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Customized supply chain design: Problems and alternatives for a production company in the food industry. A simulation based analysis

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Abstract

In our paper, we point out that an analysis of a supply chain must be very product- (and company-) specific. For this reason, we suggest an improvement model that helps enhance the performance of a specific supply chain. In this context, we introduce a target system for supply chain evaluation which is necessary to analyze different improvement alternatives. We will show that the ideal robust supply chain setting depends on the demand situation (e.g., smooth, volatile). This model will be illustrated in detail. Hence, the present research studies a product-specific supply chain in the food industry, analyzes the effects of changes carried out and shows how demand uncertainties are dealt with. To measure and analyze the performance effects (e.g., work in process, lead time) of the supply chain configuration alternatives depicted, a simulation environment is developed.

Keywords: Supply chain design; Simulation; Food industry

1. Introduction

The current literature on Supply Chain Management describes the problems faced by supply chains and provides some answers. One key problem in nearly all supply chains is the so-called bullwhip effect. This phenomenon describes the situation where quite harmless fluctuations (variance) in the demand observed by a retailer (i.e., the last link in the supply chain) are amplified through the supply chain and cause heavy fluctuations (high variance) in the demand as noticed by manufacturers. There are different approaches to identifying the causes of this effect. Sterman (1989) sees wrong decisions made by human decision makers as the major cause of the bullwhip effect, while Lee et al. (1997) show that this effect occurs even in a supply chain where all decisions are made in a completely rational way. Notwithstanding these different approaches, it is obvious that the effect can be reduced by a shorter supply chain (i.e., a smaller number of elements), by better communication between the elements making up the chain and through the chance for the manufacturer to see the real (unaltered) customer demand (Lee et al., 1997; Sterman, 1989; Simchi-Levi et al., 2000).

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The main objective of problem-solving methods in Supply Chain Management is to reduce uncertainties. Sources of uncertainty are, e.g., the forecast horizon, input data, administrative and decision processes, and inherent uncertainties (Van der Vorst et al., 1998). In the context of Supply Chain Management, improvements to the communication and information exchange between the supply chain partners occupy a key position. Various management concepts such as, for example, vendor-managed inventory (VMI), continuous replenishment program (CRP), and collaborative planning, forecasting, and replenishment (CPFR) take this circumstance into account. These methods differ in the visibility of the whole supply chain. VMI, e.g., has only a limited visibility of inventory levels in the customer's main stockholding facility. On the other hand, CPFR makes possible a total visibility of the supply chain up to point of sale (POS) data. In particular, the efficient consumer response (ECR) initiative promoted the development and implementation of these concepts in the retail and food industry (Barratt and Oliveira, 2000). The dilemma of many production companies supplying retail chain companies is that classical supply chain improvement concepts are not always supported by retailers or do not show the expected results. Other factors generally encountered are that centralized planning is not possible or suitable and, thus, the decentralized coordination of supply chains leads to difficulties. The manufacturer has to fulfill the order of the retail chain company without knowing anything about the inventory policy adopted by the companies involved in the supply chain (e.g., retailer, wholesaler) so that point of sales data is not always helpful. Topical research studies compare the benefits of information sharing with lead time and batch size reduction. The results obtained show that in some supply chain settings the reduction in lead time or batch size can have a greater impact on supply chain performance than information sharing (Cachon and Fisher, 2000).

One can reduce uncertainty by information sharing, lead time reduction, etc. (see above), but it is not possible to avoid uncertainty. Therefore, robust planning is required to handle uncertainty in the supply chain. Recent relevant literature argues that there is a need for robust supply chain planning at a tactical level so as to be able to deal with uncertain consumer demand (Van Landeghem and Vanmaele, 2002). In our research, we use robust supply chain planning (based on a supply chain simulation) at a strategic level (supply network design, layout), too. There are some interdependencies between the strategic and the tactical level. Advanced planning and scheduling software (APS) uses deterministic approaches (LP models and finite-capacity heuristics) to find an optimum. Deterministic approaches lead to problems in an uncertain environment, while a robust plan should stay valid in many possible situations. To guarantee a robust solution, we analyze the supply chain and estimate important parameters (distribution of customer orders, decision rules in the supply chain, layout of the supply chain, etc.) and build a specific simulation model of the supply chain. We use this simulation model to guarantee that our solution produces favorable results in many possible situations (simulation runs).

Additionally, we point out that an analysis of a supply chain must be very product- (and company)-specific. For this reason, we develop a method for this specific analysis which uses a target system for supply chain evaluation required for analyzing different improvement alternatives. We will show that the ideal robust supply chain setting depends on the demand situation (e.g., smooth, volatile). For this purpose, we study in detail a specific supply chain in the food industry (pasta), analyze the effects of changes made and show how demand uncertainties are dealt with. To measure and analyze the performance effects (e.g., work in process, lead time) of the supply chain configuration alternatives depicted, a simulation environment is developed. We analyze in detail the pasta producer's perspective so as to be able to model his behavior in the supply chain.

