Process Industry Supply Chains: Advances and Challenges

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Abstract

A large body of work exists in process industry supply chain optimisation. We describe the state of the art of research in infrastructure design, modelling and analysis and planning and scheduling, together with some industrial examples. We draw some conclusions about the degree to which different classes of problem have been solved, and discuss challenges for the future.

Keywords: Network design, supply chain modelling and planning, future challenges

1. Introduction

The EU has a strong position in the process industries, which constitute a significant proportion of its manufacturing base. The chemicals sector (excluding pharmaceuticals, food and drink and pulp and paper) contributes 2.4% of EU GDP. Process companies often sit in the middle of wider supply chains and as a result traditionally perform differently to companies operating at the final consumer end of the chain. In our experience, supply chain benchmarks for the process industries do not measure up well when compared with other sectors (e.g. automotive). Examples of such benchmarks are: (i) stock levels in the whole chain ("pipeline stocks") typically amount to 30-90% of annual demand, and there are usually 4-24 weeks' worth of finished good stocks; (ii) supply chain cycle times (defined as elapsed time between material entering as raw material and leaving as product) tend to lie between 1000-8000 hours, of which only 0.3-5% involve value-adding operations; (iii) low material efficiencies, with only a small proportion of material entering the supply chain ending up as product (particularly fine chemicals and pharmaceuticals, where this figure is 1-10%).

Process industry supply chains, involving manufacturers, suppliers, retailers and distributors, are therefore striving to improve efficiency and responsiveness. For "world class" performance, both the network and the individual components must be designed appropriately, and the allocation of resources over the resulting infrastructure must be performed effectively. The process industries have been hampered in this quest by both intrinsic factors (e.g. the need to influence processes at the molecular level, and wide distributions of asset ages) and technological factors (e.g. availability of tools for supply chain analysis). There are a number of reasons for this, many of which relate to details of process and plant design, and to the prevailing economic orthodoxies when key decisions were taken. It is often difficult to effect large improvements simply by changing logistics and transactional processes – fundamental changes at the process and plant level and at the interfaces between the different constituents of the value chain from product discovery to manufacture and distribution are often required. The process industries will face new challenges in the future. These include:

- A desire to move from a product-oriented business to a service-oriented business, providing life-cycle solutions for customers;
- More dynamic markets and greater competition, with shorter product life-cycles;
- Mass customisation (trying to deliver "specialty" products at "commodity" costs);
- The need to evaluate, report and improve sustainability and environmental and social impacts throughout the supply chain, and aiming to anticipate and respond to future regulation and compliance requirements (e.g. recovery and recycling of consumer products at end-of-use).

In this paper we will review some of the important relevant and associated research, as well as try to anticipate some of the emerging challenges for the sector.

1.1 Different views of the process industry supply chain

First of all, it makes sense to define what is meant by the process industry supply chain. Most companies, and indeed researchers, tend to employ a company-centric view of the supply chain, where the supply chain is seen as consisting of the enterprise in question as a central entity, possibly together with some peripheral partners, typically first-tier suppliers and customers (Lambert and Cooper, 2000). These views involve the integration of production and logistics planning across the enterprise, value-chain management, global network planning and investment appraisal. There is much less work on the "extended" supply chain, where the view is much broader, e.g. encompassing the suppliers' suppliers and the customers' customers. This is almost certainly due to (i) the relative youth of the discipline, and the fact that considerable benefits can be achieved simply by the use of company-centric views of the supply chain, and (ii) a wariness of supply chain "partners" and a lack of data sharing.

1.3 Typical supply chain problems

Supply chain problems may be divided into three categories: (i) supply chain infrastructure (network) design; (ii) supply chain analysis and policy formulation; and (iii) supply chain planning and scheduling. The first two are essentially relatively infrequent "off-line" activities associated with establishing the best way to configure and manage the supply chain network. The last involves deciding how to operate the network to respond best to the external conditions faced by the supply chain. These problems and progress in relevant research are reviewed in the next three sections. An example of a published industrial application is provided in each section as well, with a view to illustrating both academic research and state of the art in industrial practice. The paper then concludes with a view on future developments and challenges.

2. Supply Chain Network Design

The "problem" of supply chain network design is very broad and means different things to different enterprises. It generally refers to a strategic activity that will take one or more of the following decisions:

- Where to locate new facilities (be they production, storage, logistics, etc.)
- Significant changes to existing facilities, e.g. expansion, contraction or closure
- Sourcing decisions – what suppliers and supply base to use for each facility
- Allocation decisions – e.g. what products should be produced at each production facility; which markets should be served by which warehouses, etc.

These decisions aim in some way to increase shareholder value. This means that models are employed to try to exploit potential trade-offs. These may include:

i. Differences in regional production costs
ii. Distribution costs of raw materials, intermediates and products
iii. Differences in regional taxation and duty structures
iv. Exchange rate variations
v. Manufacturing complexity and efficiency (related to the number of different products being produced at any one site)
vi. Network complexity (related to the number of different possible pathways from raw materials to ultimate consumers)

Most companies do not aim to quantify the latter two explicitly, but rather employ policies (e.g. single-sourcing of customer zones; exclusive product-plant allocation) to simplify operation to the desired degree.

Models may be steady-state or dynamic and may be deterministic or deal with uncertainties (particularly in product demands). Research in this field started very early on, with location-allocation problems forming part of the early set of "classical" operations research problems, see e.g. Geoffrion and Graves (1974) who consider the problem of distribution system layout and sizing and DC-customer allocation. It was recognised early on that systematic, optimisation-based approaches should be used, and that "common-sense" heuristics might lead to poor solutions (Geoffrion and van Roy, 1979). These early models tended to focus on the logistics aspects. Clearly, much more benefit could be achieved by simultaneously considering the production aspects.

