7
Supply Chain Management and Optimization

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7.1
Introduction

Modern industrial enterprises are typically multiproduct, multipurpose and multisite facilities operating in different regions and countries and dealing with a global international clientele. In such enterprise networks, the issues of global enterprise planning, coordination, cooperation and robust responsiveness to customer demands at the global as well as the local level are critical for ensuring effectiveness, competitiveness, business sustainability and growth. In this context, it has long been recognized that there is a need for efficient integrated approaches to reduce capital and operating costs, increase supply-chain productivity and improve business responsiveness that considers various levels of enterprise management, plant-wide coordination and plant operation, in a systematic way.

A supply chain is a network of facilities and distribution mechanisms that performs the functions of material procurement, material transformation to intermediates and final products, and distribution of these products to customers. A definition provided by theSupplyChain.com (<urls>http://www.thesupplychain.com<urle>) is:

> *"SCM is a strategy where business partners jointly commit to work closely together, to bring greater value to the consumer and/or their customers for the least possible overall supply cost. This coordination includes that of order generation, order taking and order fulfilment/distribution of products, services or information. Effective supply-chain management enables business to make informed decisions along the entire supply chain, from acquiring raw materials to manufacturing products to distributing finished goods to the consumers. At each link, businesses need to make the best choices about what their customers need and how they can meet those requirements at the lowest possible cost."*

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A similar definition has also been given by Beamon (1998) by defining a supply chain as an integrated process with a number of business entities (i.e., suppliers, manufactures, distributors, retailers). A key characteristic of a supply chain is a forward flow of material from suppliers to customers and a backward flow of information from customers towards suppliers.

The supply-chain concept has in recent years become one of the main approaches to achieving enterprise efficiency. The terminology implies that a system view is taken rather than a functional or hierarchical one. Enterprises cannot be competitive without considering supply-chain activities. This is partially due to the evolving higher specialization in a more differentiated market. Most importantly, competition drives companies toward reduced cost structures with lower inventories, more effective transportation systems, and transparent systems able to support information throughout the supply chain. A single company rarely controls the production of a commodity as well as sourcing, distribution, and retail.

Many typical supply chains today have production that spans several countries and product markets are global. The opportunities for supply-chain improvements are large. Costs of keeping inventory throughout the supply chain to maintain high customer service levels (CSLs) are generally significant. There is wide scope to reduce the inventory while still maintaining the high service standards required. Furthermore, the manufacturing processes can be improved so as to employ current working capital and labor more efficiently.

It has widely been recognized that enhanced performance of supply chains necessitates (a) appropriate design of supply-chain networks and its components and (b) effective allocation of available resources over the network (Shah 2004).

In the last few years, there has been a multitude of efforts focused on providing improvements in supply-chain management and optimization. These efforts span a wide range of models, from commercial enterprise resource planning systems and so-called advanced planning systems to academic achievements (for example, linear and mixed-integer programming and multiagent systems).

- There are three main areas in supply-chain modeling research:
- supply-chain design and planning
- simple inventory-replenishment dynamics
- "novel" applications (e.g., optimization of taxation/transfer prices, cross-chain planning etc.).

The main aim of this chapter is to provide a comprehensive review of recent work on supply-chain management and optimization, mainly focused on the process industry. The first part will describe the key decisions and performance metrics required for efficient supply-chain management, while the second will critically review research work on enhancing the decision-making for the development of the optimal infrastructure (assets and network) and planning. The presence of uncertainty within supply chains will also be considered, as this is an important issue for efficient capacity utilization and robust infrastructure decisions. Next, different frameworks are presented which capture the dynamic behavior of the supply chains by establishing efficient inventory-replenishment management strategies. The subsequent section of this chapter considers management and optimization of supply chains involving other novel aspects. Finally, available software tools for supply-chain management will be outlined and future research needs for the process systems engineering community will be identified.

7.2
Key Features of Supply Chain Management

Management of supply chains is a complex task, mainly due to the large size of the physical supply network and inherent uncertainties. In a highly competitive environment, improved decisions are required for efficient supply-chain management at both strategic and operational levels, with time horizons ranging from several years to a few days, respectively. Depending on the level, one or more of the following decisions are taken:

- number, size and location of manufacturing sites, warehouses and distribution centres;
- production decisions related to plant production planning and scheduling;
- network connectivity (e.g., allocation of suppliers to plants, warehouses to markets etc.);
- management of inventory levels and replenishment policies;
- transportation decisions concerning mode of transportation (e.g., road, rail etc.) and also material shipment size.

In general, the supply chains can be categorized as domestic and international, depending on whether they are based in a single country or multiple countries, respectively (Vidal and Goetschalckx 1997). The latter case is more complex, as more global aspects need to be considered such as:

- different tax regimes and duties
- exchange rates
- transfer prices
- differences in operating costs.

It should be mentioned that effective application of suitable forecasting techniques are often critical to successful supply-chain management (see, for example, Makridakis and Wheelright (1989)). These quantitative forecasting techniques provide accurate forecasts (usually for product demands), which can then be used for planning purposes.

The quality of the efficiency and effectiveness of the derived supply-chain networks can be assessed by establishing appropriate performance measures. These measures can then be used to compare alternative systems or design a system with an appropriate level of performance. Beamon (1998) has described suitable performance measures by categorizing them as qualitative and quantitative. Qualitative performance measures include: customer satisfaction, flexibility, information and material flow integration, effective risk management and supplier performance. Appropriate quantitative performance measures include:

- measures based on financial flow (cost minimization, sales maximization, profit maximization, inventory investment minimization and return on investment);
- measures based on customer responsiveness (fill rate maximization, product lateness minimization, customer response time minimization, lead-time minimization and function duplication minimization).

7.3
Supply Chain Design and Planning

Supply-chain design and planning determines the optimal infrastructure (assets and network) and also seeks to identify how best to use the production, distribution and storage resources in the chain to respond to orders and demand forecasts in an economically efficient manner.

It is envisaged that large benefits will stem from coordinated planning across sites, in terms of costs and market effectiveness. Most business processes dictate that a degree of autonomy is required at each manufacturing and distribution site, but pressures to coordinate responses to global demand while minimizing costs imply that simultaneous planning of production and distribution across plants and warehouses should be undertaken. The need for such coordinated planning has long been recognized in the management science and operations research literature. A number of mathematical models have been presented with various features; steady-state, multiperiod, deterministic or stochastic.

