production days in all products excluding those to be produced for a day only. In the same way, the number of production days is increased if the available days of production are found to be more. The planning process is shown in figure 4 below.

[Figure 4 here]

Factory Agent – The main task of the factory agent is to decide on the sequence of production. The factory agent produces a ranking list of products based on total inventory cover at central warehouse. The factory starts production with the top ranked product if it is planned for production during that month. The factory agent decides on the stop time of production of any product by monitoring two things at regular intervals: firstly, the time to produce the planned amount and secondly, the expected time of depletion of inventory of any other product planned for production. The factory agent switches production as soon as it finds that inventory of any product falls below the safety stock. The product choice is then also based on the category of the product produced before. If all products are not produced during the month, production is carried forward to next month. The entire production, planning and control process executed by the factory agent is shown in Figure 5.

[Figure 5 here]

RDC Agent – The RDCs review inventory every day and place orders on the central warehouse when their stock levels fall below the target stock level. The target stock levels for each RDC, central warehouse and each product are set as the sum of cycle and safety stocks given by the traditional periodic review inventory model as: $F(1+L) + k\sigma\sqrt{L+1}$, where F is the average forecast sales during lead time, k is the safety factor corresponding to the target CSL (customer service level) of 96%, σ the standard deviation and L is the transit lead time of sending materials to the RDCs from the central warehouse and for central warehouse it is the average cycle time for production. The central warehouse sends exactly the amounts ordered by the RDCs . However, in case of scarcity, the central warehouse sends materials randomly to the different RDCs.

Validation – As local small scale deviance from the idealised model means that exact replication of the actual inventory profile is not possible an acceptance criterion of 15% was set. This acceptance criterion was set after discussing with supply chain managers and production planners knowledgeable about the system. Since the actual average figures result from many interventions and untoward incidents during one year, it is very difficult to model the exact timing of such incidents, the practitioners provided this level. Since only one set of actual data was available it was also not possible to test the statistical validity. We also used the Turing test (Law and Kelton, 2000) to validate the model. Time series data from actual and model were presented to the supply chain manager, production manager and distribution centre managers for the different countries. The inability of these people to agree on which set were real and which were simulated led to immediate acceptance of the model. The figures for both fell within the acceptance criteria with no differences greater than 15%. For the average inventory the mean difference was 5.3% and for average daily production amounts it was 8.2%. These results validated the baseline model as a functional representation of the real system.

[Tables 3a & b here]

Models with improvements

A set of experiments with different combinations of coordination and information sharing mechanisms are conducted. The different model configurations are listed in Table 4.

[Table 4 here]

Configuration 2

This model is developed with more frequent adjustment in the production planning of the baseline model. Each week the factory agent reviews the inventory levels of the different products at the central warehouse and checks the amount produced. If the product has already been produced to the planned amount but the central warehouse inventory drops to zero, the factory decides to produce another week’s forecasted demand to cater to the excess and communicates to the factory agent. This excess production amount will be deducted from other products’ (which are not yet produced in full) planned amounts by the central planning agent to produce all products within the available days of production in a month. All activities are controlled by the central planning agent.

Configuration 3

The assumptions in the baseline model hold for this model as well. The agent structure is divided into two stages: the functional and the decision making stage. Allwood and Lee (2005) introduced such a structure of an agent for modelling supply chain network dynamics. The agent performs monitoring of key variables and performance measures. From the differences in target and actual performance, the agent decides on the appropriate response action for the functional stage. The impact of these activities on the performance measures is fed into the decision making stage for making decisions on the appropriate actions at the next time interval.

[Figure 6 here]

Here the factory has the full autonomy to decide when to produce which product and for how long based on the information of central warehouse inventory levels (Figure 6). Each distribution centre receives orders from the markets. Forecast sales are communicated to all the members. The central warehouse sends materials to RDCs and uses no specific preference criteria for distribution. The RDCs place orders on the central warehouse based on their own stock levels.

Factory Agent – Figure 7 shows the decision making stage of the factory agent. The *functional stage* of the factory agent carries out the following functions: a) production, planning and control, b) maintenance, c) product set-ups and d) pallet arrangement. The *decision making stage* of the factory agent sets the priority to produce the products and decides how much to produce on each product. Unlike the baseline model the factory is not bound to produce a fixed quantity of products every month. The factory decides to stop production of the selected product, if any of the products' stock level could be reduced to zero before the selected product stock level in central warehouse reaches the target level. In order to avoid producing products for very small time intervals, the factory produces the products for a minimum time of 1 day. The factory uses only central warehouse stock information.

[Figure 7 here]

Distribution Centre Agent – The functional stage of the distribution centre agent implements three major functions: a) receipt and aggregation of orders from customers, b) delivery of goods to customers or distribution centres, with determination of priority in scarcity, c) inventory review, receipt of materials and replenishment order placement. A different safety stock estimation technique is introduced in the model to take care of forecast bias and lumpy demand scenarios based on increased information availability. RDCs adjust safety stock levels to compensate for the non-Normal distribution of forecast errors associated with forecast bias (Krupp, 1982). The safety stock (SS) for product i, at time t is, $SS_{t,i} = (1\text{-}FETS_{t,i})$

$\times k \times \mathrm{TICF}_{t,i} \times F_{t,i} \times T_{\max}$, F is the total aggregate forecast of product i for that time period t, $T_{\max}$ is the maximum lead time, k is the safety factor corresponding to a target CSL (96%). TICF is the time increment contingency factor and is expressed as $\frac{1}{T_{\max}}\sum_{t=1}^{T_{\max}}\left|\frac{F_{t,i}-D_{t,i}}{F_{t,i}}\right|$, D is the total aggregate actual demand of product i for that time period t. The bias of forecast from the actual mean is often expressed mathematically through the use of Forecast Error Tracking Signal (FETS) and is expressed as $\frac{1}{T_{\max}\times TICF}\sum_{t=1}^{T_{\max}}\left({(F_{t,i}-D_{t,i})}/{F_{t,i}}\right)$. RDCs decide the orders to be placed on the factory at each review period based on the difference between target stock level and their own stock levels.

Configuration 4

In this case the RDCs share their ordering information with other RDCs to jointly decide the material flows from the central warehouse, all other things remaining same as configuration 3. If for any product the total stock at the central warehouse falls below the total replenishment orders from the RDCs, the RDCs scale down their respective orders according to their order magnitude ratios. This is done after keeping aside a safety stock in that product at the central warehouse for supplying any direct orders. RDCs pull in products, which are not demanded directly from central warehouse (*X3, X4, X8, X9*), in full volume as soon as they are produced and stored in central warehouse. The central warehouse has no control over the distribution process and supplies according to the orders. The information sharing scheme is presented in Figure 8.

[Figure 8 here]

Configuration 5

The informational structure is depicted in figure 9, where the factory has access to the network-wide information on sales, forecasts, stock levels, strategies. The central warehouse and the production factory have more information sharing between them and provide more effective demand-responsive production planning. The central warehouse controls the entire distribution process and individual RDC uses a combination of replenishment procedures without sharing each other's inventory information.

[Figure 9 here]

Factory Agent – The functioning stage of the factory agent remains the same as in configuration 4. In selecting products for production, the local objective of reducing changeover time for the factory is satisfied by selecting the product with the minimum changeover time. Investigation is also made across all products for insufficiency in stock level at central warehouse to meet demand during production run-length (or network inventory during transit lead time for products not directly sold from the central warehouse). If the stock level of any product falls short of the estimated demand, that product is selected first irrespective of changeover time. After selection of a product for production the factory agent also determines how long it should be produced with detailed information on the inventory covers of all products. The decision making stage is the same as in Figure 7, only in this case the central warehouse stock and safety stocks are replaced by network inventory levels for products not directly sourced from the central warehouse.

Distribution Centre Agent – The RDCs do not share each other's order information. However RDCs do not order if the central warehouse inventory level is less than the forecasted sales of products directly sold from the central warehouse during the average production run-length period. This model uses the adjustable safety stock based approach for generating replenishment orders. In case of scarcity of materials, the central warehouse uses preference ratios based on their relative order sizes for sending materials to RDCs. Products sold in only one country market are immediately pushed by the central warehouse to their respective country markets as soon as they are produced. So the distribution process is more centralised with individual RDCs placing orders and the central warehouse deciding on the delivery volumes depending on availability. Appendix III depicts the internal architecture of the agents in this configuration.

Results & Discussion

Performance Measures

The performance of the above models with different rules, strategies and control systems will be judged in terms of the following performance measures.