An early example of a production-distribution network optimisation study in the process industries is given by Brown et al. (1987) who considered the biscuit division of Nabisco. Their model involves the opening or closing of plants, the assignment of facilities to plants and the assignment of production to facilities. The production model is based on the relative product-facility "yields". A thorough review of the work in this area was presented by Vidal and Goetschalckx (1997). They categorise previous work according to a number of characteristics, including:

- Treatment of uncertainties and dynamics and production and supplier capacity
- Ability to include single-sourcing restrictions
- Customer service and inventory features
- "International" (i.e. taxes, duties, etc.) features
- Number of "echelons" considered (see below)
- Cost non-linearities, model size and solution techniques

They conclude that features that are not well treated include stochastic elements, accurate descriptions of manufacturing processes (and hence capacity), the international aspects, extended and multi-enterprise networks and solution techniques.

In general, the works reviewed above use fairly simple representations of capacity and treat all data as deterministic. Given that many of the plants under consideration are flexible and multipurpose, and there is a wide product slate, a better representation of capacity and demand uncertainty is required for more accurate solutions.

Kallrath (2002a) addresses the issue of process and plant representation. He describes a tool for simultaneous strategic and operational planning in a multi-site production network. He aims to optimise the total net profit of a global network, where key decisions include: operating modes of equipment in each time period, production and supply of products, minor changes to the infrastructure (e.g. addition and removal of equipment from sites), and raw material purchases and contracts. A multiperiod model is formulated where equipment may undergo one mode change per period. The standard material balance equations are adjusted to account for the fact that transportation times are much shorter than the period durations. Counter-intuitive but credible plans were developed which resulted in cost savings of several millions of dollars. Sensitivity analyses showed that the key decisions were not too sensitive to demand uncertainty.

Sabri and Beamon (2000) also develop a combined strategic-operational design and planning model, with two interesting features: a multi-objective optimisation procedure is used because of the difficulty of trading off very different types of objectives, and uncertainties in lead times as well as demands are treated. However, the model is steady-state rather than dynamic.

Tsiakis et al. (2001a) show how demand uncertainty can be introduced in a multiperiod model. They argue that the future uncertainties can captured well through a scenario tree, where each scenario represents a different discrete future outcome. These should correspond to significant future events rather than just minor variations in demand. They utilise a multipurpose production model where flexible production capacity is to be allocated between different products, and determine the optimal layout and flow allocations of the distribution network.

All of the above works rely on the concept of fixed “echelons”, i.e. they assume a given fundamental structure for the network in terms of the echelons involved (e.g. suppliers, manufacturing plants, warehouses, distribution centres, customers). Thus, a rather rigid structure is imposed on the supply chain and the design procedure focuses on the determination of the number of components in each echelon and the connectivity between components in adjacent echelons. However, changes in the fundamental structure of the network (e.g. the introduction of additional echelons, or the removal or partial by-passing of existing ones) may sometimes lead to economic benefits that far exceed what can be achieved merely by changing the number of components and/or the connectivity within an existing structure. Tsiakis et al. (2001b) extend this body of work by developing a general framework that integrates the different components of a supply chain without any a priori assumption as to the fundamental structure of the network. The framework uses the concept of a flexible, generalised production/warehousing (PW) node. These PW nodes can be located at any one of a set of candidate locations, produce one or more products using one or more shared resources, hold inventories of the above products as well as of any other material in the network, and exchange material with other PW or external nodes. The functions of these nodes are therefore not specified a priori, and neither is any flow network superimposed. Rather, the node functionalities (production, storage or both) and the flows between nodes are determined as part of the optimisation. This tends to result in “leaner” networks, where storage capacity is only established where necessary. The flexible network structure also provides more scope for exploiting economies of scale in transportation.

2.1 Process/Capacity Planning

In the PSE community, the related problem of long-term capacity planning (usually at a single, albeit complex, site) has been considered by several researchers. This problem involves the long term planning of capacity in a single production site, represented by a network of processes interconnected by material streams. An initial capacity is associated with each process, and the problem must determine which processes to operate in the future (possibly choosing new processes from a candidate set) and where and when to expand capacity. In the process industries, production costs tend to dominate (e.g. Camm et al., 1997), so this decoupling of production and logistics is reasonable. One of the earliest papers in this area was by Sahinidis et al. (1989) who describe a MILP model which selects processes to operate from an integrated network, and optimises net present value. Sahinidis and Grossmann (1992) and Liu and Sahinidis (1995) describe means of improving the solution efficiency of this class of problem. Liu and Sahinidis (1996) and Iyer and Grossmann (1998) extended the model of Sahinidis and Grossmann (1992) to include multiple product demand scenarios in each period. They then propose efficient algorithms for the solution of the resulting stochastic programming problems (formulated as large deterministic equivalent models), either by projection (Liu and Sahinidis, 1996) or by decomposition and iteration (Iyer and Grossmann, 1998).

The extension of the objective beyond simple expections was presented by Ahmed and Sahinidis (1998), who argue that robustness should also be sought. They penalise downside risk, defined here as costs above the expected cost. Applequist et al. (2000) also recognise that simply optimising expected returns can lead to higher risk solutions. They introduce the concept of a risk premium, which reflects the expected return from known classes of investment of similar variance to the capacity planning problem under investigation, the idea being that any investment should at least meet the risk premium.