Early research in this field was mainly focused on location-allocation models. Geoffrion and Graves (1974) present a model to solve the problem of designing a distribution system with optimal location of the intermediate distribution facilities between plants and customers. In particular, they aim to determine which distribution centre (DC) sites to use, what size DC to have at each selected site, what customer zones to serve and the transportation flow for each commodity. The objective is to minimize the total distribution cost (transportation cost and investment cost) subject to a number of constraints such as supply constraints, demand constraints and specification constraints regarding the nature of the problem. The problem is formulated as a mixed-integer linear programming (MILP) problem, which is solved using Benders decomposition. The model is applied to a case study for a supply chain comprising 17 commodity classes, 14 plants, 45 possible distribution centre sites and 121 customer demand zones.

The risks arising from the use of heuristics in distribution planning were also identified and discussed early on by Geoffrion and van Roy (1979). Three examples were presented in the area of distribution planning demonstrating the failure of "common sense" methods to come up with the best possible solution. This is due to the failure to enumerate all possible combinations, the use of local improvement procedures instead of global ones, and the failure to take into account the interactions in the system.

Wesolowsky and Truscott (1975) present a mathematical formulation for the multiperiod location-allocation problem with relocation of facilities. They model a small distribution network comprising a set of facilities aiming to serve the demand at given points. The model incorporates two types of discrete decisions, one involving the assignment of customers to facilities and the other the location of the nodes. They consider both steady-state and time-varying demands.

Williams (1983) develops a dynamic programming algorithm for simultaneously determining the production and distribution batch sizes at each node within a supply-chain network. The average cost is minimized over an infinite horizon.

Brown et al. (1987) present an optimization-based decision algorithm for a support system used to manage complex problems involving facility selection, equipment location and utilization, and the manufacture and distribution of products. They focus on operational issues such as where each product should be produced, how much should be produced in each plant, and from which plant product should be shipped to customer. Some strategic issues are also taken into account such as location of the plants and the number, kind and location of facilities (plants). The resulting MILP model is solved using a decomposition strategy. It is applied to a real case for the NABISCO Company.

A two-phase approach was used by Newhart et al. (1993) to design an optimal supply chain. First, a combination of mathematical programming and heuristic models is used to minimize the number of product types held in inventory throughout the supply chain. In the second phase, a spreadsheet-based inventory model determines the minimum safety stock required to absorb demand and lead-time fluctuations.

Pooley (1994) presents the results of a MILP formulation used by the Ault Foods company to restructure their supply chain. The model aims to minimize the total operating cost of a production and distribution network. Data are obtained from historical records; data collection is described as one of the most time-consuming parts of the project. Binary variables characterize the existence of plants and warehouses and the links between customers and warehouses.

Wilkinson et al. (1996) describe a continent-wide industrial case study. This involved optimally planning the production and distribution of a system with 3 factories and 14 market warehouses and over 100 products. A great deal of flexibility existed in the network which, in principle, enables the production of products for each market at each manufacturing site.

Voudouris (1996) develops a mathematical model designed to improve efficiency and responsiveness in a supply chain. The target is to improve the flexibility of the system. He identifies two types of manufacturing resources: activity resources (manpower, warehouse doors, packaging lines, etc.) and inventory resources (volume of intermediate storage, warehouse area). The activity resources are related to time while the inventory resources are related to space. The objective function aims at representing the flexibility of the plant to absorb unexpected demands.

Pirkul and Jayaraman (1996) present a multicommodity system concerning production, transportation, and distribution planning. Single sourcing is forced for customers but warehouses can receive products from several manufacturing plants. The objective is to minimize the combined costs of establishing and operating the plants and the warehouses to customers.

Camm et al. (1997) present a methodology by combining integer programming, network optimization and geographical information systems (GIS) for Procter and Gamble's North American supply chain. The overall problem is decomposed into a production (product-plant allocation) problem and a distribution network design problem. Significant benefits were reported with reconstruction of Procter and Gamble's supply chain (reduction of 20% in production plants) and annual savings of $ 200m.

McDonald and Karimi (1997) consider multiple facilities that effectively produce products on single-stage continuous lines for a number of geographically distributed customers. Their basic model is of a multiperiod linear programming (LP) form, and takes account of available processing time on all lines, transportation costs and shortage costs. An approximation is used for the inventory costs, and product transitions are not modeled. They include a number of additional supply-chain related constraints such as single sourcing, internal sourcing and transportation times.

Other planning models of this type do not consider each product in isolation, but rather groups products that place similar demands on resources into families, and bases the higher level planning function on these families. More sophisticated models exist in the process systems literature. A model which selects processes to operate from an integrated network while ensuring that the network capacity constraints are not exceeded is described in Sahinidis et al. (1989). Means of improving the solution efficiency of this class of problems can be found in Sahinidis and Grossmann (1991) and Liu and Sahinidis (1995).

Uncertainty in demands and prices are modeled in Liu and Sahinidis (1996) and Iyer and Grossmann (1998) by using a number of scenarios for each time period, thus resulting in multiscenario, multiperiod optimization models. Computational enhancements of the above large-scale model have been proposed by applying projection techniques (Liu and Sahinidis 1996) or bilevel decomposition (Iyer and Grossmannn 1998). A potential limitation of these approaches is that they use expectations rather than a variability metric of the second-stage costs. Ahmed and Sahinidis (1998) resolved this difficulty by introducing a one-side robustness measure that penalizes second-stage costs that are above the expected cost. Similar measures based on expected downside risk have been developed by Eppen et al. (1989), and have recently been applied to capacity planning problems for pharmaceutical products at different stages in clinical trials (Gatica et al. 2003).

Applequist et al. (2000) focus on risk management for chemical supply-chain investments. They introduce the risk premium approach in order to determine the right balance between expected value of investment performance and associated variance. An investment decision is approved provided that its expected return is better than those in the financial market with similar variance. An efficient polytope integration procedure is described to evaluate expected values and variances.

Gupta and Maranas (2000) consider the problem of mid-term supply-chain planning under demand uncertainty. A two-stage stochastic programming approach is proposed with the first stage determining all production decisions (here-and-now) and all supply-chains decisions are optimized in the second stage (wait-and-see). This work is extended by Gupta et al. (2000) by integrating the previous two-stage framework with a chance constraint programming approach to capture the tradeoffs between customer demand satisfaction and production costs. The proposed approach was applied to the problem of McDonald and Karimi (1997).

Sabri and Beamon (2000) develop a steady-state mathematical model for supply-chain management by combining strategic and operational design and planning decisions using an iterative solution procedure. A multiobjective optimization procedure is used to account for multiple performance measures, while uncertainties in production, delivery and demands are also included.

A MILP model is proposed by Timpe and Kallrath (2000) for the optimal planning of multisite production networks. The model is multiperiod, based on a time-indexed formulation allowing equipment items to operate in different modes. A novel feature of the model is that it can accommodate different timescales for production and distribution of variable length, thus facilitating finer resolution at the start of the planning horizon. The above model was applied to a production network of four plants located in three different regions. A larger example is briefly described in Kallrath (2000), which demonstrates the use of an optimization model involving 7 production sites with 27 production units operating in fixed-batch mode.