2. Supply chain design

It is a matter of fact that even within the same industry the supply chains of companies significantly differ from each other. Hence, improvements achieved in the supply chain of one company do not guarantee the same results for another firm. Savings made by one company can, however, serve as a rough estimate for other enterprises with similar supply chains. To obtain a valid estimate for a specific supply chain, this chain must be analyzed in detail. The analysis conducted in this work is based on the main performance measures of supply chain management.

The big challenge in evaluating the possible improvements of supply chain results lies in the complex structure of such a chain. All its processes are highly interconnected; no parameter can be changed without another one being modified as a consequence. Reducing inventory will decrease storage cost, but it might also reduce service level, work in process (WIP) and working capital. According to Little's Law (Hopp and Spearman, 1996), a reduction in lead time reduces also work in process (WIP). It is therefore obvious that the problem described, i.e., to obtain a valid estimate for a specific supply chain, cannot be solved analytically, since the supply chain partners may use different order policies (e.g., (s, Q), (t, S)), whereas we wish to analyze stochastic consumer demand with different distributions as products are sold, for example, under unsteady pricing conditions.

Here, we want to introduce a procedural model (see Fig. 1) which can help to improve customized supply chain design. Starting points for the analysis of an existing supply chain are changes in the supply chain strategy or in the corporate strategy of a supply chain partner, or a continuous improvement cycle (e.g., every year). To analyze different improvement alternatives, it is necessary to establish a target system for supply chain evaluation. The product-specific consumer requirements are related to the characteristics (e.g., functional or innovative) of the finished product (Fisher, 1997). These characteristics should be the basis for developing an adequate supply chain strategy (agile, lean or, a combination of both, "leagile") for the whole supply chain. This strategy is intended to influence the selection of market winners and qualifiers out of the pool of relevant performance measures such as, e.g., quality,

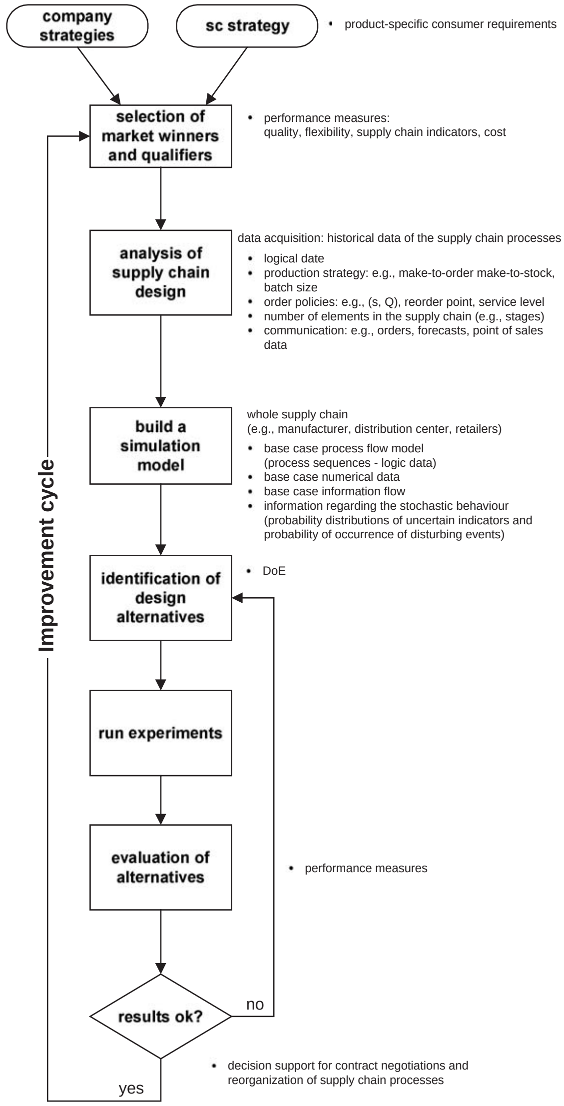

Fig. 1. Product-specific supply chain design model.

flexibility, supply chain indicators and cost. Hill (1994) delivered the basis for this classification in that he developed the concept of "order qualifiers" (baseline for entering into a competitive area) and "order winners" (specific capabilities to win the order). The wider supply chain-oriented concept of "market qualifiers" and "market winners" has been developed by Christopher and Towill (2000). Supply chain indicators can be divided further into direct indicators that can be seen by the supply chain partners (e.g., lead time, service level) and indirect indicators (e.g., work in process, cycle time variability, safety capacity, inventory) which are relevant but not visible to the supply chain partners. Therefore, market winners can be chosen only from the pool of direct supply chain indicators. However, it is obvious that there are dependencies between direct and indirect supply chain indicators. Christopher and Towill (2000) suggest market winners corresponding to the chosen supply chain strategy. A market winner for an agile supply chain is the service level (availability), for a lean supply chain it is cost and for a "leagile" supply chain it is lead time.