A fast approximation scheme for scenario-based capacity planning problems has been reported by Ahmed and Sahinidis (2003); this is guaranteed always to generate a feasible solution.

An interesting area in which significant discrete uncertainty (related to success or failure of product tests and clinical trials). The problem of testing and capacity planning in this sector has recently been reviewed by Shah (2003).

2.2 An industrial application

An industrial application is described by Camm et al. (1997) who worked on the restructuring of Procter and Gamble’s North American supply chain. A year-long project involving integer programming, network optimisation and geographical information systems (GIS) was responsible for streamlining the US manufacturing and distribution operations with annual savings of $200m. The initial network comprised 50 product lines, 60 plants, 10 distribution centres and hundreds of customer zones. A number of factors made this initiative particularly timely, including deregulation, brand globalisation for production economies, higher plant reliabilities and throughputs, and excess capacity from a series of acquisitions.

Product “sourcing” (i.e. the allocation of products to manufacturing sites) was the focus of Camm et al.’s study, with a secondary focus on distribution network design. Rather than develop a single comprehensive production-distribution optimisation model, they decomposed the problem into a product-plant allocation problem and a distribution network design problem. Raw material and manufacturing costs tended to dominate, and so the product sourcing problem was the more important of the two, and relatively independent of the distribution network design because 80-90% of production is shipped directly to customers rather than passing through P&G’s distribution network.
A family of solutions to the distribution network design problem is then made available to the product sourcing model. This simply allocates production to plants to minimise overall costs. The problem is solved as a capacitated network flow problem, with a very crude production model (each plant simply constrained in terms of total annual production across all products). The authors make the point that being able to visualise the outputs of large-scale models (via GIS in this case) is important for their credibility. Even with such a simple representation of site capacity, large savings (particularly in terms of manufacturing costs and the removal of excess capacity) were identified.

2.3 Remarks

It should be clear that a very large amount of work has been undertaken to address the infrastructure design problem, both in the OR/MS and PSE fields. However, there are a number of outstanding issues which provide challenges for ongoing research.

- It has not really been shown what an adequate description of manufacturing processes is at this level, and what the potential benefit of including more detail on the manufacturing process is. In the case study above, significant benefits were achieved with a low level of resolution; subsequent studies may require more detail.
- The international nature of many supply chains provides additional opportunities for optimisation, especially when considering features such as transfer prices, taxes, royalties and duties. Combined financial and production-distribution models should be considered (see Shapiro’s (2003) review of strategic planning).
- Most research still has the enterprise envelope as the boundary conditions. Co-ordinated optimisation across the extended supply chain should result in significant benefits (see, e.g. Lin et al., 2000).
- The full range of uncertainty is not explored (e.g. raw material availabilities and prices, product prices, international aspects, etc.)
- Perhaps most importantly, from the process engineering perspective, is that there is no connection between process design and supply chain operation. We have seen many examples where process design has compromised supply chain operation (see, e.g. Shah, 2003). Backx et al. (1998) concur, and introduce the concept of supply chain conscious process operation. Process design for supply chain efficiency will be an important future research area. We will return to this in section 5.

3. Supply Chain Simulation and Policy Analysis

Dynamic process simulation has long been recognised as a useful tool for understanding and improving processes. Similarly, supply chain simulation is becoming a popular tool to formulate policy. As illustrated as far back as 1958 by Forrester, the processes used at different nodes of the supply chain result in a variety of different dynamic behaviours, often to the detriment of overall performance. Hence simulation is useful in identifying the potential dynamic performance of the supply chain as a function of different operating policies, ahead of actual implementation of any one policy. In most cases, the simulations are stochastic in that they repetitively sample from distributions of uncertain parameters to build up distributions of performance measures, rather than point values.

Beamon (1998) presented a review of supply chain models and partitioned them into “analytical” (i.e. purely declarative) and “simulation” (i.e. including procedural elements). Analytical models are used to optimise high-level decisions involving unknown configurations, taking an aggregate view of the dynamics and detail of operation (e.g. supply chain network design). On the other hand, simulation models can be used to study the detailed dynamic operation of a fixed configuration under operational uncertainty, and can be used to evaluate expected performance measures for the fixed configuration to a high level of accuracy. Although the field of “Industrial Dynamics” is very large, it tends to concentrate on logistics and inventory planning and normally ignores production or has a very simplistic representation of production. We shall therefore concentrate on research with a significant production element here.

Bose and Pekny (2000) use a model predictive control (MPC) framework to understand the dynamic behaviour of a consumer goods supply chain. They study different levels of co-ordination between the supply and demand entities. They also consider forecasting techniques, particularly for promotional demands. The forecasting model sets desired inventory targets which the scheduling model (based on MILP optimisation) tries to meet. This is performed in a repetitive, rolling horizon approach. It allows clear conclusions to be drawn regarding promotion and inventory management and the benefits and drawbacks of different degrees of co-ordination.

Perea-Lopez et al. (2001) study a polymer supply chain where the manufacturing process is a single stage batch multiproduct reactor, supplying a warehouse, distribution network and retailers. They capture the supply chain dynamics by the balance of inventories and the balance of orders in terms of ordinary differential equations, together with the definition of shipping rates to the downstream product-nodes, subject to some physical bounds and initial conditions for the inventory and order values. The model therefore assumes the material and order flows to be continuous. A variety of different supply chain control policies are evaluated; these are based on a decentralised decision making framework. They identify the policies that best mitigate perturbations. They extend this work (Perea-Lopez et al., 2003) to include MILP-based scheduling in an MPC framework, whereby regular solutions are generated based on the current state and portions of the solution implemented. A centralised approach where all decisions are taken simultaneously by a co-ordinator is contrasted with a decentralised approach where each entity makes decisions independently. The benefits of central co-ordination are clear, with increases in profit of up to 15% observed in the case study presented.