- Network Customer Service Level (CSLN) is taken to be the fill rate, which is the total quantity sold to the end customer over the total quantity ordered, averaged across all products, all markets and the entire time horizon. The expression for CSLN is taken from Hung et al (2006).
- Total production change over time (CO) and Average Production Run-Length (APR). These performance measures are considered after interviewing the production managers at central factory. The manufacturer measures production efficiency by measuring CO and APR. Thus the production manager's goal is to maximise APR and minimise CO.
- The total average network inventory (NAVI) is the total on-hand stock-level in the whole network across all distribution centres and products averaged over the time horizon. This performance measure is the standard used across the organisation. The expression for NAVI is taken from Hung et al (2006).
- Average time taken to return to steady state after disturbances expressed by the average number of days the system takes to attend to a drop in inventory (when the drop in inventory is 10%). The 10% level emerged after several discussions with the supply chain manager. This actually shows how fast the distribution centre agents react to drops in inventory by ordering on time.
- The average variation in weekly replenishment orders expressed by the bullwhip effect (calculated as the ratio of variance of weekly replenishment order to the variance of weekly customer demand). The bullwhip measure has been taken from Chatfield et al. (2004).
- Total number of stock outs across the network through out the time of simulation. This measure was considered after discussion with the supply chain manager to show the vulnerability of the system.

The agent based models developed above for both the baseline system and the systems with proposed improvements are run as terminating simulation for one year with 5 different replications of demand data obtained from the organisation (justification shown in Appendix I). The appropriate theoretical demand distributions are determined using distribution-fitting software, Stat::Fit^{TM} (Geer Mountain Software Corp, 1996, the goodness of fit are shown in Appendix II). In situations where no theoretical distribution is found to fit the data, empirical distributions are determined using the raw data points. All the performance measures are averaged across the five replications.

Findings & Discussions

A one-way Anova analysis is carried out between the results obtained from different configurations. This is carried out to understand the impact of different strategies on four different performance measures (CSLN, NAVI, APR, average response time). Such techniques are extensively used in literature to understand the impact of different combinations of strategies in supply chain performance. Zhao et al.(2002) used ANOVA analysis to examine the impact of different combinations of forecasting mechanism and information sharing on the total costs and service levels of supply chains. It was found from the ANOVA analysis that, forecast model selection and information sharing strategy have significant impact on all performance measures. They then used post-hoc tests to conclude that for all forecasting models, order information sharing performs much better than demand- or no- information sharing. In a similar manner, Holweg et al. (2005) used multiple scenario (make-to-stock, make-to-order and balanced demand leveling, production stability and responsiveness) based Taguchi experimentation and ANOVA analysis to understand the impact of different operational strategies (ordering buffers, scheduling decision time delays for supplier and original equipment manufacturer, rescheduling frequency represented by specific parameters) on the inventory and production adaptation costs for both supplier and manufacturer. Different combinations of the different strategies and scenarios are also evaluated through ANOVA analysis. Dong and Chen (2005) employed ANOVA and Tukey's test to investigate the effects of different combinations of component commonality on supply chain performance criteria such as delivery time, fill rate and cost in an integrated environment.

Deleted: Such ANOVA analysis has been carried out by Holweg et al. (2005), Zhao et al. (2002) to determine the contribution of different factors on multiple performance criteria as cost, service level etc.

Deleted:

Table 5a lists the results of Anova test carried out to compare the multiple cases with one another. To gauge the significance of improvement achieved by adopting the different procedures in the different configurations, the average network inventory across all RDCs for the five replications, CSLN, average response time and APR are compared between configurations individually. The Anova result (F-test) shows that there exists significant difference in the above performance measures for different combinations of information sharing and coordination mechanisms. However, in order to understand which configurations performed best, Tukey's test (for equal population variance assumption, given by non-significant Levene's test) is carried out (Morgan et al., 2004, p151). From the statistical tests (Table 5b), it can be observed that configuration 5 results in significant rise in CSLN without significant increase in inventory levels compared to the baseline model. Configuration 5 achieves significant reduction in response time in comparison to the baseline model. APR in configuration 5 is significantly higher than the baseline configuration. While investigating the statistical test results for other configurations, NAVI reduces significantly for configurations 3 and 4 compared to the baseline model. No significant rise in CSLN is found to occur in configurations 2 compared to the baseline configuration. Configurations 3 and 4 also register significant rise in APR compared to the baseline model. In Table 5c homogeneous subsets are formed by grouping the configurations for which no significant difference is observed in each of the performance levels. As can be seen, configurations 1 and 2 have no significant difference in terms of performance. Configurations 3, 4 and 5 are significantly different in terms of CSLN, however there is no significant difference in APR among them. Configuration 5 gives the most significant difference in response time compared to all others. However, there is no significant difference in NAVI between configurations 1, 2 and 5.

[Figures 10a, b, c here, Tables 5a, 5b, 5c here]

Figure 10 shows the over-all performance of the configurations described above. From the figure it can be concluded that the system performance is the worst in the first two configurations. Hence centrally coordinated material flow and decision making with limited decision making authority for all members without any network-wide coordination (the baseline model) or information sharing actually deteriorates the performance and even introducing weekly production plan reviews (configuration 2) does not improve the performance at all. However, introducing the decentralised informational structure with full autonomy (configuration 3) to the different agents actually improved the NAVI position, CSLN (97.2%), number of changeovers, average production run-length (Figures 10a and 10b). But the number of stock outs does not change and the average response time to disturbance actually increases. This is because, the RDCs being autonomous now base their ordering decisions on the real sales, forecasts and own stock information while the material flow is still being controlled by central warehouse (how much material to send where and when). This results in the agents ordering in response to slight disruptions, but since the central warehouse decides the material flow the RDCs might not be getting the supplies when they need them. This results in the average response time rising to 7 days in comparison to 5.6 days in the baseline case. So although the performance apparently improves but the system is more vulnerable to even small amounts of demand-forecast mismatches highlighted by no change in the total number of stockouts averaged across the five replications. So although very frequent information flow for deciding the production improves the production performance by reducing the number of changeovers and increasing the APR, but it is not enough in improving the stockout situation. Configuration 4 drastically improves performance in terms of CSLN (98.5%), total number of stockouts (29) compared to configuration 3, while maintaining the same level of NAVI. This shows that coordination between different members of the supply chain is absolutely essential to improve the performance of the supply network under uncertainty. The number of changeovers and average production run-lengths do not change but the average response period gets reduced to 6 days, though it is more than the baseline case. So even though the different RDCs start collaborating to generate replenishment orders sensibly, yet the system is not able to sense and respond to the disturbances. The factory agent in configurations 3 and 4 base its decisions on central warehouse stock information and has limited visibility of the entire network stock information. Inability to produce the right material at the right time because of lack of information increases the average response time for the entire network. So far, configuration 4 gives the best result but the bullwhip effect is the highest (Figure 10c). This shows that only incorporating coordination mechanism without full information sharing between different members may actually deteriorate supply chain performance under uncertainty.

In all the above configurations, the factory bases all decisions on local information of central warehouse stock which does not give enough visibility to disruption in the entire network. In the fifth configuration very little difference in NAVI from the baseline model is observed but the CSLN increases to 99.8%. APR (4.4 days) and number of changeovers (80) improves. The average response time is reduced considerably in configuration 8 to 3.4 days. The total number of stockouts averaged over 5 replications is just 13. Investigating the average bullwhip effects across all products in major RDCs (shown in Figure 10c), the lowest bullwhip effect (3.4) is observed in configuration 5. Considering all performance measures, configuration 5 is found to be the best under different sets of demand data.

Normally in the literature the decentralised information structure in the supply chain implies individual members make decisions on the basis of local information available to them. In the findings, it is seen that the centralised system (with both centralised coordination and information sharing mechanism) represented by configurations 1 and 2 results in the worst performance in dealing with uncertain demand. But the decentralised information structure with each agent having full local information, no information sharing between agents (configuration 3) does not improve the performance of the supply chain in all aspects. In configuration 4, the RDCs start coordinating and making decisions based on not only own stock levels and targets but also on global inventory information. That results in higher CSLN but since the factory makes decisions based on local stock information and does not use the global information fully, the other performance measures do not improve. In configuration 5, members access global information for making decisions both in deciding the production and the replenishment order quantities. This results in best performance in managing uncertainty.

The strategy to pull materials from the central warehouse in case of need by the different RDCs is tested in configurations 1 to 3. In configurations 4 and 5, products not directly demanded from central warehouse are sent to respective markets as soon as they are produced. Also the reason for better performance of configuration 5 in responding to uncertainty is the use of global inventory information, product demands and characteristics by the factory. The factory senses the time better in configuration 5 when these products need to be produced based on network information and produces them. Then the central warehouse immediately pushes them to the respective RDCs. So a combination of centrally coordinated material flow and global information sharing improves the ability of the supply network to cope with totally uncertain demand spikes.