Bok et al. (2000) present a multiperiod optimization model for continuous process networks with main focus on operational decisions over short time horizons (one week to one month). Special features of the supply chain are taken into account such as sales, intermittent deliveries, production shortfalls, delivery delays, and inventory profiles and job changeovers. A bilevel decomposition solution procedure is proposed to reduce computational effort and deal with larger scale problems.

Tsiakis et al. (2001) describe a multiperiod MILP model for the design of supply-chain networks. The model determines production capacity allocation among different products, optimal layout and flow allocations of the distribution network by minimizing an annualized network cost. Demand uncertainty is also introduced in the multiperiod model using a scenario-based approach with each scenario representing a possible future outcome and having a given probability of occurrence.

Papageorgiou et al. (2001) present an optimization-based approach for pharmaceutical supply chains to determine the optimal product portfolio and long-tem capacity planning at multiple sites. The problem is formulated as a MILP model, taking into account both the particular features of pharmaceutical active ingredient manufacturing and the global trading structures. Particular emphasis is placed upon modeling of financial flows between supply-chain components. A comprehensive review on pharmaceutical supply chains is given by Shah (2003).

Kallrath (2002) describes a multiperiod mathematical model that combines operational planning with strategic aspects for multisite production networks. The model is similar to the one presented by Timpe and Kallrath (2000) but allows flexible production unit-site allocation (purchase, opening, shutdown), and raw material purchases and contracts. Sensitivity analyses were also performed, indicating that the optimal strategic decisions were stable up to a 20% change in demand.

Ahmed and Sahinidis (2003) propose a fast approximation scheme for solving multiscenario integer optimization problems, which is particularly relevant to capacity planning problems under discrete uncertainty.

Jackson and Grossmann (2003) describe a multiperiod nonlinear programming model for the production planning and distribution of multisite continuous multiproduct plants where each production plant is represented by nonlinear process models. Spatial and temporal decomposition solution schemes based on Lagrangean decomposition are proposed, to enhance computational performance.

Ryu and Pistikopoulos (2003) present a bilevel approach for the problem of supply-chain network planning under uncertainty. The resulting optimization problem is then solved efficiently using parametric programming techniques.

Levis and Papageorgiou (2004) extend the previous work of Papageorgiou et al. (2001) to consider the uncertainty of outcome of clinical trials. They propose a two-stage, multiscenario MILP model to determine both the product portfolio and the multisite capacity planning, while taking into account the trading structure of the company. A hierarchical solution algorithm is proposed to reduce the computational effort needed for the solution of the resulting large-scale optimization models.

Neiro and Pinto (2004) present an integrated mathematical framework for petroleum supply-chain planning by considering refineries, terminals and pipeline networks. The problem is formulated as a multiperiod, mixed-integer nonlinear programming model, and essentially extends previous work (Pinto et al. 2000) for single refinery operations with nonlinear process models and blending relations. The case study solved represents part of a real-world petroleum supply-chain planning problem in Brazil involving four refineries, five terminals and pipeline networks for crude oil supply and product distribution.

7.3.1
MultiSite Capacity Planning Example

Consider a multisite pharmaceutical capacity planning example (Levis and Papageorgiou 2004) with seven potential products (P1–P7) subject to clinical trials, four alternative locations (A–D), where A and B are the sales regions, A is the intellectual property (IP) owner, and B, C and D are the candidate production sites.

The entire time horizon of interest is 13 years. In the first 3 years, no production takes place and the outcomes of the clinical trials are not yet known. Initially, there are two suites already in place at production site B. Further decisions for investing in new manufacturing suites are to be determined by the optimization algorithm. It is assumed that the trading structure is given together with the internal pricing policies as shown in Fig. 7.1.

Five out of seven potential products are selected in the product portfolio while the optimal enterprise-wide pharmaceutical supply chain is illustrated in Fig. 7.2 where location C is not chosen.

The investment decision calendar is illustrated in Fig. 7.3. Note that investment decisions for additional manufacturing suites are taken in the early time periods while the clinical trials are still on going. The proposed investment plans take into account the construction lead-time (2 and 3 years for nonheader and header suites, respectively) and safeguard the availability of the newly invested equipment right after the end of the clinical trials phase.

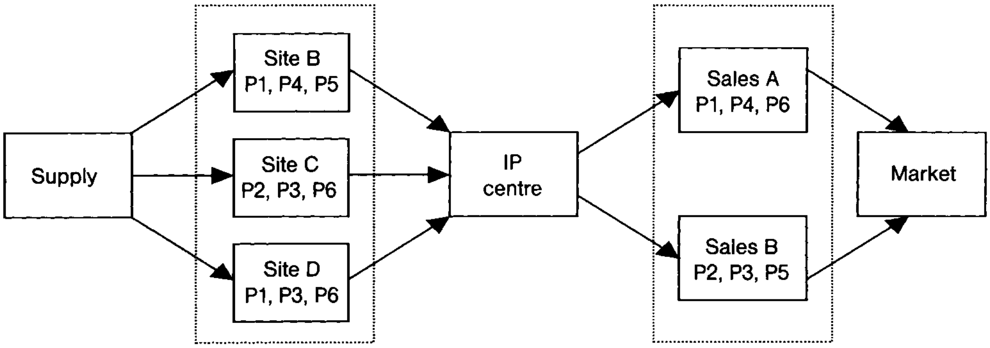

Figure 7.1 Trading structure of the company. *P1–P7* Potential products subject to clinical trials, *A–D* four alternative locations where *A* and *B* are the sales regions, *A* is the intellectual property (*IP*) owner, and *B*, *C* and *D* are the candidate production sites