Supply chains can be thought of as distributed systems with somewhat decentralised decision making (especially for short-term decisions). The multi-agent based approach is a powerful technique for simulating this sort of system. Agent-based simulation techniques have been reported by Gjerdrum et al. (2000), García-Flores and Wang (2002) and Julka et al. (2002a, b). In all cases, the different players in the supply chain are represented by agents who are able to make autonomous decisions based on the information they have available and messages they receive. The agents include warehouses, customers, plants, and logistics functions. In Gjerdrum et al. (2000) and García-Flores and Wang (2002), the plant decision making involved production scheduling; the plant agent used a commercial schedule optimisation package — agent-based systems have the advantage of being able to provide wrappers to existing software. The other agents used a variety of rules (e.g. to generate orders or to manage inventory). Agents are able to negotiate solutions from different starting points. Wang et al. (2002) have a single plant supply chain and evaluate different inventory management policies, while Gjerdrum et al. (2000) have two plants and also evaluate the effect of different product sourcing rules. Julka et al. (2002b) consider the operation of a refinery and demonstrate the usefulness in crude procurement, demand tracking and retrofit analyses. Overall, the agent-based approach is a good framework for the abstraction and modular development of supply chain models, and is supported by some good software development tools that have been widely used in other sectors (e.g. telecoms).

Hung et al. (2003a) developed a flexible, object-oriented approach to the modelling of dynamic supply chains. This is based a generic node which has inbound material mangement, material conversion and outbound material management capabilities, and can be specialised to describe plants, warehouses etc. Both physical processes (e.g. manufacturing, distribution and warehousing) and business processes are modelled. By the latter, we mean how decisions are taken at the different nodes of the chain, who takes them, what tools/methods are used etc. This means that the logic of software tools used for decision-making at various nodes (e.g. DRP and MRP) are replicated in the simulation tool. The aim of this approach is to suggest non-invasive improvements to the operation of the supply chain. Such improvements may come about through changes in parameters (e.g. safety stocks) or business processes (e.g. relationships between agents). In order to assess future performance, uncertainties need to be taken into account. These include product demands, process yields, processing times, transportation lead times etc. A stochastic simulation approach that samples from the uncertain parameters is a useful way of determining expected future performance as well as confidence limits on future performance measures. Because the uncertainty space is very large, and uncertainties are time varying, Hung et al. (2003b) developed a very efficient (quasi Monte Carlo) sampling procedure. Shah (2003) describes two pharmaceutical studies based on this.

An area where stochastic simulation is finding increased use is in refining the results of relatively coarse optimisation models. In this case, optimisation models are used to determine important structural and parametric decisions, and simulation is used to evaluate the distributions of performance measures and constraints more accurately. This has been reported by Karabakal et al. (2000) who studied the VW distribution network in the USA and Gnoni et al. (2003) who develop a robust planning procedure for a multi-site automotive components facility.

Blau et al. (2000) consider the “value-chain” problem of risk management at the development stage in the pharmaceutical industry. This is a long, costly and inherently risky process with a large up-front commitment. The aim of their work is to support the process of product selection and test planning while managing risk effectively. The development activities are modelled as a probabilistic activity network, where each activity has a time, precedence relations, resource requirements and probability of success. The risk of a set of decisions must be balanced against the potential reward. The risk/reward ratio can then be used to compare different drug candidates. A screening process removes any obviously unpromising candidates, and then the remainder must be sequenced through the development pipleline. A heuristic approach using simulation with local rules in response to trigger events (e.g. failure of a test) is employed. This aims to process tasks as quickly as possible and although there is no guarantee of not violating resource constraints, these violations are usually not large.

Subramanian et al. (2001, 2003) extend this work to take explicit account of the resource requirements of the problem. They make the point that a single-level mathematical programming problem cannot hope to capture all these features. On the other hand, simulation techniques cope well with the stochastic elements, but require local, myopic rules to resolve conflicts or make choices as they arise. They therefore developed an integrated optimisation-simulation framework (SIM-OPT), where a simulator reverts to an optimisation layer (with different degrees of optimisation) to resolve conflicts or make choices such as task sequencing. The results show that using optimisation far outperforms the typical local rules used in classical simulation. By repetitive simulation, the statistical trends can be tracked and corporate policy (particularly in relation to risk and resourcing) can be analysed. Also, data from the inner simulation loop can be used to update parameters in the optimisation loop.

3.1 An industrial application (D’Alessandro and Baveja, 2000)

The polymers and resins business of Rohm and Haas was being squeezed by powerful customers and suppliers and had not been able to increase prices of key products between 1992 and 1997. An ERP system was rolled out between 1992 and 1995, but because underlying processes did not change, the expected productivity improvements did not materialise. The division therefore undertook a study to try to improve supply chain margins. Prior to the study, the policy was quite chaotic, aiming to serve all customers equally with constant disruptions to production plans. The study involved (i) a review of customer service policy; (ii) a review of product demand management; and (iii) a review of production planning and manufacturing management.