At this level of the analysis, it is essential that all data of the whole supply chain network be available. The analysis of the supply chain design can be carried out on the basis of historical data (e.g., of the last year). This includes the collection of logical data (e.g., process flow diagrams), POS data but also order policies (parameter: reorder point, service level ⇔ safety stock), production strategy (make-to-stock, make-to-order, batch size, service level) and the number of elements in the supply chain. In case one partner in the supply chain (e.g., a retail chain company) has problems in sharing information because of its restricted information-sharing policy, the analysis can be carried out on the basis of historical data.

The next step consists in building a simulation model of the whole supply chain. It contains: a base case process flow model (logical data) and numerical data, stochastic behavior of uncertain indicators as well as disturbing events and information flow. After the validation has been effected, the simulation environment can be used to evaluate different supply chain design alternatives.

Therefore, the next step is the identification of design alternatives. This includes the design of experiments (DoE), i.e. the range of each decision variable (such as the variation of number of elements in the supply chain, batch size, reorder points, or target service level) and company-specific process as well as supply chain process alternatives (e.g., process flow model).

After running these experiments using simulation (with sufficient replications $\geqslant 20$), the effects of changes in the setup of a product-specific supply chain design on the overall work in process, fill rate (service level) and times (e.g., cycle time), which are the key supply chain indicators for some industries, can be studied in detail. It is obvious that there are dependencies between these key supply chain indicators and other performance measures (cost, quality, flexibility). The market winners must be selected out of this set of performance measures. This market winner performance measure triggers the evaluation of supply chain design alternatives, which should provide decision support for contract negotiations between supply chain partners and for the reorganization of supply chain processes. If the obtained results are not satisfactory the design alternatives have to be refined and simulated again.

However, also improvement alternatives at the level of the business processes of a company involved in the supply chain, which change the input parameters of the simulation model, may be evaluated. In our case study (Section 3), the main focus is on the manufacturer's point of view. Consequently, a simulation model for the production process is necessary that can be used to generate the manufacturer input parameters for the supply chain simulation model (Section 4), too. On the one hand, we use the process simulation tool ProcessModel to simulate in detail the manufacturer's production and order fulfillment processes and, on the other hand, we use Matlab to simulate the supply chain. ProcessModel combines flowcharting, process modeling with animation and simulation of process executions and makes a discrete event simulation possible which enables "what-if" analyses. ProcessModel is a process engineering tool for visualizing, analyzing, and improving business processes (McPherson and Munro, 2000). Comparable simulation tools, which can be used for process simulation, are CACI International Inc.'s SimProcess, Process Simulation Applications suite (former Tecnomatix Technologies Ltd.'s SIMPLE++), Systems Modeling Corp.'s Arena, etc. Matlab is a mathematics analysis and calculation tool that uses mainly vector and matrix analysis to solve mathematical and technical problems. For our supply chain simulation, we chose Matlab because of its simple programming language and the availability of mathematical and statistical functions (Mathworks, 1998).

Supply chain design alternatives may have different requirements as regards the visibility of the supply chain. Restrictions due to the company specific strategy of supply chain partners involved (e.g., retail chain companies) reduce the set of alternatives. We can observe differences concerning supply chain structures (two stages, three stages), inventory policies (reorder point policy under periodic review, reorder point policy under continuous monitoring), changes of the production process parameters (reorder point, batch size) and process management (make-to-order, make-to-stock).

3. Case study

The company described is a medium-sized enterprise in the food industry which faces supply chain management problems typical of food chains (Fransoo and Wouters, 2000). The firm manufactures primarily a large variety of pasta products and is working in a very competitive environment, since Italian producers try to enter the pasta market under study. Its main customers are, on the one hand, a small number of large retail chain companies and, on the other hand, many small retailers. Thus, the company is dealing with several different lean supply chain networks. In such partnerships, the retail chain companies occupy a dominant position. So, the measures crucial to the firm in question are the product price (cost, market winner), on-time delivery and flexibility. However, since the information-sharing policy of the retail chain companies is very restrictive, the practical realization of a win–win situation cannot be achieved by adopting prominent supply chain management concepts such as, e.g., CPFR. This means that it is not possible to realize the reduction, or even elimination, of uncertainty in the supply chain networks through information-sharing improvements made by the operative management.

The pasta producer can be characterized by flow shop oriented production design, sequence-dependent setup times and a divergent flow. Limited shelf life does not play an important role, because the durability of the finished product is more than 1 year.

3.1. Manufacturer model

Using ProcessModel, we developed a simulation model for the production and order fulfillment by the pasta manufacturer. The purpose of this model is to conduct experiments regarding these processes. The model can be used to quantify relevant performance indicators and to evaluate them.

The following steps are carried out to build the simulation model. The first step is to gather and validate the data used to define the model. Data are of two types, i.e. logic and numeric. Logic data define the process sequence and how decisions are made, which can be illustrated via flowcharts. Numeric data define demand, activity times, etc. The second step consists in constructing the simulation model and in the model validation. The third step is to conduct the experiments planned.