The supply chain literature suggests that uncertainty can be reduced through monitoring, detecting and acting on the weakest signals. The factory based on the daily local knowledge (configurations 2 to 4) or global and local knowledge (configuration 5) of the inventory levels decides on the production cycle time and sequence. Similarly, by monitoring the daily error and bias in forecasts, the RDCs adjust the safety stock amounts. This is not carried out in the centralised cases (configurations 1 and 2) and is evident in the long response time to disturbances. More stock-outs occur due to lack of monitoring at regular intervals and not having effective signalling system that can trigger the appropriate actions. The factory in the baseline case with monthly or weekly reviews is totally guided by the central planning and produces exactly the amounts that are specified in the production plan. There is very little scope for the factory to react to any variations in the inventory levels across the network. Similarly, the RDCs in the configurations 1and 2 base their orders on fixed safety stock covers determined by the standard deviation of demand and cycle stock determined by the fixed forecasts during lead time without any attempt to take into consideration the deviations of actual sales from the forecasts. However, too frequent monitoring without proper use of information by the key members of the network does not improve performance under uncertainty. As in configuration 3, regular use of information of forecast bias and error to decide the safety stock levels though improves CSLN but actually deteriorates performance on all other fronts. In fact, the system remains vulnerable to disturbances reflected in no change in the number of stockouts. In configuration 4, the factory and RDCs use daily monitoring and information sharing but in absence of proper use of information this configuration results in over-reaction in the form of high bull-whip effects. Configuration 5 achieves agility without over-reaction by selectively reacting to disturbances (inventory drops) based on information on product characteristics (annual forecasts, sales, standard deviation of demand). So to manage uncertain situations requires proper use of global and local information available.

Another advantage of proper use of information shared is the increased flexibility in configuration 5. Based on full visibility of network stock levels, the factory agent is modelled to identify and produce for longer periods products, which are high demand (from the forecast) or are selling in large quantities (from the cumulative sales data, the error in forecasts). However, the factory produces these products for very short run-lengths also when the need arises. Flexibility in the production process in configuration 5 helps the factory to decide the amount and the time of production of each product so that no product, at the time of intense demand, gets produced excessively and thus limits the time of production of other products. So the ability of the production system, without hampering the production efficiency in the form of changeover time, to respond to rapid changes in demand is possible through basing decisions relying on both global and local information. So introducing full visibility along with ability to use information properly helps building flexibility to effectively manage uncertainty. The factory sets up control procedures to determine the exact time of production of products, which are not directly demanded from the central warehouse by looking at the network inventory of these products (not used in any other configurations apart from configuration 5). Whereas, the factory uses the central warehouse stock information and forecast of direct demand from the central warehouse to determine the production time for all other products.

Hence from this discussion, it is clear that the best combination of information sharing and coordination is obtained in configuration 5, where material flow is controlled centrally through frequent use of proper local and global network-wide information.

Limitations of the findings

Our findings are based on specific case example of a supply chain network with specific problem assumptions (infinite raw materials, rush orders) and parameter settings. Additional research based on data from different supply chain network structures and operating environments, relaxing some of the assumptions to include raw materials portion of the supply chain would be valuable.

Managerial Implications

Our research provides clear guidelines what combination of information sharing and coordination mechanisms manufacturers with integrated production-distribution systems need to adopt to perform well under gross mismatch between actual and forecast demands. First, the information sharing should be full and some initiatives need to be taken by supply chain and manufacturing directors to implement this. We were surprised that, in spite of possessing enterprise resource planning software, there is a glass barrier between the factory and the downstream supply chain. The production planner mentioned, “My responsibility ends at factory gate”. As a result, huge backlogs appeared in both central warehouse and country distribution centres resulting in customer back-orders due to not manufacturing and stocking the right products at the right time and place. In this aspect, our research showed the benefits of decentralised decision making, centrally coordinated material flow and full information sharing

Conclusion

The findings from the experiments and the comparison of the performance of different model configurations are discussed below,

- Coordination and information sharing are necessary but the right combination of the two mechanisms is needed to improve the supply chain's response to demand-forecast mismatch;
- Centrally coordinated material flow and centrally controlled decision making on supply chain member activities deteriorates the performance of supply chains under uncertain demand and even increasing the frequency of information flow for resource (production) planning does not help;
- Decentralised decision making with centrally controlled material flow, increased information sharing among partners (product sales, forecast information) and daily information flow for production planning improves the customer service level but does not improve the vulnerability to uncertain events;
- Decentralised decision making and material flow coordination by the supply chain downstream members along with daily local stock information based production planning and increased shared-information based ordering decision coordination helps in improving the performance of the make-to-stock supply chain in all aspects but raises bullwhip and increases the reaction time to disturbances;
- Finally, decentralised decision making and centrally coordinated material flow along with daily local stock and global inventory information based production planning, increased shared-information based ordering decisions helps in improving the performance of the make-to-stock supply chain in all aspects;

The important contribution of this research is to study and provide methods for improving the management of uncertainty in a complex multi-product, multi-country real-life make-to-stock production/distribution system. This research studies different coordination and information sharing mechanisms, suggests their combined applications, applies them to understand their effectiveness in improving the supply chain performance under uncertainty and identifies the best combination responsible for improving the resilience of the supply chain. This research shows that, information sharing alone or coordination alone is insufficient in addressing the uncertainties. This research also increases the scope for further research in this field. Similar research can be extended to make-to-order supply chains and the effects of information sharing and coordination can be found out. Also this research mainly addresses the problems of a single organisation's supply chain. So once multiple companies are involved the coordination mechanisms might involve more complexity and require research in further depth. Finally, this research just examines two of the different practices. Researchers can study the other practices for finding the effective combinations among them.

Appendix I

The agent based model is run as a terminating solution for one year because every year the situation is different for the company and also the company reviews and changes the product portfolio every year. So to assess the performance of the supply chain dynamically for a different set of strategies, it is sensible to run the simulation as terminating and carry out the analysis. Since the initial conditions for such simulations normally affect the performance measures, these conditions (inventory levels at all RDCs and central warehouse) are representative of those for the actual system. The initial state of the model at the beginning of the simulation is that no orders are in the supply chain network and all machines in the factory are idle. The entire supply chain system is idle until orders begin to arrive in the system.

The network inventory performance measure is considered for estimation of number of replications for each scenario. The absolute error is the half length of the confidence interval (95%) and from the pilot of 5 runs it is found to be 7752, with mean 144519 and the standard deviation of 6236. The ratio of half length of confidence interval to the mean, after 5 runs, is found to be less than the allowable percentage error (Díaz-Emparanza I, 2002). Thus 5 replications are conducted for statistical reliability of the results. Application of an incremental approach shown in the following algorithm is used to obtain the calculations and justifications for taking 5 runs:

1) Make an initial number of m>=2 runs and calculate initial estimates $\overline{X}(m)$ and $S^2(m)$.
2) Decide the size of the allowable percentage error $\varepsilon = \left|\overline{X}(m) - \mu\right| / |\mu|$
3) Calculate the adjusted percentage error $\varepsilon' = \varepsilon / (1+\varepsilon)$
4) Decide the level of significance α
5) Calculate the new $\overline{X}(n)$ and $S^2(n)$.
6) Calculate the half-length of the confidence interval: $\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}$
7) If $\frac{\delta(n,\alpha)}{\left|\overline{X}(n)\right|} \le \varepsilon'$ use $\overline{X}(n)$ as an unbiased point estimate for μ, else make one more replication and go back to 5.

$\overline{X}(m)$: estimate of real mean μ from m simulation runs
$S^2(m)$: estimate of real standard deviation σ from m simulation runs
$t_{n-1,1-\alpha/2}$: Critical value of the t-test for n-1 degrees of freedom and significance α
μ : Actual network inventory measure obtained from real case as 136050

For m=3, $\overline{X}(3) = 140562$, *S(3)*= 4158, $\varepsilon = 0.034$, $\varepsilon' = 0.033$, $\frac{\delta(3,0.05)}{\left|\overline{X}(3)\right|} = 0.037 > \varepsilon'$

For m=4, $\overline{X}(4) = 143365$, *S(4)*= 6554, $\varepsilon = 0.054$, $\varepsilon' = 0.051$, $\frac{\delta(4,0.05)}{\left|\overline{X}(4)\right|} = 0.057 > \varepsilon'$

For m=5, $\overline{X}(5) = 144519$, *S(5)*= 6236, $\varepsilon = 0.062$, $\varepsilon' = 0.058$, $\frac{\delta(5,0.05)}{\left|\overline{X}(5)\right|} = 0.054 < \varepsilon'$

Hence the number of simulation runs is 5.