The review of customer service policy recognised that treating all customers uniformly was not a good idea and placed unnecessary stress on the supply chain. The customer base was then arranged into four tiers, where the first tier reflected very important customers responsible for a significant proportion of demand, and the fourth tier represented the long tail of very low volume customers with erratic demands. This fourth tier was then not serviced directly, but rather through distributors who managed stock themselves.

There was no formal demand management policy prior to the study, and most products were made to stock with a view to supplying on short lead times. In the study, products were categorised into four quadrants based on demand volume and demand variability. The contribution of products in each quadrant to the prevailing inventory costs was found to be very different. This resulted in a new strategy, whereby some capacity was dedicated to high volume, low variability products, which were made to stock for low lead times. This results in far fewer changeovers. The low volume, high variability

products were to be made to order. Customers would have to expect longer lead times and would be expected to order in production batch multiples.
In order to identify how to allocate products to production capacity and to estimate the new lead times, a discrete-event supply chain simulation model was developed. Different rules for make to stock and make to order products were evaluated, and it was found that segregating the resources for these classes of products was beneficial. Overall an estimated improvement in throughput of 15% was achieved, and millions of dollars were saved while operating a more predictable, less stressful system. Again, the simulation model is not very complicated, but still identifies significant benefits.

3.2 Remarks

This is very much an emerging area, and one which is expected to expand rapidly. One key issue is the integration of business process modelling with the physical aspects (recipes, resources etc.). There is no consensus yet on frameworks for addressing this. A simulation engine needs to replicate or incorporate algorithms used at certain parts of the supply chain. The emerging frameworks appear to be agent-based and object-oriented, both of which are suited to modelling complex systems with degrees of distributed decision making. These complex, stochastic, discrete-event models contain adjustable parameters. The application of optimisation procedures (probably gradient-free) to select good values for these is another interesting avenue to pursue.

4. Supply Chain Planning

Supply chain planning considers a fixed infrastructure over a short- to medium-term, and 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. Optimisation methods have found considerable application here. A feature of these problems is that the representation of the production process depends on the gross margin of the business. Businesses with reasonable to large gross margins (e.g. consumer goods, specialties) tend to use “recipe-based” representations, where processes are operated at fixed conditions and to fixed recipes. Recipes may also be fixed by regulation (e.g. pharmaceuticals) or because of poor process knowledge (e.g. food processing). On the other hand, businesses with slimmer margins (e.g. refining, petrochemicals) are moving towards “property-based” representations, where process conditions and (crude) process models are used in the process representation, and stream properties are inferred from process conditions and mixing rules. We shall consider each of these in turn.

4.1 Recipe-based planning

Here, process descriptions based on fixed recipes have been used to optimise production, distribution and storage across multiple sites, normally using MILP models.
Wilkinson et al. (1996) describe a continent-wide industrial case study. This involved optimally planning the production and distribution of a system with three factories and fourteen market warehouses and over a hundred products. It was found that the ability of the model to capture effects such as multipurpose operation, intermediate storage and changeovers gave rise to counter-intuitive results, such as producing materials further

away from demand points than would be expected. This balances the complexity associated with producing many products in each factory with the extra distribution costs incurred by concentrating the manufacture of specific products at specific sites.

McDonald and Karimi (1997) describe a similar problem for multiple facilities which produce products on single-stage continuous lines for a number of geographically distributed customers. Their model is of multiperiod form, and takes account of capacity constraints, transportation costs and shortage costs. An approximation is used for the inventory costs, and product transitions are not modelled. They include a number of additional supply chain related constraints such as single sourcing, internal sourcing and transportation times.

Kallrath (2002b) presented a comprehensive review on planning and scheduling in the process industry. He identifies the need for careful model formulation for the solution of complex problems in reasonable computational times. He describes briefly how careful modelling and algorithm design enables the solution of a 30-day integrated refinery scheduling problem.

Neumann et al. (2002) describe a planning tool that can be used at all levels in the supply chain, including network design, supply chain planning and short-term scheduling. They emphasise the importance of demand management in supply chain planning, but focus mainly on the scheduling application.

Berning et al. (2002) describe a multisite planning-scheduling application which uses genetic algorithms for detailed scheduling at each site and a collaborative planning tool to co-ordinate plans across sites. The plants all operate batchwise, and may supply each other with intermediates, creating interdependencies in the plan. The scale of the problem is large, involving of order 600 different process recipes, and 1000 resources.

Timpe and Kallrath (2000) present a mixed integer optimisation-based multisite planning model which aims to give accurate representations of production capacity. It is a multiperiod model, where (as in Kallrath, 2002a) each unit is assumed to be in one mode per period – this enables the formulation of tight changeover constraints. An interesting feature of the model is that the grid spacings are shorter at the start of the horizon (closer to scheduling) and longer later on (closer to planning). The problem solved involved four sites in three geographical regions. A similar problem (albeit with continuous process networks) is considered by Bok et al. (2000) who develop a bilevel problem-specific decomposition scheme to deal with larger scale problems.

The approaches above assume deterministic demands. Gupta and Maranas (2000) and Gupta et al. (2000) consider the problem of mid-term supply chain planning under demand uncertainty. Gupta and Maranas (2000) utilise a two-stage stochastic programming approach, where production is chosen here-and-now while distribution decisions are optimised in a wait-and-see fashion. This makes sense, since production tends to be the main contributor to lead times. Gupta et al. (2000) investigate the trade-offs between customer demand satisfaction and production costs, using a chance-constrained approach applied to the problem of McDonald and Karimi (1997).