In our simulation setting, the production process is modeled as a make-to-stock process (see Fig. 2) with a reorder point heuristic under continuous review (Cachon, 2001). This is a simplification of reality, because for some products (10%) the food manufacturer adopts a make-to-order strategy. However, normally the lead time of a make-to-order process is longer than the delivery time requested. Therefore, make-to-stock (lead time zero, Hopp and Spearman, 1996) is the standard production strategy for the pasta producer. Furthermore, in many cases, reorder point heuristics probably are not optimal, but they are simple to implement and intuitively reasonable, and they are optimal in a serial supply chain with batch ordering (Chen, 1997).

In detail: The manufacturer receives orders (batch ordering) from his customers (distribution centers or retailers). The manufacturer uses a reorder point (s_m) policy to place his internal production orders for a batch size (Q_m) or an integer multiple (X) of this batch size ($S_m = Q_m \times X$; $X \leqslant OB/Q_m + 1$), if the finished-good inventory (I_f) $\leqslant s_m$ and orders are not filled of

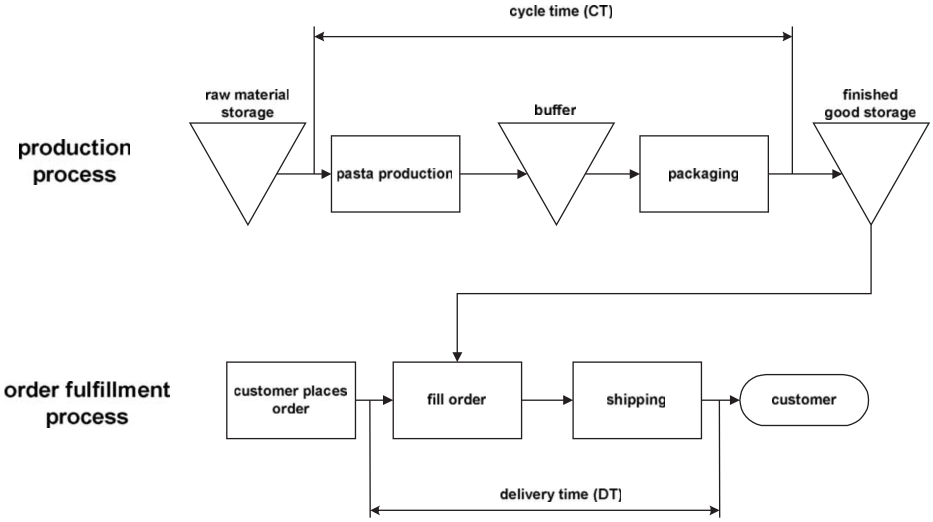

Fig. 2. Process flow diagram.

an ordered batch $(OB) \geqslant Q_m$. The upper limit of this new batch size (S_m) is the maximal free capacity of the buffer. If the manufacturer is able to fill the order, he ships the products immediately. If he is out of stock, the products are shipped as soon as possible. In any case, delivery must not take longer than 1 week for each product ordered. The manufacturer replenishes his inventory from perfectly reliable sources; therefore, the goods ordered from the supplier are always received after a constant lead time.

The collection and validation of numeric data are based on sales statistics of the company in question. We applied an ABC-XYZ classification method to cluster the products (Zäpfel, 1996). Different production strategies and supply chain structures on the basis of these nine (AX, AY, …) categories are suggested.

The ABC-XYZ classification method is an extension of the classical ABC method. Reasons are that a classification need not be done on the basis of the distribution by value curve alone (Silver et al., 1998). The ABC-XYZ classification method takes value and variability of demand into account (e.g., coefficient of variation of weekly demand). Class *X* products are characterized by a low coefficient of variation (e.g., standard deviation/mean $<\frac{2}{3}$), class *Y* products by a medium coefficient and class *Z* products by a high coefficient of variation.

For our simulation model, we choose one AX product for which we fit an analytical distribution (see Table 1). The whole product range is equally taken into consideration but only on an aggregate level.

3.2. Results

Now, we are able to conduct the experiments planned. We start with a demand situation which leads to a utilization (u) of the bottleneck resource of approximately 60% and choose the reorder points (s_m) so that the manufacturer offers a target value of 98% immediate fill rate (= service level of the manufacturer—SL_m) in scenario 1 or a 91% SL_m in scenario 11, which represent the starting points of our experiments. Additionally, we conduct some experiments with a utilization (u) of the bottleneck resource of approximately 80% (see Table 2 and Fig. 3).