Appendix II

Table A-II: Theoretical Distribution Fitting to the historical demand data

	X1	X2	X5	X10	X11	X7	X6	X12
France	Pearson6	Beta	Weibull	Weibull	Beta	Beta	Beta	Weibull
	min 0	min 0	min 0	min 0	min 0	min 0	min 0	min 0
	beta 571.5	max 315.54	alpha 0.930674	alpha 1.24066	max 612.066	max 1200	max 129.152	alpha 1.28232
	p 1.39	p 0.589835	beta 47.446	beta 65.0995	p 0.684728	p 1.154	p 0.656633	beta 23.9272
	q 11.14	q 3.62644			q 3.88996	q 9.413	q 5.1559	
	pValue 0.444	p Value 0.425	p Value 0.651	p Value 0.409	p Value 0.23	p Value 0.42	p Value 0.141	p Value 0.246
	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49
	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)
	adstat = 0.853	adstat = 0.883	adstat = 0.597	adstat = 0.909	adstat = 1.31	adstat = 0.891	adstat = 1.67	adstat = 1.26

	X1	X5	X6	X10	X11	X12	X7
UK	Weibull	Weibull	Pearson6	Beta	Beta	Weibull	Pearson6
	min 0	min 0	min 0	min 0	min 0	min 0	min 0
	alpha 1.68265	alpha 1.36153	beta 3519.07	max 2617.65	max 215	alpha 1.16757	beta 419.382
	beta 187.552	beta 64.4731	p 0.716988	p 2.8728	p 1.20139	beta 102.672	p 2.11824
			q 56.301	q 34.1202	q 14.9117		q 6.84759
	p Value 0.357	p Value 0.643	pValue 0.378	p Value 0.632	p Value 0.378	p Value 0.937	pValue 0.375
	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49
	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)
	adstat = 1	adstat = 0.605	adstat = 0.962	adstat = 0.617	adstat = 0.962	adstat = 0.301	adstat = 0.967

	X1	X5	X11	X7
Italy	Weibull	Weibull	Pearson6	Pearson6
	min 0	min 0	min 0	min 0
	alpha 0.86041	alpha 0.841547	beta 200.734	beta 28.4015
	beta 41.6885	beta 80.5614	p 1.06842	p 1.1221
			q 2.62625	q 1.26744
	p Value 0.566	p Value 0.225	pValue 0.233	pValue 0.311
	adstat 2.49	adstat 2.49	adstat 2.49	adstat 2.49
	(at 0.005)	(at 0.005)	(at 0.005)	(at 0.005)
	adstat = 0.692	adstat = 1.32	adstat = 1.3	adstat = 1.09

An example of theoretical distribution fitting to historical demand data is shown above. This exercise is repeated for all products in all markets.

Appendix III

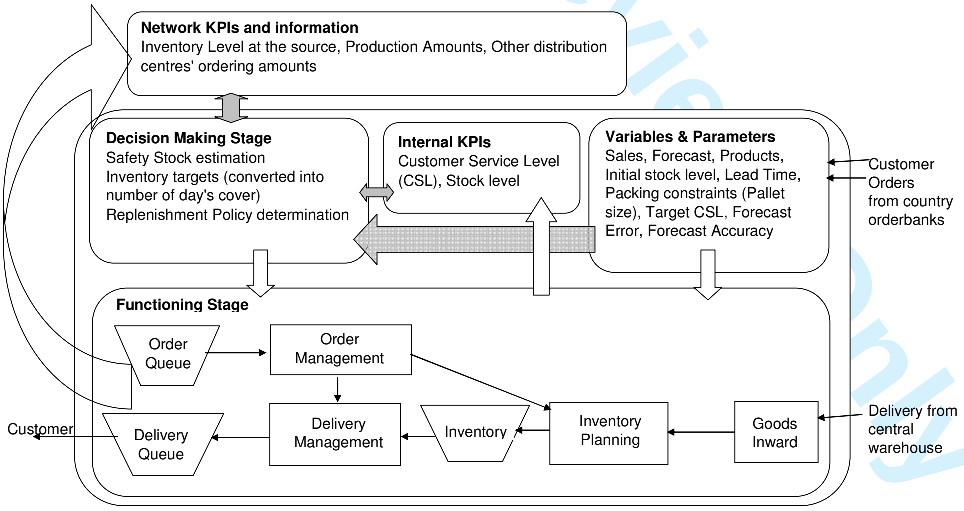

Figure A-IIIa: The agent structure for the distribution centre agent used in the model

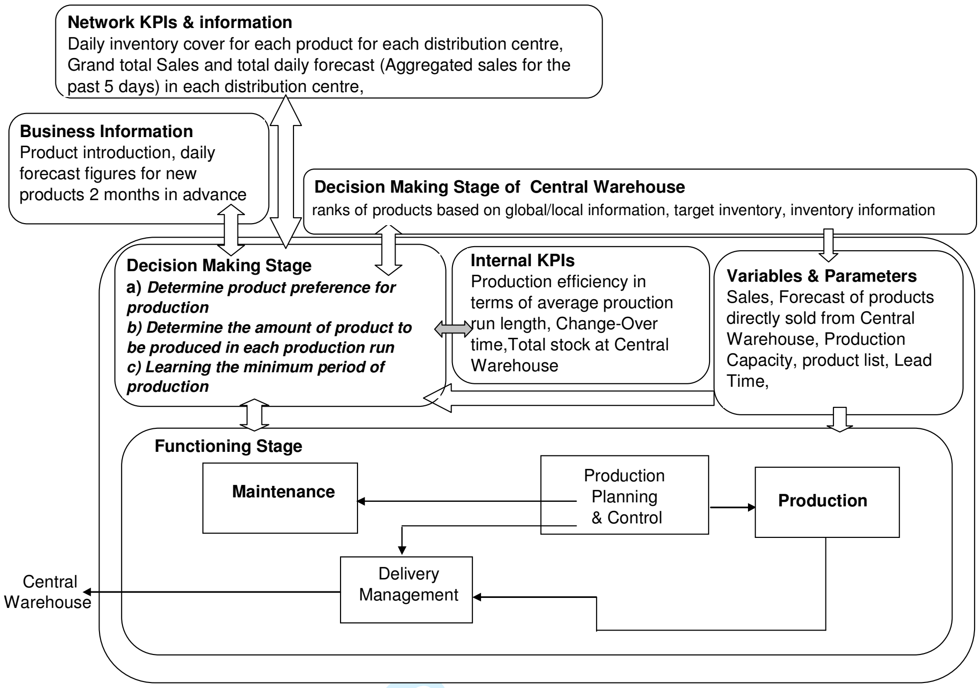

Figure A-IIIb: The agent structure for the production factory agent used in the model

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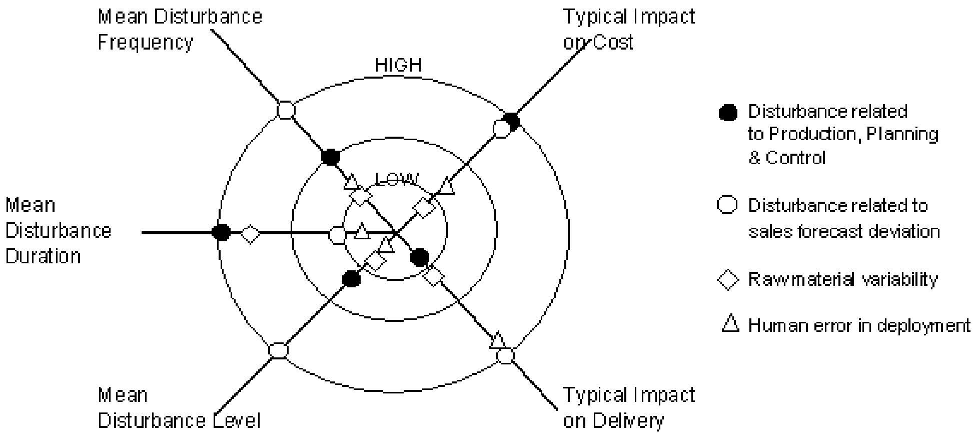