Ryu and Pistikopoulos (2003) aim to deal with two problematic features in supply chain planning: (i) hierarchical decision structures with interdependence of the decisions of different agents; and (ii) uncertainty in data. They develop a bi-level approach which elegantly captures the interdependence of the solutions and solve the problem using a parametric programming approach.

4.2 Property-based planning

This is a relatively new field, but one which is likely to grow, given the consolidation of lower margin facilities into "world-scale" complexes. Jackson and Grossmann (2003) propose a multiperiod nonlinear programming model for the production planning and product distribution of multi-site continuous multiproduct plants. They represent the plants by nonlinear process models. Hence the operating conditions and key properties form part of the model variables. A typical problem involves 12 one-month periods, up to 5 markets, 4 sites and 118 products. A Lagrangean decomposition scheme is used, comparing spatial decomposition (i.e. between sites) and temporal decomposition (i.e. decoupling time periods via the inventory carry-overs). The less intuitive temporal decomposition method was found to be superior.

Although not strictly a "supply chain" planning problem, the area of refinery planning and scheduling has seen the use of process models. For example, Moro et al. (1998) and Pinto et al. (2000) describe a refinery planning model with non-linear process models and blending relations. They demonstrate that industrial scale problems can in principle be solved using commercially available mixed integer non-linear programming solvers. Wenkai et al. (2003) briefly describe a large refinery scheduling and inventory management model and introduce the concept of marginal value analysis which identifies critical streams and operations.

Neiro and Pinto (2003) extend this work to a set of refinery complexes, and also add scenarios to account for uncertainty in product prices. To ensure a robust solution, the decision variables are chosen "here and now". They demonstrate that non-linear models reflecting process unit conditions and mixture property prediction can be used in multisite planning models. They also show that there are significant cost benefits in solving for the complex together rather than for the individual refineries separately.

4.3 An industrial application (Kegler et al., 2003)

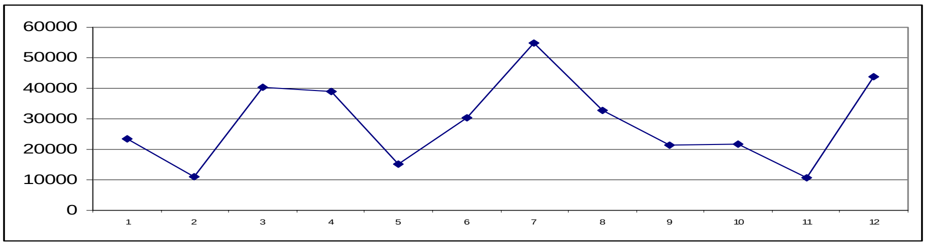
Syngenta produce and sell many varieties of seed corn hybrids. These are subject to both yield and demand uncertainties, and suffer from long lead times because the production process involves growing the hybrids in the year before they are needed and sold from inventory. They may remain in inventory for a few successive seasons before they reach their expiry date. Syngenta's customers (farmers) must choose which hybrids to plant during their growing season. This choice will depend on a number of factors including the location, soil, weather and their experience with particular hybrids in the previous growing season. An interesting feature is that there is a North American (NA) production (planting) season and a South American (SA) one six months later. This means that a "classical" two-stage stochastic programming technique may be applied.

When planning the production of year n, the inventory on hand for the demands in year n and the costs for NA and SA production are known. The demands in years n and $n+1$ and the yields for NA and SA are unknown but can be represented by distributions. The yields relate to the key decision variables which are the areas to plant for each hybrid.

The variance in the distribution of demand for year n is much smaller than $n+1$ since information on year $n-1$ is available. The two stage approach uses the expected value for year n and commits to the areas planted in NA. The second stage decisions are the areas to plant for each hybrid in SA. These are not selected here and now, but rather the uncertain variables are discretised into scenarios and the areas are determined on a wait-and-see basis. At the end of the first stage, the actual NA yields are known, and the demand for year *n* is known with very little uncertainty. At the end of the NA growing season, the model is re-run to select the best here-and-now values for the SA production areas, based on the new yield information. The objective function in both optimisation models is the maximisation of expected gross margin. The results were quite different from historical plans, with considerably higher predicted margins (increases of $5m per annum). Qualitatively speaking, the SA production was historically used as a stop-gap, while the new approach used it more systematically. The model had no complicated resource constraints since there is no upper bound on the total area planted. This means that each hybrid can be considered independently. Again, this study illustrates the benefits of systematic approaches, even if the models used are not very complicated.

4.4 Remarks

Many of the points made in section 2.3 hold here as well, especially with respect to process design, global trade and classes of uncertainty. Romero et al. (2003) show how to integrate financial and planning models at the plant level; similar models at the enterprise level are needed. More work needs to be undertaken on multi-enterprise (extended) supply chain planning. For illustration, below is an order profile for a product of one of our collaborators. The dynamics are generated by their customer's re-ordering policy. What would be better – an optimised plan trying to meet hundreds of order profiles like this, or a collaborative plan, driven by smoother end-user demands?
The property-based planning area is bound to grow, with gradual convergence of supply chain and process simulation/optimisation models.