We use a simple heuristic to choose the adequate batch size (Q_m) of 3000 kg (6000 products × 0.5 kg average product weight), which utilizes the bottleneck activity of the production process for one 8-hour shift. The simulation results show for scenarios with an s_m value of 4820 kg

Table 1
Fitted analytical distribution

Product category	Number of demand weeks	Demand/week mean (M_CD)	Demand/week (standard deviation) std(M_CD)	Variation coefficient (CV)	Demand distribution (DD)	Kolmogorov–Smirnov test (p-value)
AX	52	4282 kg	1228 kg	0.29	Normal	0.357

Table 2
Manufacturer alternatives

Scenario	Input parameter			Output parameter					
	Q_m (kg)	s_m (kg)	u (%)	CT	std (CT)	WIP_m (kg)	std (WIP_m) (kg)	SL_m	std (SL_m)
1	3000	4820	60	2.39	0.60	8031	838	0.98	0.00
2	1500	4820	60	2.24	0.59	8174	691	0.98	0.01
3	6000	4820	60	2.47	0.56	9603	752	0.99	0.00
4	9000	4820	60	3.66	0.66	10,621	1335	0.98	0.00
5	12,000	4820	60	4.79	0.63	12,242	988	0.96	0.02
6	3000	4820	80	3.21	0.93	10,364	1538	0.95	0.06
7	1500	4820	80	3.02	0.84	9711	1300	0.96	0.04
8	6000	4820	80	3.29	0.80	12,655	1454	0.98	0.03
9	9000	4820	80	4.50	1.11	13,866	2054	0.97	0.04
10	12,000	4820	80	5.20	0.93	16,346	1704	0.96	0.03
11	3000	3340	60	2.43	0.69	6640	680	0.91	0.01
12	1500	3340	60	2.14	0.40	6351	155	0.85	0.02
13	6000	3340	60	2.66	0.64	8128	732	0.94	0.02
14	9000	3340	60	3.54	0.70	9488	647	0.95	0.02
15	12,000	3340	60	4.88	0.66	10,793	818	0.93	0.02
16	3000	3340	80	3.01	1.00	9298	853	0.88	0.04
17	1500	3340	80	2.96	0.79	8578	480	0.85	0.03
18	6000	3340	80	3.22	0.82	11,082	1243	0.92	0.05
19	9000	3340	80	4.42	0.77	12,785	1241	0.93	0.03
20	12,000	3340	80	5.10	0.86	14,843	1263	0.91	0.04

(see Table 2 and Fig. 3) that the work in process (WIP_m) for scenario 1 is at the lowest level. These results are not significant exceptions because scenarios 7, 12 and 17 show that a reduced Q_m could decrease the WIP_m as compared to the standard batch size (3000 kg). WIP_m is defined as the average inventory between the pasta production and its shipping to the customer (see Fig. 2).

Although, due to high standard deviations (std), no significant results are obtained, a certain trend can be observed. An integer number of batches show improved SL_m results in a small range of batch sizes. On the one hand, not in all scenarios can a high WIP_m be correlated with a high SL_m and, on the other hand, it is comprehensible that there is a relationship between Q_m and cycle time in days (CT). When comparing, e.g., scenarios 1 and 4, one note that both scenarios have the same service level, but WIP_m of scenario 4 is approximately 30% higher than in scenario 1.

The simulation results can be used to determine the most appropriate values of decision variables (e.g., batch size, reorder point), which yield the required level of performance (service level).

In general, the simulation results[1] show that the manufacturer has only some traditional possibilities to improve the performance measures

[1] In our simulation, we used 25 repetitions of each run to get a picture of the result fluctuations.