Figure1a: Map of different disturbances faced by the paper tissue manufacturer

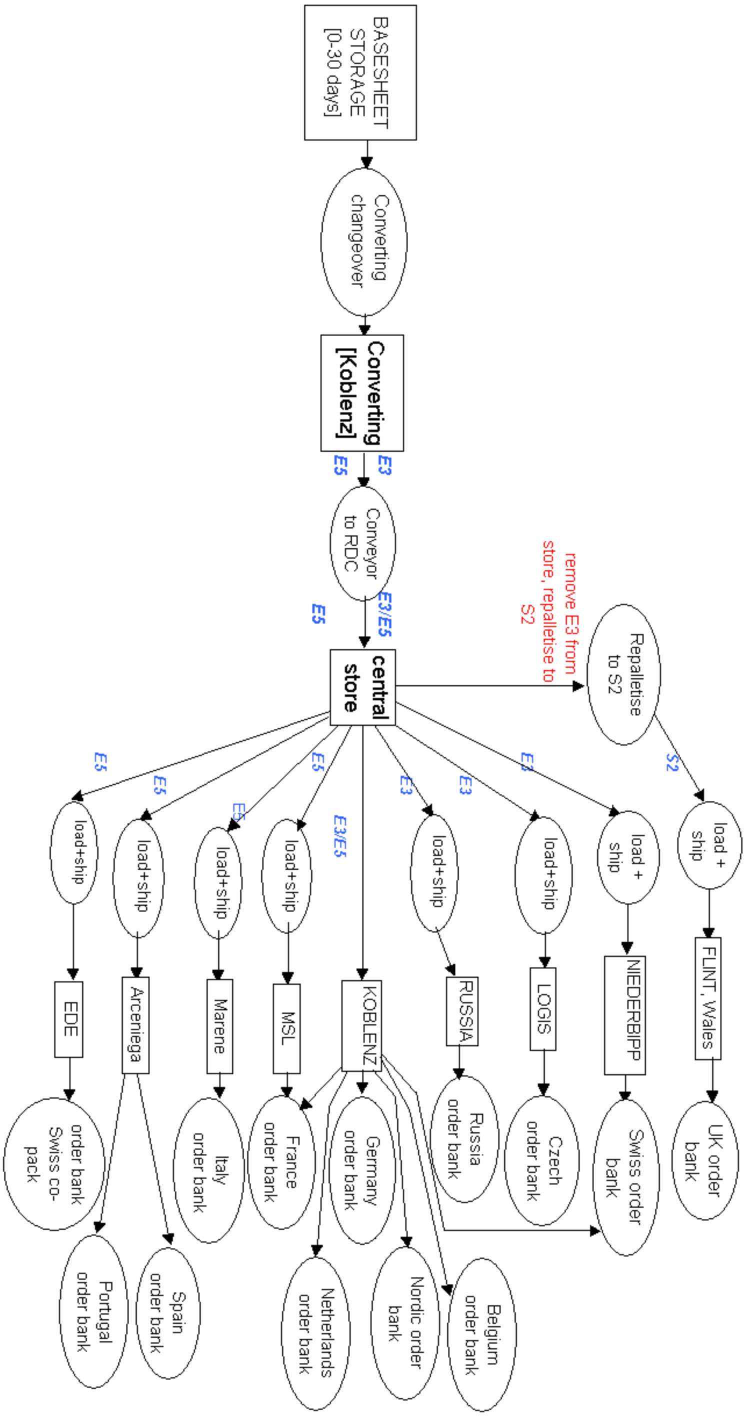


Figure 1: Paper tissue company product process flow

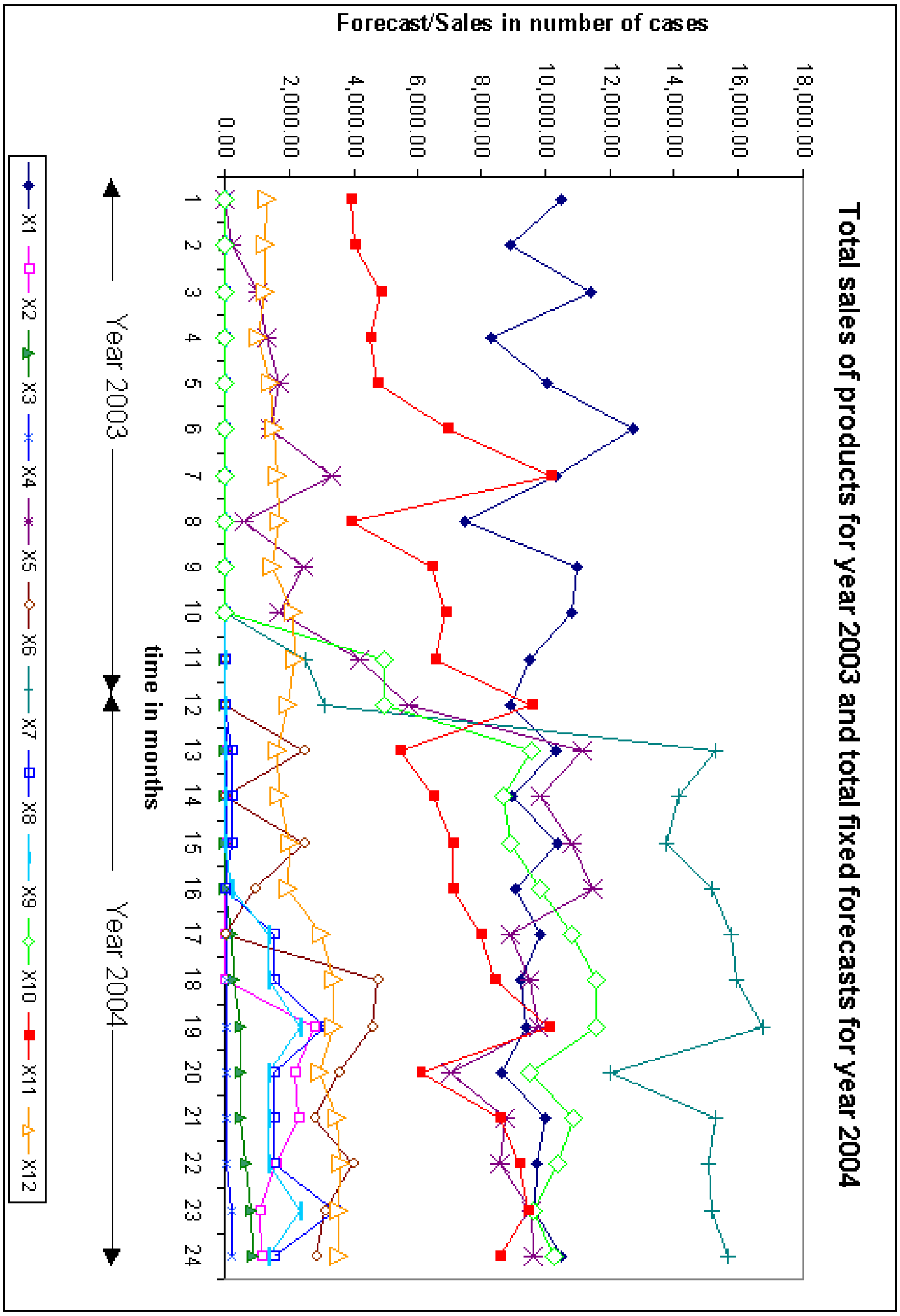


Figure 2: Total fixed forecasts for the different products for years 2003 and 2004