5. Future Developments and Challenges

A number of challenges have already been posed in sections 2.3, 3.2 and 4.4 above. We see two generic important future challenges:
Improved design for existing processes. A distinguishing feature of process industry supply chains is that supply chain performance is very strongly affected by the flexibility and responsiveness of the production process. This is not the case to the same extent in other industries. For example, consider the multimedia products supply chain. Here, efficient forecasting, flexible warehouses and real-time downstream supply chain management and adaptation are critical; production is very straightforward (stamping out CDs and DVDs) and often a lead time of one day can be assumed for a product. We believe "process design for supply chain responsiveness" is an important area that has not receive much attention so far. The process industries have not fully grasped the

concept of mass customisation. For example, instead of using a single reactor to produce different complete polymers from monomers, why not try to develop building blocks of medium molecular weights and combine them as appropriate? To what extent can intermediates be made at “worldscale” centralised facilities and specialised products be configured at flexible, near-market facilities?

Effective design of “new” supply chains. It is evident that the process industry supply chains of the future will be quite different from those of the past. In addition, a number of new supply chains (parts of which may already be present) will emerge. There exists a relatively short window of opportunity to explore the optimal configuration of such supply chains before they develop organically – this may be of vital importance in informing national and international policy as well as strategic decisions in industry. Examples of such “supply chains of the future” include: (i) hydrogen, and more generally, supply chains to support fuel cells; (ii) water; (iii) fast response therapeutics (particularly vaccines) for civilian and homeland security uses; (iv) energy – the provision of the energy needs for a country can be viewed as a supply chain which is subject to significant decarbonisation pressures; (v) life science products; (vi) crops for non-food use and biorefineries; (vii) gas-to-value (i.e. generating high value products (e.g. very low sulphur diesel) from natural gas in situ); and (viii) waste-to-value and reverse production systems (closed loop supply chains, see e.g. Realff et al., 2000).

Although research in basic sciences related to emerging industries is currently flavour of the month, supply chain research as applied to these will be important. Wang (2000) notes that enablers for emerging industries (e.g. micro-nano technology, biotechnology and advanced material technology) are information technology, supply chain management, modelling and simulation, human development and knowledge management.

6. References

Ahmed, S. and N.V. Sahinidis, 1998, Robust process planning under uncertainty, *Ind.Eng. Chem. Res*., **37**, 1883-1892.

Ahmed, S. and N.V. Sahinidis, 2003, An approximation scheme for stochastic integer programs arising in capacity expansion, *Ops. Res.*, **51**, 461-47.

Applequist, G.E., J.F. Pekny and G.V. Reklaitis, 2000, Risk and uncertainty in managing chemical manufacturing supply chains, *Computers chem. Engng.*, **24**, 2211-2222.

Backx, T., O. Bosgra and W. Marquardt, 1998, Towards intentional dynamics in supply chain conscious process operations, *AIChE Symp. Ser*. **320(94)**, 5-20.

Beamon, B.M., 1998, Supply chain design and analysis: models and methods, *In.t J. Prod. Econ.* **55**, 281-294.

Berning, G., M. Brandenburg, K. Gursoy, V. Mehta and F,-J. Tölle, 2002, An integrated system for supply chain optimisation in the chemical process industry, *OR Spectrum*, **24**, 371-401.

Blau, G., B. Mehta, S. Bose, J. Pekny, G. Sinclair, K. Keunker and P. Bunch, 2000, Risk management in the development of new products in highly regulated industries. *Comput. Chem. Eng*., **24**, 1005-1011.

Bok, J.K., I.E. Grossmann and S. Park, 2000, Supply chain optimization in continuous flexible process networks, *Ind. Eng. Chem. Res.*, **39** 1279-1290.

Bose, S. and J.F. Pekny, 2000, A model predictive framework for planning and scheduling problems, a case study of consumer goods supply chain, *Computers chem. Engng.*, **24**, 329-335.