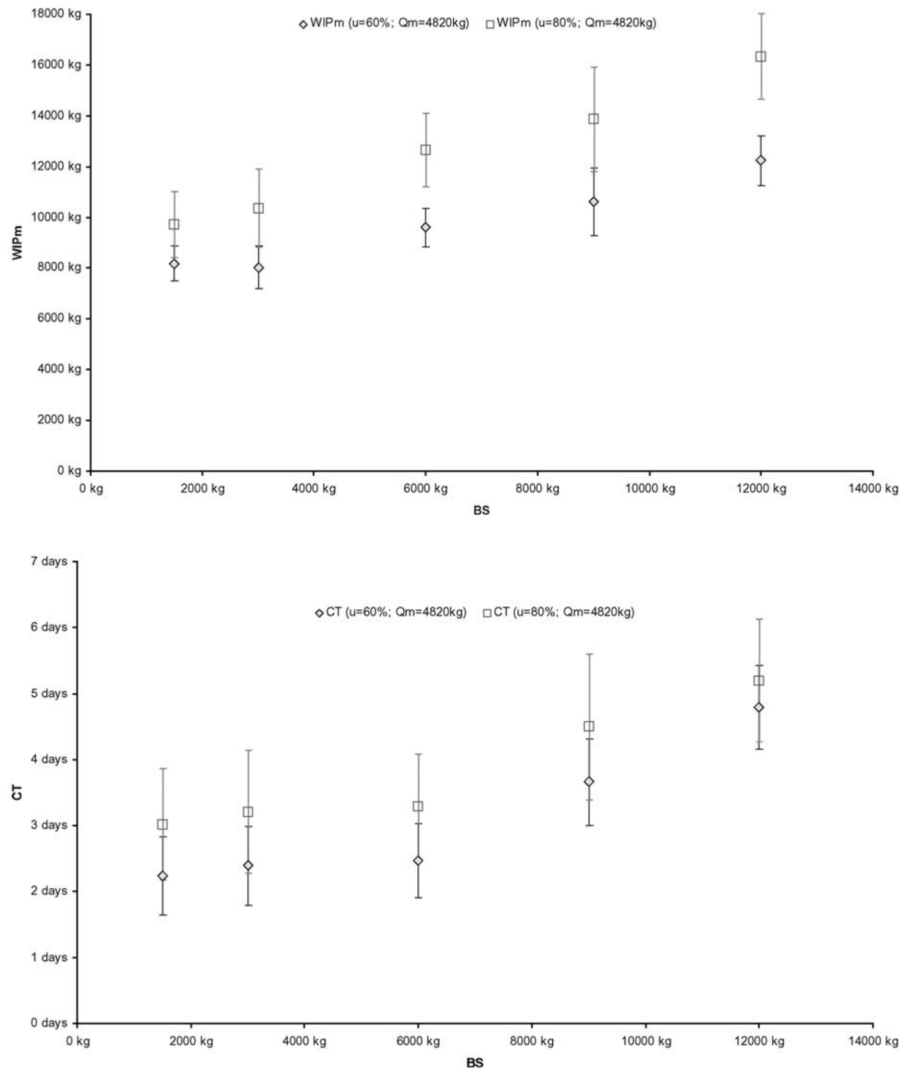

Fig. 3. Selected simulation results (mean and standard deviation).

illustrated by varying the input parameters, under the terms of a make-to-stock process layout. Another fundamental possibility would be to choose a demand-driven production strategy for some products (Lin and Shaw, 1998). This strategy would also affect the customers of the company under consideration e.g., through longer delivery times. Due to the existing dependencies, it is not possible to analyze one factor alone, but the effects on the whole supply chain must be taken into consideration. This is one of the reasons why we have to build a simulation model for the whole supply chain network, which allows a look at more substantial improvement alternatives.

4. Detailed analysis of a specific supply chain

Here, we show that the ideal (robust) design of a supply chain depends on the characteristics of the product and of the companies involved in the supply chain. We use the method described above (Section 2) to study one specific improvement alternative and show that for different demand patterns different layouts of the supply chain are favorable. We analyze one specific improvement alternative for illustrating our method. As the decision which improvement alternative should be tested is very supply chain-specific, we examined alternatives suggested by the pasta manufacturer in question.

To explain the evaluation framework, it is necessary to point out that the product under consideration is a standard (functional) product. But due to price promotions, it is possible that demand variability is very high. In general, a standard product goes well together with a lean supply chain, as the measure "cost" (market winner) is very important. In our example, WIP is an important supply chain indicator with a direct impact on costs and must be reduced; simultaneously, the service level, being a market qualifier, should remain unchanged.

To perform our simulation for the whole supply chain network, we simulated the behavior of retailers and of the distribution center via Matlab and used our manufacturer simulation environment (see Section 3) to analyze the producer. There is a lot of literature available on two-echelon models with stochastic demand and order batch sizes, which assume retailers may order each period (Van der Vorst et al., 1998). Such papers can be used to study the relationship between batch size and supply chain performance, but they do not analyze how the supply chain design influences manufacturer performance as they do not study the manufacturer processes in detail.

As we had no information on the consumer demand seen by a single retailer, we used the demand observed by the producer (total demand for the product) to generate artificial retailer demand. On the basis of real-life data of the company in question, we generated two different distributions to model the artificial demand the retailers had to fulfill per day.

The demand observed by the producer was available on a weekly basis since the producer plans on such a basis, and all scheduling decisions and customer-specific deliveries are done once a week. So, we had to perform two tasks:

- distribute the total weekly demand to get the daily demand;
- distribute the total daily demand to the retailers.

As we had no additional information on seasonality and the size of single retailers, we used uniform distributions to divide weekly demand and total demand to retailers.

Following this approach, we generated two sets (smooth and volatile demand) of customer demand distributions:

1. *Generate total demand*

Through the information on the real distribution of product AX (see Table 1), we generated a set of 50 (number of simulation runs in the supply chain simulation) weekly demands using a normal distribution with the parameters $\mu = 4282$ and $\sigma = 1228$ for the smooth demand. To generate the volatile demand, we used the same mean demand but a standard deviation of 16,000. If the distribution generated values lower than zero for 1 week, we replaced demand by zero.

2. *Distribute weekly demand to days*

Using a uniform distribution, we generated six numbers for each week (one for each day) and, proportional to this number, assigned the demand of each week to the 6 days. Example 1 shows this process.