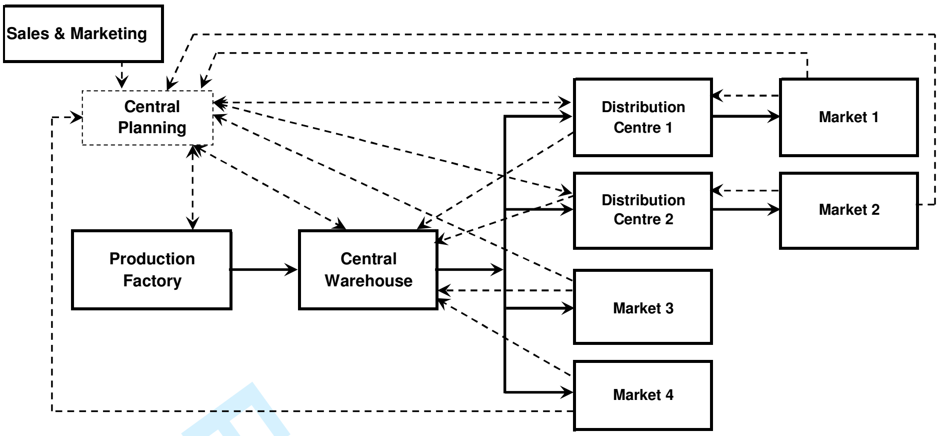


Figure 3: Centralised informational structure for the supply network

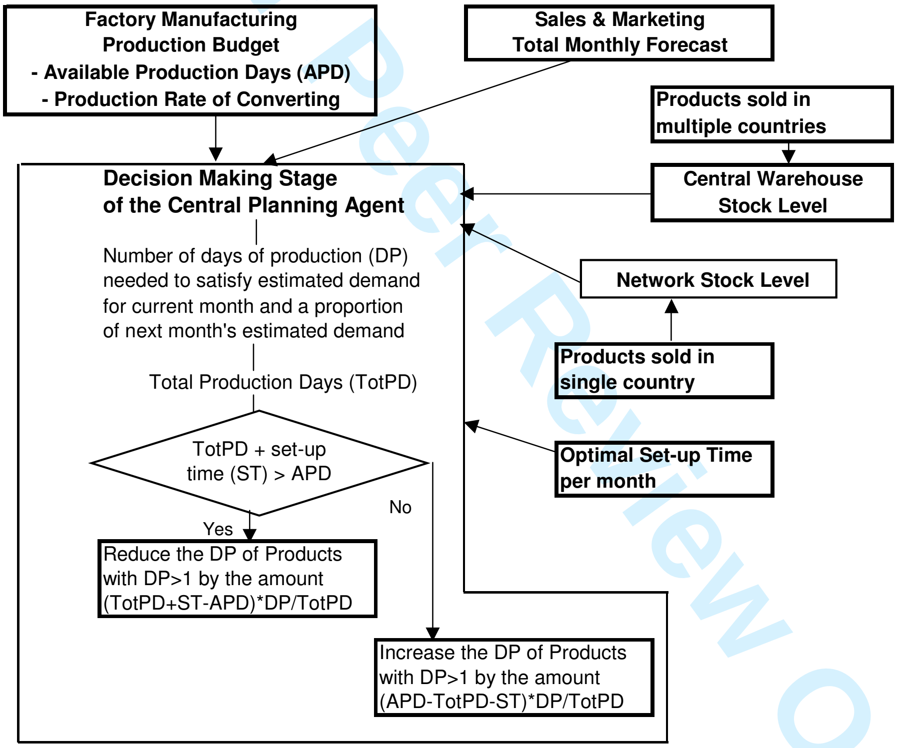


Figure 4: The planning process of the central planning agent

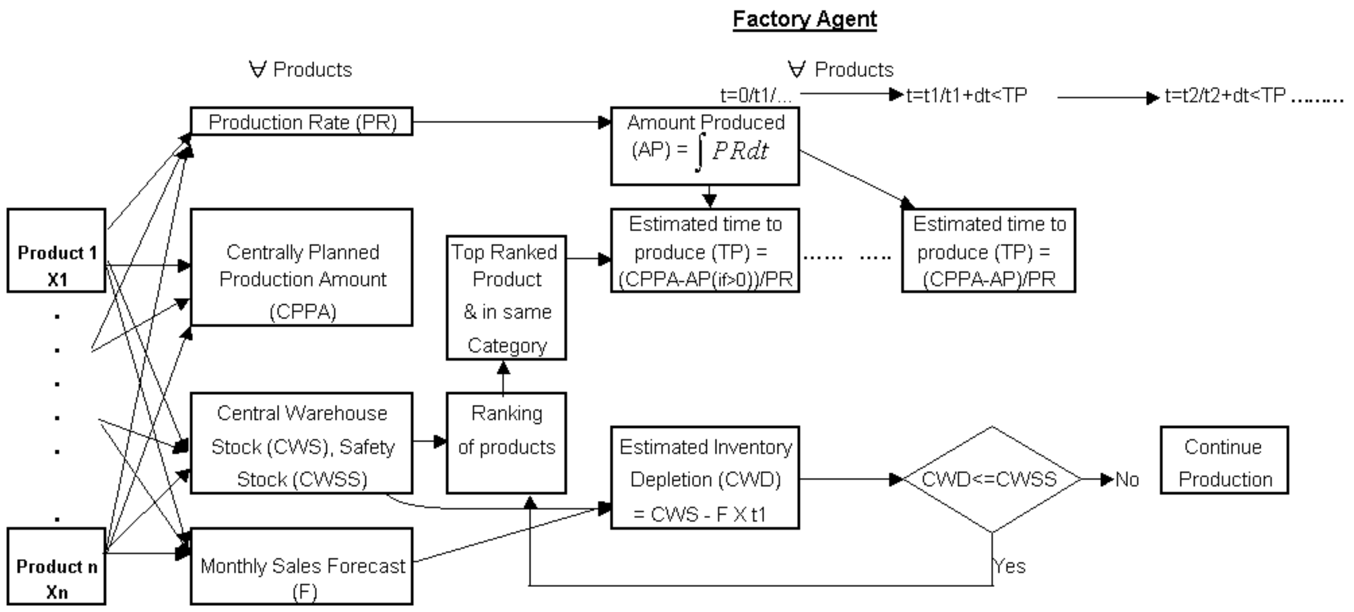


Figure 5: Monthly Production, Planning and Control by Factory Agent in Baseline Model