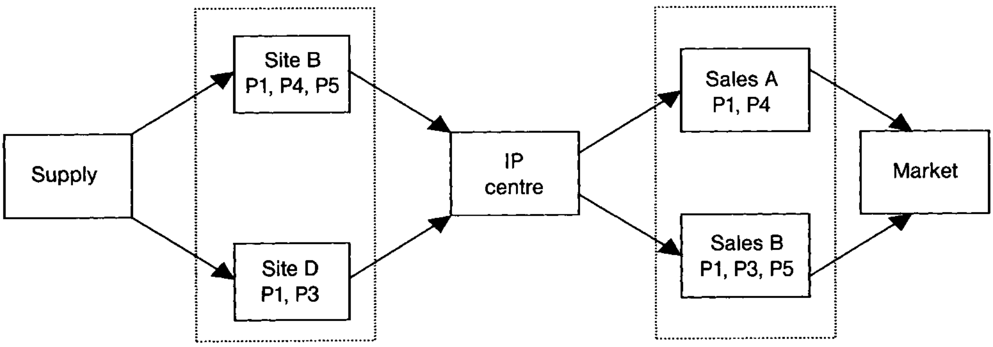

Figure 7.2 Optimal business network

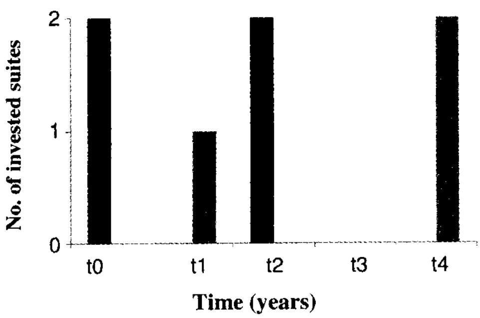

Figure 7.3 Investment decisions calendar. *Black*: site B; *grey*: site D

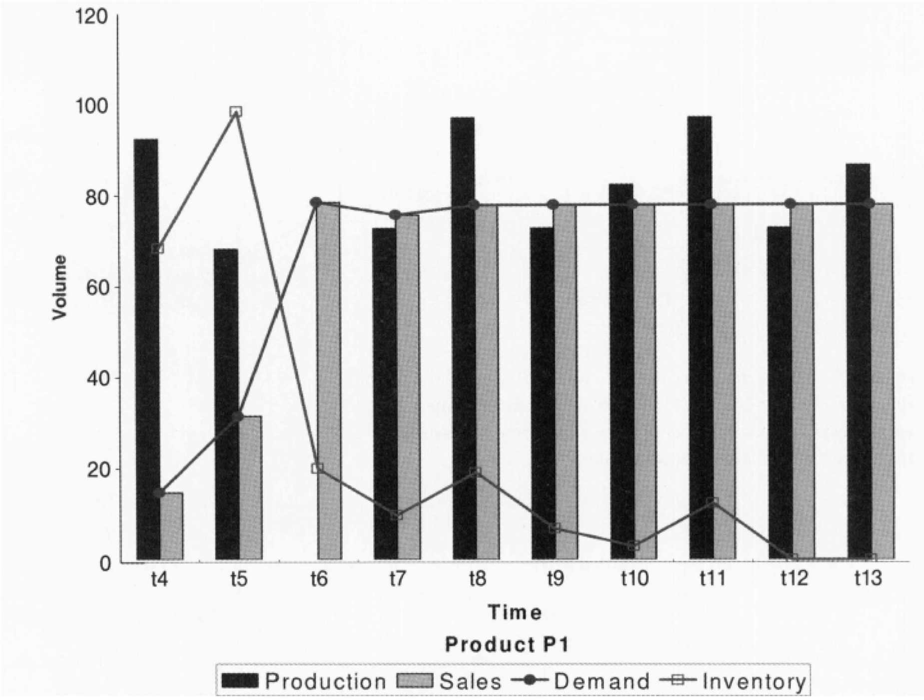

Figure 7.4 Characteristic profiles for the product P1

Operational variables (detailed production plans, inventory and sales profiles) for the selected products are also determined as illustrated in Fig. 7.4. In particular, the production of product P1 is taking place at both manufacturing sites B and D. Mainly due to the proposed investment plan and production policy, the total manufactured amount of P1 fully satisfies customer demand at all time periods.

7.4 Analysis of Supply Chain Policies

The operation of supply chains is a complex task, mainly due to the large physical production and distributions network flows, the inherent uncertainties and the dynamics associated with the internal information flow. At the operations level, it is crucial to ensure enhanced responsiveness to changing market conditions. In this section, different frameworks are presented which capture the dynamic behavior of the supply chains by establishing efficient inventory-replenishment management strategies.

Beamon (1998) provides a comprehensive review of supply-chain models and classifies them as analytical and simulation. Analytical models usually use an aggregate description of supply chains and optimize high-level decisions involving unknown configurations, while simulation models can be used to study the detailed dynamic operation of a fixed configuration under operational uncertainty.

In general, simulation is particularly useful in capturing the detailed dynamic performance of a supply chain as a function of different operating policies. Usually, these simulations are stochastic, thus deriving distributions of characteristic performance measures based on samples from distributions of uncertain parameters.

Gjerdrum et al. (2000) describe a procedure for modeling of the physical and decision-making business process aspects of a supply chain. A specialty chemical process with international markets, secondary manufacturing plants and primary manufacturing plants illustrates the model. The above procedure proposes pragmatic, noninvasive policy and parameter modifications (e.g., safety stocks) that improve performance measures such as average inventory levels, probability of stock-outs and customer service levels (CSLs) are identified. A stochastic simulation approach is then proposed using the above procedure and sampling from the uncertain parameters to assess future performance of the supply chain.

The above work has recently been extended by Hung et al. (2004) adopting an object-oriented approach to model both physical processes (e.g., production, distribution) and business processes of the supply chain. An efficient sampling procedure is also developed which reduces significantly the number of simulations required.

A model predictive control (MPC) framework for planning and scheduling problems is adopted by Bose and Pekny (2000). The framework consists of forecasting and optimization modules. The forecasting module calculates target inventories for future periods, while the optimization module attempts to meet these targets in order to ensure the desired CSL while minimizing inventory. Simulation runs are then performed to study the dynamics of a consumer goods supply chain focusing on promotional demand and lead time as the main control parameters. Different coordination structures of the supply chain are also investigated.

Van der Vorst et al. (2000) present a method for modeling the dynamic behavior of food supply chains by applying discrete-event simulation based on time colored Petri-nets. Alternative designs of the supply-chain infrastructure and operational management and control are then evaluated with the main emphasis being placed upon distribution of food products.

Perea-Lopez et al. (2001) describe a dynamic modeling approach for supply-chain management by considering the flow of material and information within the supply chain. The impact of different supply-chain control policies on the performance of supply chains is evaluated using a decentralized decision-making framework. This is demonstrated through a polymer case study with one manufacturing site, one distribution network and three customers.

Perea et al. (2003) extend their previous work (Perea et al. 2001) by proposing a multiperiod MILP optimization model within an MPC strategy. A centralized approach is adopted where the corresponding MILP model considers the whole supply chain, involving suppliers, manufacturing, distribution and customers simultaneously. The benefits of centralized over decentralized management are then emphasized with a case study with profit increases of up to 15 %.

Agent-based techniques have recently been reported in the process systems literature for the efficient management of supply-chain systems. Garcia-Flores et al. (2000) and Garcia-Flores and Wang (2002) present a multiagent modeling system for supply-chain management of process industries. Retailers, warehouses, plants and raw material suppliers are modeled as a network of cooperative agents. A commercial scheduling system is integrated in the multiagent framework, as plant scheduling usually dominates the supply-chain performance. A case study with a single multipurpose batch plant of paints and coatings is then used to illustrate capabilities of the system.