Example 1: Distribution of demands
Weekly demand = 4312
Random number for days:

1	0.5726043
2	0.31914889
3	0.72081334
4	0.85098355
5	0.79438343
6	0.99466277
Σ	4.25259628

Daily demand:

$1 = (4312/4.25) \times 0.57$	580.60
$2 = (4312/4.25) \times 0.32$	323.61
$3 = (4312/4.25) \times 0.72$	730.88
$4 = (4312/4.25) \times 0.85$	862.87
$5 = (4312/4.25) \times 0.79$	805.48
$6 = (4312/4.25) \times 0.99$	1,008.56

3. *Distribute daily demand to 50 retailers.*

Using a uniform distribution, we spread out the demand of each day to 50 retailers (using the procedure of step 2).

4.1. Three-stage supply chain

In this setting, 50 retailers receive daily orders from their consumers and use a fixed reorder cycle (reorder time (t) 6 days–1 week) and a variable reorder quantity (S_r) policy to determine the orders to place with their supplier, the distribution center (see Fig. 4).

The orders placed by the retailers are transmitted to the distribution center. If the DC is able to fill the order, it ships the products immediately within a fixed delivery time of 2 days. If it is out of stock, it ships the product as soon as possible. The DC reports to the producer and receives its supplies within 1 week. The distribution center uses a reorder point (s_d) policy to place its orders with the producer. If the number of products on stock falls below s_d, a fixed order quantity (Q_d) will be ordered. If the fictive stock (products on stock + products expected to be received in the future—customer orders) is negative, a multiple (X) of the order quantity ($S_d = Q_d \times X$) will be ordered. To guarantee an average service level of 98% for the retailers and a service level of 98% for the distribution center, we identified an S_r of $\leqslant 1000$, an s_d of 20,000; an $S_d \in \{20,000; 40,000\}$ and an s_m of 42,000 ($S_m = 3000 \times X$; see Section 3) for the volatile demand and an S_r of $\leqslant 200$, an s_d of 20,000 and an s_m of 30,000 ($S_m = 3000 \times X$; see Section 3) for the smooth demand.

4.2. Two-stage supply chain

To simulate the two-stage supply chain, we used a similar setting. We modeled the retailers using Matlab and the producer using ProcessModel. The retailers are modeled like those in the three-stage supply chain. They reported their demand (using a variable reorder quantity s_r) to the manufacturer. We analyzed the behavior of the supply chain for different producer delivery times. To guarantee a retailer service level of 98%, we found an S_r of $\leqslant 2000$ (6 days fixed delivery time) and an s_m of 54,480 ($S_m = 3000 \times X$; see Section 3) for volatile and an S_r of 180 (4 days fixed delivery time) and an s_m of 4300 ($S_m = 3000 \times X$; see Section 3) for smooth demand (see Fig. 5).

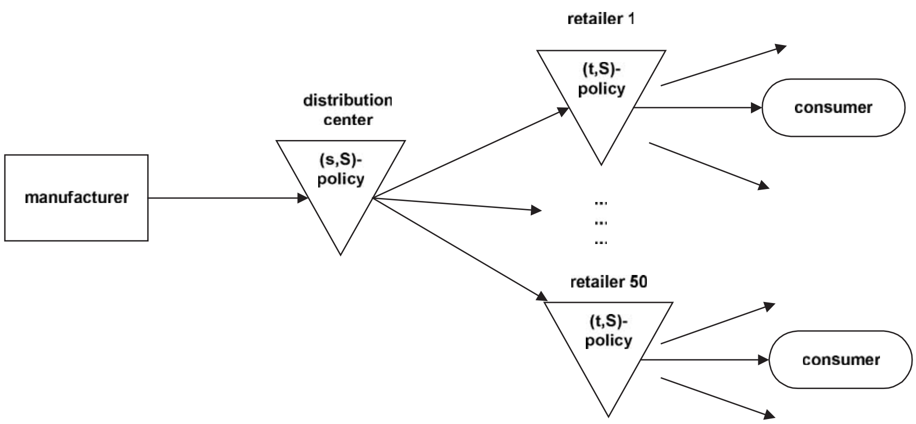

Fig. 4. Three-stage supply chain.

4.3. Results

Table 3 displays the results found in our simulation experiments. It shows the work in process at each stage of the supply chain (manufacturer (WIP_m), distributor (WIP_d) and retailer (WIP_r)) as well as the service level (SL_d, SL_r) at this stage. In scenarios 1 and 3, the supply chain is operated as illustrated above (three-stage supply chain; see Section 4.1) and in scenarios 2 and 4, it is operated without a distribution center (two-stage supply chain; see Section 4.2).

While in a situation with smooth demands, a shorter supply chain (no distribution center, scenario 2) means lower work in process (WIP =12,055) as compared to a three-stage supply chain (scenario 1, WIP =61,427), the streamlined supply chain leads to worse results for volatile demands. Scenario 1 (smooth demand) shows how the bullwhip effect increases WIP of the distribution center and WIP of the manufacturer (see Table 4). Hence, for smooth demands the simulation shows the best results for the two-stage supply chain.

Scenario 3 (volatile demand) illustrates how the pooling effect caused by the distribution center reduces the overall WIP. In comparison to scenario 4, a win–win situation (lower WIP) for the manufacturer and the retail chain company (distribution center + Σ retailer) can be realized.