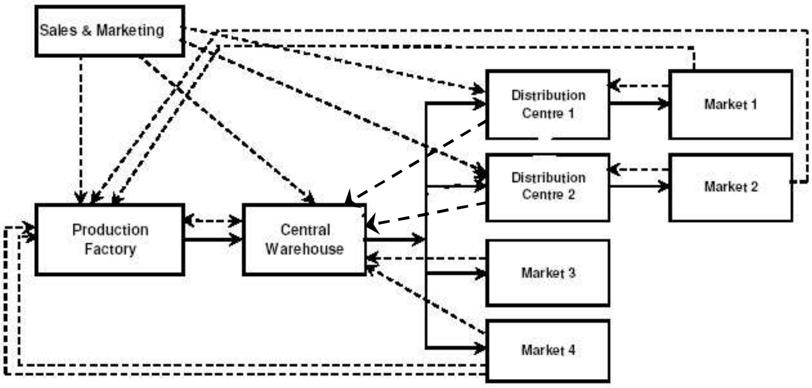


Figure 6: The information sharing mechanism for Model Configuration 3

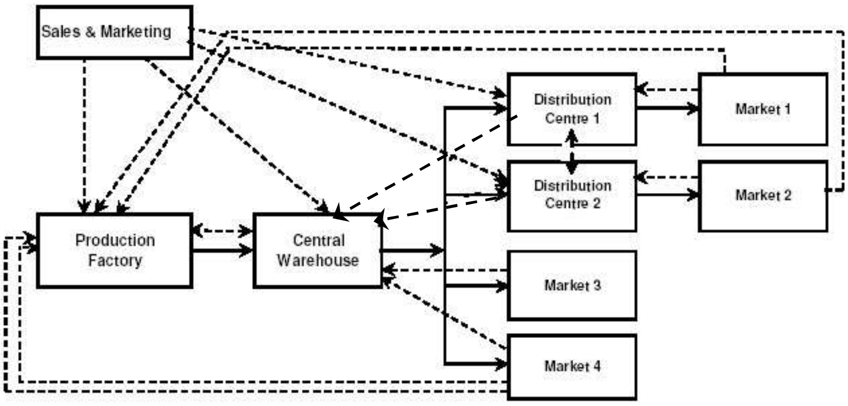


Figure 8: The information sharing mechanism for Model Configuration 4

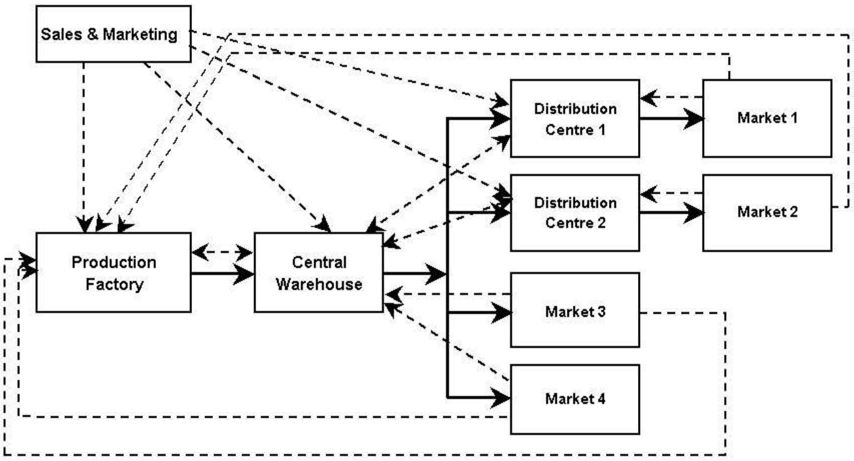


Figure 9: Decentralised informational structure for the supply network

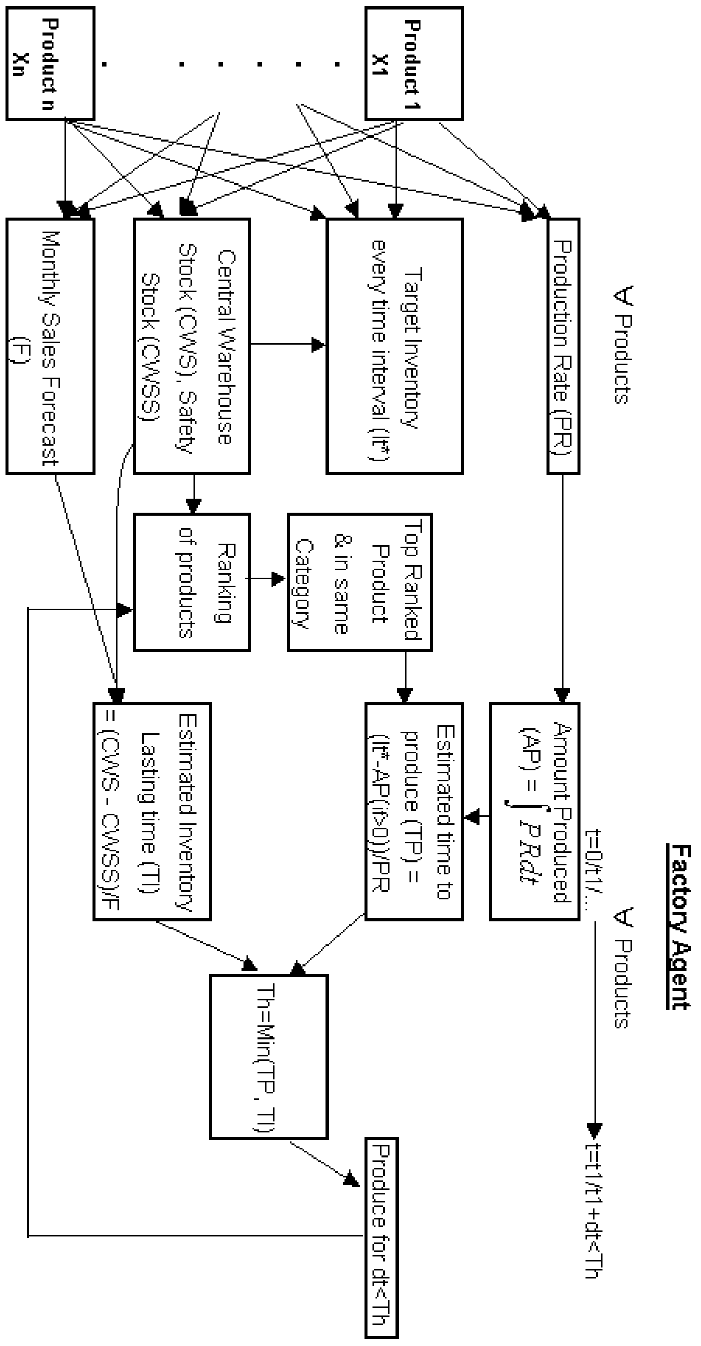


Figure 7: Decision making stage of the factory agent in Configurations 3 & 4

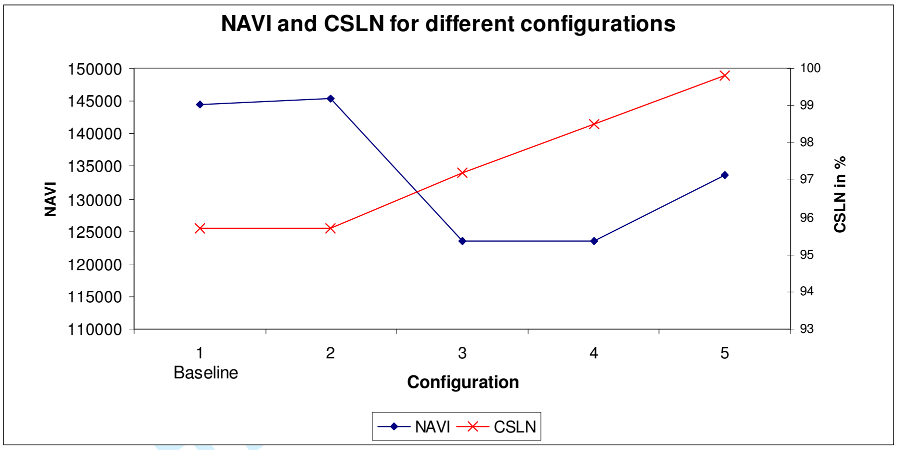


Figure 10a: NAVI and CSLN for different configurations

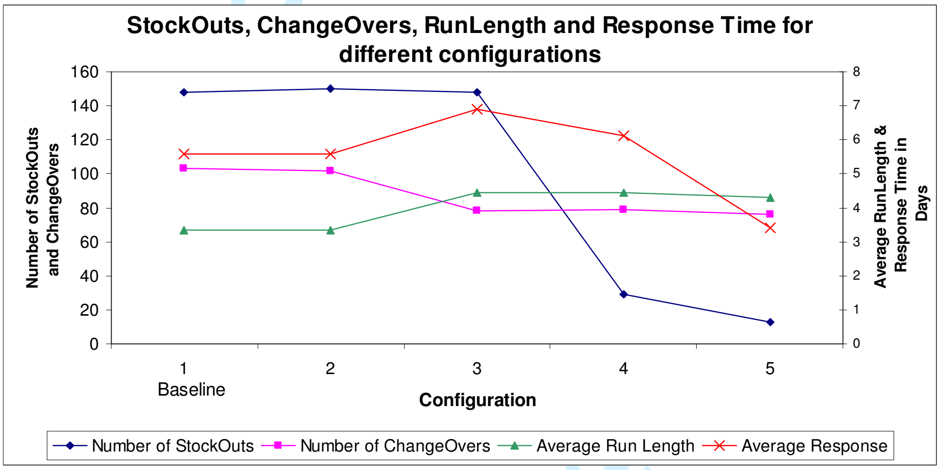


Figure 10b: Number of stockouts, changeovers, APR and average response time for different model configurations

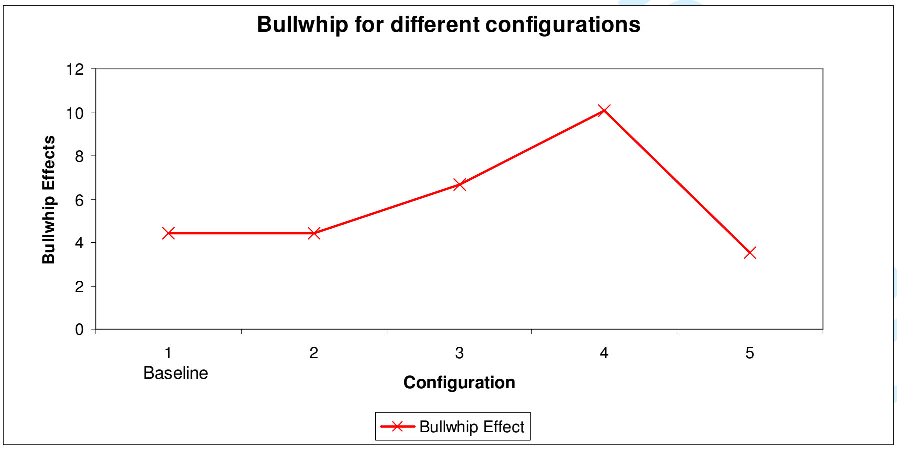


Figure 10c: Bullwhip Effects for different configurations

Table 1 Suitability of different approaches in addressing the research questions

Method	Description/ Critique	Assessment of suitability
Qualitative Research (Kenis and Knoke 2002)	Qualitative research methods of interviewing is necessary to identify certain best practices, people's opinions on certain practices	to address the research gap,the intentions of firms and the results of their collaborative or individual behaviour needs to be addressed and it is difficult to collect longitudinal data over a long time over the entire network
System Dynamics (Parunak et al., 1998; Owen et al., 2008)	Aggregate dynamic representation of systems Use of averaged parameters results in long term equilibrium Time and space invariant rules No representation of individual decision making Use of continuous material and order flows, while in reality flows are often discrete	Aggregate deterministic descriptions are limited in their ability to reproduce the behaviour of each individual member of the supply chain network and hence is not suitable
Optimisation Methods (Kafoglis, 1999; Blackhurst et al., 2005;Berning et al. 2002)	Central assumption that there exists an optimal set of solutions which either minimises costs or maximises profit This optimal set of solutions is time invariant Methods calculate the static equilibrium, which is not observed in reality Optimises technical parameters and does not explore each individual member's decision making process The abstractions and assumptions limit the extent to which the models reflect reality of complex inter-organisational relationships Is more suited for isolated system analysis and becomes mathematically intractable when integrated system needs to be considered	Traditional optimisation models have a different aim, which is to search for an optimal solution for a problem as opposed to exploration of behavioural dynamics essential for addressing the research gap
Discrete Event Simulation Models (DES) (Kelton et al., 2007; Yu et al., 2007; Pugh, 2006; Becker, 2006)	Used to understand the time-based behaviour of systems; a variable clock holds the time up to which the physical system is simulated; a data structure named event list maintains a set of events which control the activities; this form of simulation is event driven and all events occur chronologically Any processing in the model needs to be done only through the DES servers	The algorithm cannot be readily adapted for concurrent execution on a number of processors, since the event list cannot be partitioned for such executions The sequentiality is an impediment in modelling distributed systems such as the supply chain network, required for addressing the research questions Such type of models cannot be used in cases where decisions need to be taken at variable intervals and concurrently These models cannot model the decision points at very small intervals as it is very laborious and difficult to validate Interactions and intelligent decision rules are hard to model
ABM (Parunak et al., 1998; Jennings, 2001; Gjerdrum et al., 2001; Holland, 1995, 1998; Axelrod, 1997)	Disaggregate method of using local rules for individual computational entities representing each member of the supply chain Potential for introduction of diversity and adaptation into a computer model Explicitly models the decision making process for each agent	Extremely useful bottom-up methodology for addressing the research gap More closer representation of real world supply network possible as ABM allows more detailed in-depth representation of each member

Table 2: Monthly Sales and Forecast Figures for different products sold in German market