A similar approach has also been reported by Gjerdrum et al. (2001a) to simulate and control a demand-driven supply-chain network system, with the manufacturing component being optimized through mathematical programming. A number of agents have been used, including warehouses, customers, plants, and logistics functions. The plant agent, which is responsible for production scheduling, is using optimization techniques while the other agents of the supply chain are mainly rule-based. The proposed system is then applied to a supply chain with two manufacturing plants by investigating the effect of different replenishment policies in the supply-chain performance.

Julka et al. (2002a,b) propose an agent-based framework for modeling, monitoring and management of process supply chains. A refinery application is considered for the efficient management of crude oil procurement business process by investigating the impact of different procurement policies, demand fluctuation and changes in plant configuration.

7.4.1
A Pharmaceutical Supply Chain Example

A pharmaceutical supply chain example (Gjerdrum et al. 2000) is shown in Fig. 7.5. A primary manufacturing plant is situated in Europe. Secondary formulation sites in Asia and America receive AI from this plant and produce final products for the main warehouses in Japan and the US. There are two main SKUs in the Japanese market: products A and B. Also, in the US market there are two principal products, C and D.

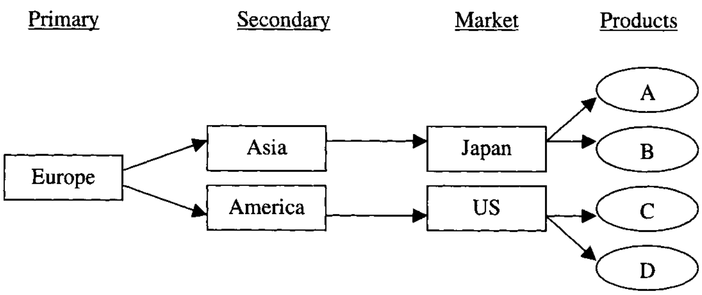

Figure 7.5 A supply chain example

There are also several other product SKUs that share secondary manufacturing resources (in Asia and America) which are handled by other (not explicitly modeled) warehouses e.g., in Europe.

The CSL deemed sufficient for this supply chain by decision-makers (called the target CSL) is 97 %. The low figure is due to large inventories held at external warehouses downstream in the supply chain, which will buffer against any temporary stock-outs. Occasional SKU stock-outs are therefore not considered to be harmful since the end consumer is not affected. Therefore, the aim of this case study is to reduce inventory while maintaining the target CSL.

The demand-management SKU data is presented in Table 7.1.

Table 7.1 Demand management SKU base case data.

	Product A	Product B	Product C	Product D
Safety stock (weeks)	6	6	6	6
MOQ (units)	10,000	5000	5000	20,000
Deviation from forecast (%)	25	20	25	25
Pack size (units)	12	30	30	30
Initial stock (units)	15,000	15,000	60,000	60,000

The production data are given in Tab. 7.2.

Table 7.2 Secondary manufacturing site base case data

	Asia	USA
Safety stock (kg)	50	150
AI Order quantity (kg)	30	130
Production capacity (h week−1)	60	60
Production rate (units h^{-1})	650	1200
Flexibility of production (%)	40	25
Initial AI stock (kg)	80	180

One of the most important supply-chain performance indicators is the amount of unutilized working capital in the chain. By closely tracking simulated inventory, substantial costs can be taken out of the supply chain. This must be done while maintaining required high CSLs, low probabilities of stock-outs and supply-chain efficiency in general. Therefore, we simulate the inventory levels as well as the more traditional customer-focused aspects of the supply-chain performance. Each simulation is repeated 100 times to ensure statistically trustworthy results.

CSL is defined as part-fill on-time. When there is inventory enough at hand, the sales equal demand. When inventory runs out, it is assumed that inventory that is there can be sold while the rest of the demand is left unfulfilled.

The probability of stock-out (PSO) is simply the number of times the inventory is zero divided by the total number of data points, i.e., the horizon length times the number of simulated simulation runs. Hence, this complete supply chain is dynamically simulated over a prespecified horizon of, e.g., 2 years. First, initialization of the model is performed with respect to fixed policy parameters, business processes and initial stock levels. At each time-step (e.g., each week) in the horizon, input parameters and model data from previous time steps are collected. Actual sales and machine breakdown are generated from stochastic distributions. Stock positions, current supply-chain orders and forecasts are then updated and evaluated. When any model variables violate the current procedures or policies (such as the safety stock) the model issues new directions of action (such as issuing new orders).

To obtain statistically significant results of the stochastic process, the simulation is repeated over a number of runs. At each run, informative data are collected. Finally, all the supply-chain simulation results are extracted and evaluated.

The experiments presented in Table 7.3 demonstrate the response of the supply chain to changes in internal and external parameters. These experiments are useful in that they provide information on whether current policies and external factors can be modified while maintaining strong supply-chain performance. INV is the horizon-average finished product (SKU) inventory. High demand variability represents a complex market to forecast. High order quantity shows what happens if a typical service level parameter is modified. Although these parameters obviously affect the performance levels, it seems that the demand management performance levels are not severely affected by the demand variability or the order quantity. The ramping and decreasing demands give conservative measures, since it is assumed that the forecast will not be updated during the horizon. The US market is able to handle a soaring demand better, due to fewer conflicting products.

Table 7.3 Supply-chain experiments. *CSL* Customer service level, *PSO* probability of stock-out, *INV* horizon-average finished product inventory

Experiment	Product A (Asia)			Product C (USA)		
	CSL (%)	PSO (%)	INV	CSL (%)	PSO (%)	INV
Base case	*98.33*	*1.81*	*48,074*	*98.81*	*1.33*	*105,041*
High demand variability	98.05	2.18	48,678	97.76	2.31	107,315
High order quantity	97.94	2.30	58,688	98.21	1.96	109,049
Soaring demand	95.52	4.54	43,997	98.73	1.22	112,554
Collapsing demand	99.83	0.19	54,645	99.51	0.75	111,789

In Fig. 7.6, the expected number of stock-outs for various policies of safety stock is shown for product C in the US market. The value represents the risk of a stock-out occurring during the simulated period.

In Fig. 7.7, the CSL defined as part-fill on-time is shown for different policies of weekly forward cover stock for product C. It can be seen that a policy of 4 weeks of forward cover will just about be sufficient to satisfy the target CSL of 97%.

In Fig. 7.8, the resulting mean average inventory values for various stock policies are shown for product C. The 4 weeks forward cover corresponds to an average inventory of about 70,000 units. This value can then be utilized to calculate the market inventory cost.