In the food chain under study, the retail chain companies are not willing to implement an everyday low price strategy. Therefore, for many products consumer demand variability is high and must be managed through the supply chain. In such a case, in our simulation environment a three-stage supply chain shows the best performance.

Finally, we analyze in detail the bullwhip effect mentioned. We calculate a measure (W) that shows how demand is amplified at each echelon (W_m = manufacturer, W_d = distribution center, W_r = retailer). We measure the bullwhip effect at

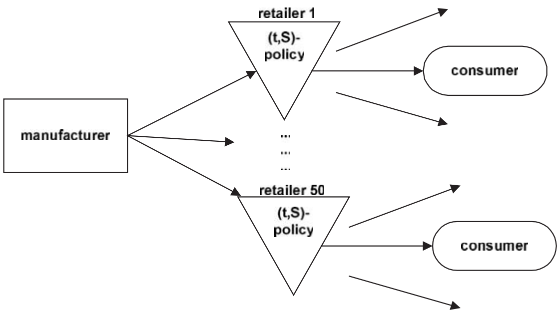

Fig. 5. Two-stage supply chain.

Table 4
Bullwhip effect

Scenario	W_m	W_d	W_r	W_{total}
Smooth				
1	1.31	1.37	5.19	9.28
2	1.14	—	1.86	2.13
Volatile				
3	1.08	0.42	2.78	1.25
4	0.33	—	4.07	1.33

Table 3
WIP results

Scenario	Manufacturer		Distribution center				One retailer (average)				WIP	std (WIP)
	WIP_m	std (WIP_m)	WIP_d	std (WIP_d)	SL_d	std (SL_d)	WIP_r	std (WIP_r)	SL_r	std (SL_r)		
Smooth												
1	40,070	184	15,313	399	0.98	0.01	121	4	0.98	0.01	61,427	441
2	7226	896	—	—	—	—	97	4	0.98	0.01	12,055	897
Volatile												
3	46,965	1401	30,386	931	0.98	0.03	856	34	0.99	0.01	120,143	1699
4	65,557	2072	—	—	—	—	2177	99	0.98	0.02	174,395	2187

a particular echelon in the supply chain as the quotient of the coefficient of variation of demand generated by this echelon (D_{out}) and the coefficient of demand received by this echelon (D_{in}) (Fransoo and Wouters, 2000):

$$W = \frac{c_{out}}{c_{in}},$$

where

$$c_{out} = \frac{\sigma(D_{out}(t, t+T))}{\mu(D_{out}(t, t+T))}$$

and

$$c_{in} = \frac{\sigma(D_{in}(t, t+T))}{\mu(D_{in}(t, t+T))}.$$

Table 4 shows the bullwhip effect at each particular echelon. Additionally, we calculate the total bullwhip effect (W_{total}) of the whole supply chain, which is the coefficient of variation of the manufacturer divided by the coefficient of variation of consumer demand. The results correspond to the WIP results (see Table 3) and illustrate how the distribution center (three-stage supply chain) reduces the bullwhip effect in scenario 3 (volatile demand).

We analyzed the possible improvements of a supply chain at a strategic level by varying the number of its elements and show that bullwhip effect is a complex problem, but there is an interaction with the tactical level, too. Further improvements could be caused by varying parameters of the supply chain at the tactical level for robust handling of a specific stochastic customer demand (e.g., inventory policy, production strategy, batch sizes, reorder points).

5. Conclusion

In our investigation, the improvement and simulation models developed allow further research on the analysis of supply chains and suggest that universally valid statements based on the behavior of specific supply chains can be quite doubtful, e.g., in our simulation environment the bullwhip effect cannot always be reduced by a shorter supply chain. This is an interesting result because in the literature it is mentioned (see Section 1) that the bullwhip effect can be reduced by a shorter supply chain. Therefore, it is necessary for supply chain design at the strategic and tactical level to take the product-specific stochastic customer demand into account.

We analyzed supply chain network settings within the framework of traditional information sharing (inventory policies). However, we ask whether it is necessary for the manufacturer to use POS data to improve on production planning and on the performance of the entire supply chain. Especially in an environment of high demand variability caused by, e.g., sales promotions and if the retailer is not willing to change his ordering policy, POS data will not always improve the manufacturer's situation, because they are not relevant to the order fulfillment process. Fransoo and Wouters (2000) also state that benefits of transfer detailed consumer demand in some cases are likely to be marginal. Thus, it is important to find out the mechanics of the problems (e.g., bullwhip effect) encountered in the supply chain.

For the company presented in our case study the detailed supply chain analysis (see Section 4) carried out under the framework of our product-specific supply chain design model is a new possibility for the manufacturer to initiate supply chain process changes.

Therefore, further research should discuss possibilities of how the results of our analysis carried out under the framework of our product-specific supply chain design model can be used for contract negotiation between manufacturer and retail chain companies. This is also the starting point for our next research activities.

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