Products		Jan-04	Feb-04	Mar-04	Apr-04	May-04	Jun-04	Jul-04	Aug-04	Sep-04	Oct-04	Nov-04	Dec-04
X1	Forecast	1303	1065	1129	1112	1157	1007	1212	1063	1043	945	1113	1092
	Sales	1364	952	1087	1047	1040	1153	985	1126	1066	1246	937	822
X2	Forecast	0	0	0	0	0	0	1300	1040	800	800	500	250
	Sales	0	0	0	0	0	0	44	97	228	183	364	204
X5	Forecast	1191	1191	1191	1191	1200	1600	1650	1125	1500	1500	1800	1500
	Sales	2664	806	1819	1491	1396	1035	1419	1958	1372	1563	3185	1596
X6	Forecast	350	0	350	350	0	1300	1210	675	500	2000	1500	1357
	Sales	0	0	0	0	138	77	244	2103	825	1254	1793	1547
X7	Forecast	1401	1401	1401	2976	3400	3000	3300	2250	3000	3000	3000	3000
	Sales	2435	1820	3472	3373	2235	3565	3171	3029	2867	2744	3439	3044
X10	Forecast	699	699	699	1240	2251	2125	2035	1326	2140	2140	1600	1450
	Sales	507	2806	1504	1149	1344	2381	1575	1312	1117	2492	788	1070
X11	Forecast	702	1450	2000	1999	2146	2000	1980	1350	1800	1800	2500	1800
	Sales	2148	1786	1342	2104	1655	1745	1670	1707	3394	2119	3023	3024
X12	Forecast	102	157	300	302	300	300	264	177	350	350	350	350
	Sales	128	303	248	207	190	351	425	326	336	270	344	476

Table 3a: Validation Results - Inventory Figures

Product Code	RDC	RDC Average Inventory		
		Actual	Model	Difference
X5	UK	741	751	1.35%
X10	Koblenz	19784	19879	0.48%
X5	Niederbipp	195	175	10.26%
X2	France	309	312	0.97%
X7	Italy	4032	3487	13.52%

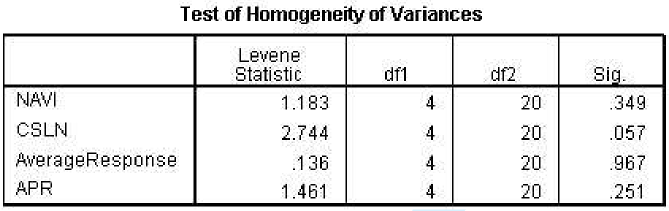
Table 3b: Validation Results - Production Figures

Product Code	Average Production Amounts		
	Actual	Model	Difference
X5	298	290	2.68%
X6	94	94	0.00%
X7	533	473	11.26%
X9	44	48	9.09%
X10	366	322	12.02%
X11	343	308	10.20%
X12	117	131	11.97%

Table 4: Experiment Formulation

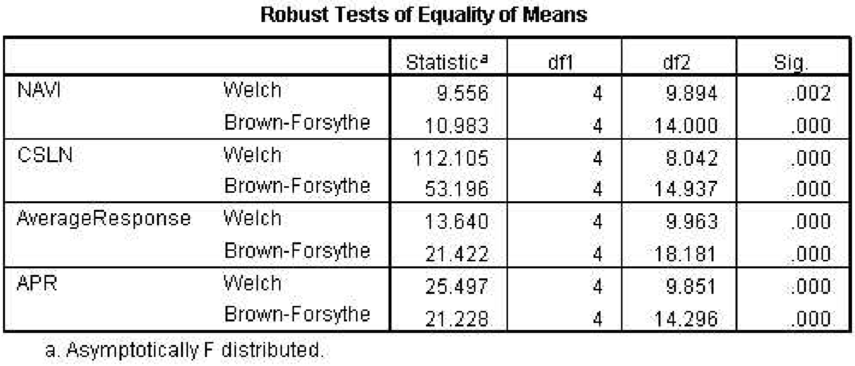
Configuration	Coordination Mechanism	Information Sharing
1, Baseline	1) Centrally coordinated material flow 2) Centrally controlled decision making	1) No information sharing among partners 2) Less Frequent (monthly) information flow for production planning
2	1) Centrally coordinated material flow 2) Centrally controlled decision making	1) No information sharing among partners 2) More Frequent (weekly) information flow for production planning
3	1) Centrally coordinated material flow 2) Decentralised individual decision making	1) Partial information sharing among partners 2) Very frequent (daily) information flow for production planning & safety stock adjustment
4	Joint material flow and decision making	1) Partial information sharing among partners 2) Very frequent (daily) information flow for production planning & safety stock adjustment
5	1) Centrally coordinated material flow 2) Decentralised individual decision making	1) Full information sharing among partners 2) Very frequent (daily) information flow for production planning & safety stock adjustment

Table 5a: Anova



Test of Homogeneity of Variances

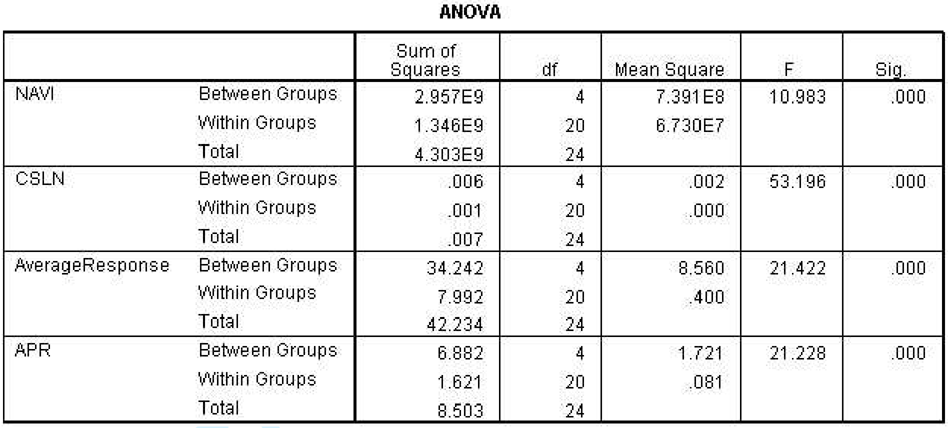
	Levene Statistic	df1	df2	Sig.
NAVI	1.183	4	20	.349
CSLN	2.744	4	20	.057
AverageResponse	.136	4	20	.967
APR	1.461	4	20	.251



Robust Tests of Equality of Means

		Statistic^a	df1	df2	Sig.
NAVI	Welch	9.556	4	9.894	.002
	Brown-Forsythe	10.983	4	14.000	.000
CSLN	Welch	112.105	4	8.042	.000
	Brown-Forsythe	53.196	4	14.937	.000
AverageResponse	Welch	13.640	4	9.963	.000
	Brown-Forsythe	21.422	4	18.181	.000
APR	Welch	25.497	4	9.851	.000
	Brown-Forsythe	21.228	4	14.296	.000

a. Asymptotically F distributed.



ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
NAVI	Between Groups	2.957E9	4	7.391E8	10.983	.000
	Within Groups	1.346E9	20	6.730E7		
	Total	4.303E9	24			
CSLN	Between Groups	.006	4	.002	53.196	.000
	Within Groups	.001	20	.000		
	Total	.007	24			
AverageResponse	Between Groups	34.242	4	8.560	21.422	.000
	Within Groups	7.992	20	.400		
	Total	42.234	24			
APR	Between Groups	6.882	4	1.721	21.228	.000
	Within Groups	1.621	20	.081		
	Total	8.503	24			

Table 5b: Tests of significance

Multiple Comparisons

Dependent Variable		(I) Config	(J) Config	Mean Difference (I-J)	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
NAVI	Tukey HSD	Baseline	2	-902.411	1.00	-16428	14623
			3*	21048.86	0.00	5523	36575
			4*	20959.77	0.01	5434	36486
			5	-2497.91	0.99	-18024	13028
CSLN	Tukey HSD	Baseline	2	4.2E-05	1.00	-0.01	0.01
			3*	-0.01466	0.00	-0.02	0.00
			4*	-0.02771	0.00	-0.04	-0.02
			5*	-0.04088	0.00	-0.05	-0.03
AverageResponse	Tukey HSD	Baseline	2	0.022324	1.00	-1.17	1.22
			3*	-1.31483	0.03	-2.51	-0.12
			4	-0.42653	0.82	-1.62	0.77
			5*	2.233866	0.00	1.04	3.43
APR	Tukey HSD	Baseline	2	0	1.00	-0.54	0.54
			3*	-1.092	0.00	-1.63	-0.55
			4*	-1.07	0.00	-1.61	-0.53
			5*	-1.05	0.00	-1.59	-0.51

*. The mean difference is significant at the 0.05 level.

Table 5c

NAVI

	Config	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a]	3	5	123471	
	4	5	123560	
	1	5		144520
	2	5		145422
	5	5		147017
	Sig.		1.000	.988

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

CSLN

	Config	N	Subset for alpha = 0.05			
			1	2	3	4
Tukey HSD[a]	2	5	.96			
	1	5	.96			
	3	5		.97		
	4	5			.99	
	5	5				.998
	Sig.		1.000	1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

AverageResponse

	Config	N	Subset for alpha = 0.05		
			1	2	3
Tukey HSD[a]	5	5	3.4		
	2	5		5.6	
	1	5		5.6	
	4	5		6.1	6.1
	3	5			6.9
	Sig.		1.000	.793	.212

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

APR

	Config	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a]	1	5	3.4	
	2	5	3.4	
	5	5		4.4
	4	5		4.4
	3	5		4.5
	Sig.		1.000	.999

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.