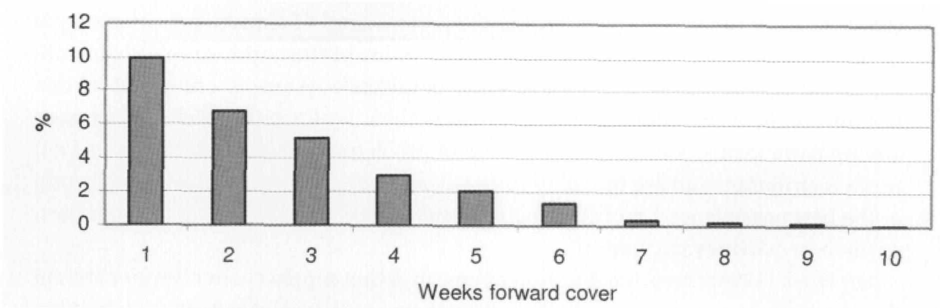

Figure 7.6 Probability of stock-out

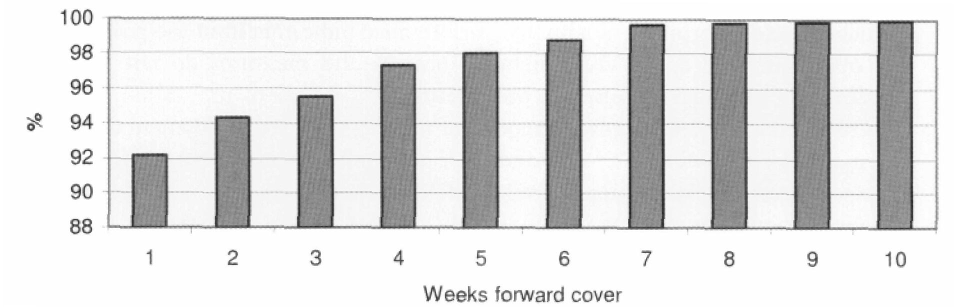

Figure 7.7 Customer service level

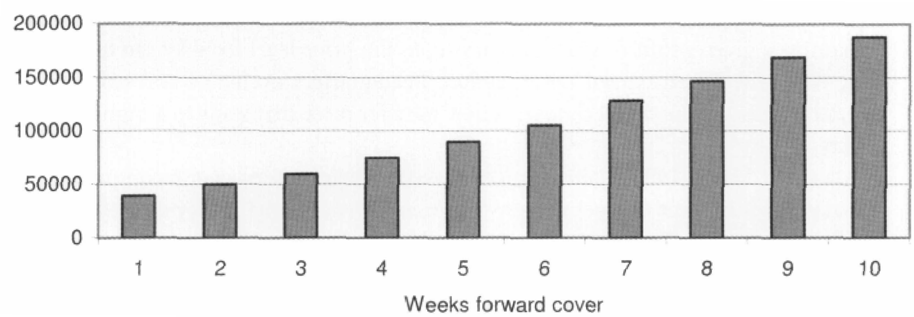

Figure 7.8 Average inventory

7.5 Multienterprise Supply Chains

In recent years, the concept of multienterprises has gained increasing attention, since it promotes all the benefits of extended multienterprise collaboration. The determination of policies that optimize the performance of the entire supply chain as a whole, while ensuring adequate rewards for each participant is crucial and the relevant work is very limited.

Conflicting interests in general extended multienterprise supply chains frequently lead to problems in how to distribute the overall value to each member of the supply chain. A simple approach to enhancing the performance of a multienterprise supply chain is to maximize the summed enterprise profits of the entire supply chain subject to various network constraints. When the overall system is optimized in this fashion, there is no automatic mechanism to allow profits to be fairly apportioned among participants. Solutions to this class of problems usually exhibit quite uneven profit distribution and are therefore impractical. They do however give an indication of the best possible total profit attainable in the supply chain as well as an indication of the best activities to carry out.

van Hoek (1998) raises the question of how to divide supply-chain revenues among the players in a supply-chain system when there is no leading player to determine how distribution of benefits should be handled. He states that supply-chain control is no longer based on direct ownership but rather on integration over interfaces of functions and enterprises. Traditional performance indicators limit the possibilities of optimizing the supply-chain network because the measures do not correctly address the wide opportunities for improvement.

Cohen and Lee (1989) deliver a model for making resource deployment decisions in a global supply-chain network and solve different scenarios using an extensive mixed-integer nonlinear programming (MINLP) model. They also discuss several "policy options" for plant utilization, supply and distribution strategies.

Pfeiffer (1999) describes transfer pricing in a supply chain consisting of procurement, manufacturing and selling units of one single company. His theoretical model handles one commodity at each node and does not include any capacity constraints. He proposes a transfer-price system governed by the headquarters, which fixes a specific transfer-price level. Each node optimizes its own decisions independently to maximize a given profit function, according to the price level fixed by the headquarters. After the decentralized optimization, headquarters evaluates and collects the overall results obtained and chooses a new transfer price that leads to a higher profitability.

Alles and Datar (1998) claim that cost-based transfer prices of the companies are usually based in their competitive environment. The enterprise may cross-subsidize products in order to increase their ability to increase prices. Often, transfer prices for relatively lower cost products are decreased. The authors give evidence that transfer prices are determined based on strategic decisions rather than on internal cost systems.

Jose and Ungar (2000) propose an approach to decentralized pricing optimization of interprocess streams in chemical industry companies. Their iterative auction method determines the prices of process streams so as to maximize an objective for a single chemical company, while each division within the company is constrained by its available resources. The approach is interesting in that each division conceals its private information from the other parties within the so-called micro supply chain. It normally takes several iterations for a model to converge, and the user has to define the limited amount of slack resources utilized. One of the main conceptual differences between their approach and the one presented in this paper is that they regard the channel members as adversarial and competitive for resources rather than cooperative. Also, they use a slack resource iterative auction approach, whereas in this paper the solution approach is to solve a noniterative separable MILP problem.

Ballou et al. (2000) stress the importance of common objectives in the supply chain. Unattainable improvements for single companies in terms of cost savings and customer service enhancements can be obtained by cooperative companies. The authors point out that problems arise if some of the firms benefit at the expense of the others. The conflict resolution between supply-chain partners must be of focal interest, and to keep the coalitions intact, the rewards of cooperation must be redistributed. They identify three means to achieve this:

1. *Metrics* could be developed to capture the nature if interorganizational cooperation to simplify benefit analysis.
2. *Information sharing* mechanisms could transfer information about the benefits of cooperation among the members in the supply chain.
3. *Allocation methods* could be developed that *fairly* distribute the rewards of cooperation between the members.

According to Pashigian (1998), multiproduct industries form a new market structure characterized by novel market relationships among companies. Collusion takes place when the firms in an industry join together to set prices and outputs. Such an agreement is said to form a cartel. However, game theorists insist that there is an inherent incentive for each firm to cheat on such an agreement, in order to gain more profits for itself.

Vidal and Goetschalckx (1997) present a nonconvex optimization model together with a heuristic solution algorithm for the management of a global supply by maximizing the after-tax profits of a multinational corporation. The model also considers transfer prices and the allocation of transportation costs as explicit decision variables.

Gjerdrum et al. (2001b, 2002) present a MINLP model including a nonlinear Nash-type objective function for fair profit optimization of an n-enterprise supply-chain network. The supply-chain planning model considers intercompany transfer prices, production and inventory levels, resource utilization, and flows of products between echelons. Efficient solution procedures for the above model are described by Gjerdrum et al. (2001b, 2002) based on separable programming and spatial branch-and-bound respectively. Computational results indicate profits very close to those obtained by simple single-level optimization (e.g., maximization of total profit), but more equitably distributed among partners.

Chen et al. (2003) propose a fuzzy decision-making approach for fair profit distribution for multienterprise supply-chain networks. The proposed framework can accommodate multiple objectives such as maximization of the profit of each participant enterprise, the CSL, and the safe inventory level.

7.6
Software Tools for Supply Chain Management

The coordination of operations on a global basis requires the implementation and use of software to support these decisions. State-of-the-art software requires the ability to perform constraint-based, multisite planning that can become extremely complex. Modern software supply-chain tools aim to integrate traditionally fragmented views of operations, and to provide a holistic view of the problem, rather than linking separate planning operations.

7.6.1 Aspen Technologies (<urls>http://www.aspentech.com<urle>)

Aspen MIMI supply-chain suite includes the Aspen Strategic Analyzer that can be used to identify strategic and operational options such as capacity addition, production constraints and distribution modes. Aspen is the leading provider of supply-chain solutions in the process industry, by market share.

7.6.2 i2 Technologies (<urls>http://www.i2.com<urle>)

Supply-Chain Optimization is a holistic solution and framework to help companies create a macrolevel model for the entire supply chain that controls an integrated workflow environment. The user may select to extend the capabilities and study in depth specific areas of the supply-chain problem, such as logistics, production, demand fulfilment and profit/revenue analysis.

7.6.3 Manugistics (<urls>http://www.manugistics.com<urle>)

Network Design and Optimization is a supply-chain design and operation package that is part of the Manugistics supply-chain suite. Among its capabilities is the design of a supplier, manufacturing site and distribution site network in the most effective way. The process considers inventory levels, production strategy, production and transportation costs, lead times and other user-specified constraints.

7.6.4 SAP AG (<urls>http://www.sap.com<urle>)

MySAP SCM (Supply-Chain Management) is designed to be a complete supply-chain solution. The supply network planning and deployment tool assists planners to balance supply and demand while simultaneously considering purchasing, manufacturing, inventory and transportation constraints. Integrated with other support tools, it aims to provide a complete optimization framework.

7.7
Future Challenges

It is clear that considerable research work has been done on process supply-chains especially in the areas of network design and planning. However, a number of issues provide interesting challenges for further research.

As many modern supply chains are characterized by their international nature, optimization-based decisions are required for various features such as taxes, duties, transfer prices, etc. Systematic integration of business/financial and planning models should be considered for efficient supply-chain management (see, for example, Shapiro (2003), Romero et al. (2003), Badell et al. (2004), Badell M., Romero J., Huertas R., Puigjaner L. Comput. Chem. Eng. 28 (2004) p. 45–61).

Significant effort has already been put into supply-chain modeling under uncertainty commonly related to product demands. The treatment of uncertainty still requires research effort to capture more aspects such as product prices, resource availabilities etc. In order to ensure that investment decisions are made optimally in terms of both reward and risk, suitable frameworks for the solution of supply-chain optimization problems under uncertainty are required. Most of the existing frameworks are suitable for two-stage problems, while there is a need for appropriate multistage, multiperiod optimization frameworks for supply-chain management.

As most of the resulting optimization problems, and predominantly cases under uncertainty, will be of large scale, there is great scope for developing efficient solution procedures. Aggregation and decomposition techniques are envisaged as such promising solution alternatives. It should be mentioned that it is quite important to maintain industrial focus for the successful development of such solution methods.

The analysis of supply-chain policies for process industries has recently emerged and this research area is expected to expand. Suitable frameworks seem to be the ones based on agents, MPC and object-oriented systems. A key issue here is the appropriate integration of business and process aspects (see, for example, Hung et al. (2004)).

Another emerging research area is the systematic incorporation of sustainability aspects within supply-chain management systems, necessitating the development of multiobjective optimization frameworks (see, for example, Zhou et al. (2000), Hugo and Pistikopoulos (2003)).

Finally, research opportunities are evident in the appearance of new types of supply chain, associated, for example, with hydrogen (fuel cells), energy supply, water provision/distribution, fast response therapeutics and biorefineries.

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References

1 *Ahmed S. Sahinidis N. V.* Ind. Eng. Chem. Res. 37 (1998) p. 1883–1892
2 *Ahmed S. Sahinidis N. V.* Oper. Res. 51 (2003) p. 461–47
3 *Alles M. Datar S. Manage.* Sci. 44 (1998) p. 451–461
4 *Applequist G. E. Pekny J. F. Reklaitis G. V.* Comput. Chem. Eng. 24 (2000) p. 2211–2222
5 *Ballou R. H. Gilbert S. M. Mukherjee A. A.* Ind. Market. Manage. 29 (2000) p. 7–18
6 *Beamon B. M.* Int. J. Prod. Econ. 55 (1998) p. 281–294
7 *Bok J. K. Grossmann I. E. Park S.* Ind. Eng. Chem. Res. 39 (2000) p. 1279–1290
8 *Bose S. Pekny J. F.* Comput. Chem. Eng. 24 (2000) p. 329–335
9 *Brown G. G. Graves G. W. Honczarenko M. D.* Manage. Sci. 33 (1987) p. 1469–1480
10 *Camm J. D. Chorman T. E. Dill F. A. Evans J. R. Sweeney D. J. Wegryn G. W.* Interfaces 27 (1997) p. 128–142
11 *Chen C. L. Wang B. W. Lee W. C.* Ind. Eng. Chem. Res. 42 (2003) p. 1879–1889
12 *Cohen M. A. Lee H. L.* J. Manuf. Oper. Manage. 2 (1989) p. 81–104
13 *Eppen G. D. Marti R. K. Schrage L.* Oper. Res. 37 (1989) p. 517–527
14 *García-Flores R. Wang X. Z.* OR Spectrum 24 (2002) p. 343–370
15 *Garcia-Flores R. Wang X. Z. Goltz G. E.* Comput. Chem. Eng. 24 (2000) p. 1135–1141
16 *Gatica G. Papageorgiou L. G. Shah N.* Chem. Eng. Res. Des. 81 (2003) p. 665–678
17 *Geoffrion A. M. Graves G. W.* Manage. Sci. 20 (1974) p. 822–844
18 *Geoffrion A. M. van Roy T. J.* Sloan Manage. Rev. Summer (1979) p. 31–42
19 *Gjerdrum J. Jalisi Q. W. Z. Papageorgiou L. G. Shah N.* 5th Annual International Conference of Industrial Engineering Theory – Applications and Practice, Hsinchu, Taiwan, 2000
20 *Gjerdrum J. Shah N. Papageorgiou L. G.* Prod. Planning Control (2001a) p. 12 81–88
21 *Gjerdrum J. Shah N. Papageorgiou L. G.* Ind. Eng. Chem. Res. 40 (2001b) p. 1650–1660
22 *Gjerdrum J. Shah N. Papageorgiou L. G.* Eur. J. Oper. Res. 143 (2002) p. 582–599
23 *Gupta A. Maranas C. D.* Ind. Eng. Chem. Res. 39 (2000) p. 3799–3813
24 *Gupta A. Maranas C. D. McDonald C. M.* Comput. Chem. Eng. 24 (2000) p. 2613–2621
25 *Hugo A. Pistikopoulos E. N.* Proceedings of the 8th International Symposium on Process Systems Engineering, 2003, A and B , 214–219
26 *Hung W. Y. Kucherenko S. Samsatli N. Shah N.* J. Oper. Res. Soc. 2004 55 (2004) p. 801–813
27 *Iyer R. R. Grossmann I. E.* Ind. Eng. Chem. Res. 37 (1998) p. 474–481
28 *Jackson J. R. Grossmann I. E.* Ind. Eng. Chem. Res. 42 (2003) p. 3045–3055
29 *Jose R. A. Ungar L. H.* AIChE J. 46 (2000) p. 575–587
30 *Julka N. Srinivasan R. Karimi I.* Comput. Chem. Eng. 26 (2002a) 1755–1769
31 *Julka N. Srinivasan R. Karimi I.* Comput. Chem. Eng. 26 (2002b) 1771–1781
32 *Kallrath J.* Chem. Eng. Res. Des. 78 (2000) p. 809–822
33 *Kallrath J.* OR Spectrum 24 (2002) p. 219–250
34 *Levis A. A. Papageorgiou L. G.* Comput. Chem. Eng. 28 (2004) p. 707–725
35 *Liu M. L. Sahinidis N. V.* Ind. Eng. Chem. Res. 34 (1995) p. 1662–1673
36 *Liu M. L. Sahinidis N. V.* Ind. Eng. Chem. Res. 35 (1996) p. 4154–4165
37 *Makridakis S. Wheelright S. C.* Forecasting methods for Management, 1989, Wiley, New York
38 *McDonald C. M. Karimi I. A.* Ind. Eng. Chem. Res. 36 (1997) p. 2691–2700
39 *Neiro S. M. S. Pinto J. M.* Comput. Chem. Eng. 2004 28 (2004) p. 871–896
40 *Newhart D. D. Stott K. L. Vasko F. J.* J. Oper. Res. Soc. 44 (1993) p. 637–644
41 *Papageorgiou L. G. Rotstein G. E. Shah N.* Ind. Eng. Chem. Res. 2001 40 275–286
42 *Pashigian B. P.* Price Theory and Applications 1998 McGraw Hill Boston
43 *Perea-Lopez E. Ydstie B. E. Grossmann I. E.* Comput. Chem. Eng. 27 (2003) p. 1201–1218
44 *Perea-Lopez E. Ydstie B. E. Grossmann I. E. Tahmassebi T.* Ind. Eng. Chem. Res. 40 (2001) p. 3369–3383
45 *Pfeiffer T.* Eur. J. Oper. Res. 116 (1999) p. 319–330
46 *Pinto J. M. Joly M. Moro L. F. L.* Comput. Chem. Eng. 24 (2000) p. 2259–2276
47 *Pirkul H. Jayarama V.* Transp. Sci. 30 (1996) p. 291–302
48 *Pooley J.* Interfaces 24 (1994) p. 113–121
49 *Romero J. Badell M. Bagajewicz M. Puigjaner L.* Ind. Eng. Chem. Res. 42 (2003) p. 6125–6134

50 *Ryu J. H. Pistikopoulos E. N.* Proceedings of the 4th International Conference on Foundations of Computer-Aided Process Operations,(2003) p. 297–300

51 *Sabri E. H. Beamon B. M.* Omega 28 (2000) p. 581–598

52 *Sahindis N. V. Grossmann I. E.* Comput. Chem. Eng. 15 (1991) p. 255–272

53 *Sahindis N. V. Grossmann I. E. Fornari R. E. Chathranthi M.* Comput. Chem. Eng. 13 (1989) p. 1049–1063

54 *Shah N.* Proceedings of the 4th International Conference on Foundations of Computer-Aided Process Operations (2003) p. 73–85

55 *Shah N.* Escape–14 conference 2004

56 *Shapiro J.* Proceedings of the 4th International Conference Conference on Foundations of Computer-Aided Process Operations (2003) p. 27–34

57 *Timpe C. H. Kallrath J.* Eur. J. Oper. Res. 126 (2000) p. 422–435

58 *Tsiakis P. Shah N. Pantelides C. C.* Ind. Eng. Chem. Res. 40 (2001) p. 3585–3604

59 *van der Vorst J. G. A. J. Beulens A. J. M. van Beek P.* Eur. J. Oper. Res. 122 (2000) p. 354–366

60 *van Hoek R. I.* Supply Chain Manage. 3 (1998) p. 187–192

61 *Vidal C. J. Goetschalckx M.* Eur. J. Oper. Res. 98 (1997) p. 1–18

62 *Voudouris V. T.* Comput. Chem. Eng. 20S (1996) p. S1269–S1274

63 *Wesolowsky G. O. Truscott W. G.* Manage. Sci. 22 (1975) p. 57–65

64 *Wilkinson S. J. Cortier A. Shah N. Pantelides C. C.* Comput. Chem. Eng. 20S (1996) p. S1275–S1280

65 *Williams J. F.* Manage. Sci. 29 (1983) p. 77–92

66 *Zhou Z. Y. Cheng S. W. Hua B.* Comput. Chem. Eng. 24 (2000) p. 1151–1158