Brown, G.G., G.W. Graves and M.D. Honczarenko, 1987, Design and operation of a multicommodity production/distribution system using primal goal decomposition, *Management Science*, **33**, 1469-1480.
Camm, J.D., T.E. Chorman, F.A. Dill, J.R. Evans, D.J. Sweeney, G.W. Wegryn, 1997, Blending OR/MS, judgment, and GIS: restructuring P&G's supply chain, *Interfaces*, **27:1**, 128-142.
D'Alessandro, A.J. and A. Baveja, 2000, Divide and conquer: Rohm and Haas' response to a changing specialty chemicals market, *Interfaces*, **30:6**, 1-16.
Forrester, J., 1958, Industrial dynamics: a major breakthrough for decision makers. *Harvard Business Review*, **July-August**, 37-66.
García-Flores, R. and X.Z. Wang, 2002, A multi-agent system for chemical supply chain simulation and management support, *OR Spectrum*, **24**, 343-370.
Geoffrion, A.M. and G.W. Graves, 1974, Multicommodity distribution system design by Benders decomposition, *Management Science*, **20**, 822-844.
Geoffrion, A.M. and T.J. van Roy, 1979, Caution: common sense planning methods can be hazardous to your corporate health, *Sloan Management Review*, **Summer**, 31-42.
Gjerdrum, J., N. Shah and L.G. Papageorgiou, 2000, A combined optimisation and agent-based approach for supply chain modelling and performance assessment, *Production Planning and Control*, **12**, 81-88.
Gnoni, M.G., R. Iavagnilio, G. Mossa, G. Mummolo and A. Di Leva, 2003, Production planning of a multi-site manufacturing system by hybrid modelling: A case study from the automotive industry, *International Journal of Production Economics*, **85**, 251-262.
Gupta, A., and C.D. Maranas, 2000, A two-stage modeling arid solution framework for multisite midterm planning under demand uncertainty, *Ind. Eng. Chem. Res.*, **39**, 3799-3813.
Gupta, A., C.D. Maranas and C.M. McDonald, 2000, Mid-term supply chain planning under demand uncertainty: customer demand satisfaction and inventory management, *Computers and Chemical Engineering*, **24**, 2613-2621.
Hung, W.Y., N. Samsatli and N. Shah, 2003a, Object-oriented dynamic supply chain modelling incorporated with production scheduling, *Proc. International Conference on Industrial Engineering and Production Management (IEPM 03), Porto, Portugal*, 304-313.
Hung W.Y., S. Kucherenko, N. Samsatli and N. Shah, 2003b, An efficient sampling technique for stochastic supply chain simulations, *Proc. 2003 Summer Computer Simulation Conference (SCSC 2003),* July 2003, Montreal, , Simulation Series **35(3)**, 101-106.
Iyer, R.R. and I.E. Grossmann, 1998, A bilevel decomposition algorithm for long-range planning of process networks, *Ind. Eng. Chem. Res*., **37**, 474-481.
Jackson, J.R. and I.E. Grossmann, 2003, Temporal decomposition scheme for nonlinear multisite production planning and distribution models, *Ind. Eng. Chem. Res.*, **42**, 3045-3055.
Julka, N., R. Srinivasan and I. Karimi, 2002a, Agent-bases supply chain management-1: framework, Computers chem. Engng., 26, 1755-1769.
Julka, N., R. Srinivasan and I. Karimi, 2002b, Agent-bases supply chain management-1: a refinery application, Computers chem. Engng., 26, 1771-1781.
Kallrath J., 2002a, Combined strategic and operational planning – an MILP success story in chemical industry, *OR Spectrum*, **24**, 315-341.
Kallrath J., 2002b, Planning and scheduling in the process industry, *OR Spectrum*, **24**, 219-250.
Karabakal N., A. Gunal, and W. Ritchie, 2000, Supply-chain analysis at Volkswagen of America, Interfaces, 30(4), 46-55.
Kegler, G. P. C. Jones, R. D. Traub and T. J. Lowe, 2003, Managing the seed-corn supply chain at Syngenta, *Interfaces*, **33:1**, 80-90.
Lambert, D.M. and M. Cooper, 2000, Issues in supply chain management, *Ind. Mktg. Mgt.*, **29**, 65-83.
Lin, G., M.Ettl, S. Buckley, S. Bagchi, D.D. Yao, B.L. Naccarato, R. Allan., K.Kim and L. Koenig, 2000, Extended-enterprise supply-chain management at IBM personal systems group and other divisions, *Interfaces*, **30**, 7-25.
Liu, M.L. and N.V. Sahinidis, 1995, Computational trends and effects of approximations in an MILP model for process planning, *Ind. Eng. Chem. Res*., **34**, 1662-1673.

Liu, M.L. and N.V. Sahinidis, 1996, Optimization in process planning under uncertainty, *Ind. Eng. Chem. Res.*, **35**, 4154-4165.
McDonald, C.M. and I.A. Karimi, 1997, Planning and scheduling of parallel semicontinuous processes. 1. Production planning, *Ind. Eng. Chem. Res.*, **36**, 2691-2700.
Moro L.F.L., A.C. Zanin and J.M. Pinto, 1998, A planning model for refinery diesel production
Comput. Chem. Eng. **22**, S1039-S1042.
Neumann, K., C. Schwindt and N. Trautmann, 2002, Advanced production scheduling for batch plants in process industries, *OR Spectrum*, **24**, 251-279.
Neiro, S.M.S. and J.M. Pinto, 2003, Supply chain optimisation of petroleum refinery complexes, *Proc.4th Intl. Conf. on Foundations of Computer-Aided Process Operations*, 59-72.
Perea-Lopez E., B.E.Ydstie and I.E. Grossmann, 2001, Dynamic modelling and decentralised control of supply chains, *Ind. Eng. Chem. Res*., **40**, 3369-3383.
Perea-Lopez E., B.E.Ydstie and I.E. Grossmann, 2003, A model predictive control strategy for supply chain optimisation, *Computers and Chemical Engineering*, **27**, 1201-1218.
Pinto, J.M., M. Joly and L.F.L. Moro, 2000, Planning and scheduling models for refinery operations, *Computers chem.. Engng*. **24**, 2259-2276
Realff M.J., J.C. Ammons JC and D. Newton, 2000, Strategic design of reverse production systems, *Computers and Chemical Engineering*, **24**, 991-996.
Romero, J., M. Badell, M. Bagajewicz and L. Puigjaner, 2003, Integrating budgeting models into scheduling and planning models for the chemical batch industry, *Ind. Eng. Chem. Res.*, **42**, 6125-6134.
Ryu, J.-H. and E.N. Pistikopoulos, 2003, A bilevel programming framework for enterprise-wide supply chain planning problems under uncertainty, *Proceedings of Fourth International Conference on Foundations of Computer-Aided Process Operations*, 297-300.
Sabri E.H. and B.M. Beamon, 2000, A multi-objective approach to simultaneous strategic and operational planning in supply chain design, *Omega*, **28**, 581-598.
Sahinidis, N.V, I.E. Grossmann, R.E. Fornari and M. Chathrathi, 1989, Optimization model for long-range planning in the chemical-industry, *Computers chem.. Engng*, **13**, 1049-1063.
Sahinidis, N.V. and I.E. Grossmann, 1992, Reformulation of the multiperiod MILP model for capacity expansion of chemical processes, *Operations Research*, **40**, S127-S144.
Shah, N., 1998, Pharmaceutical supply chains: key issues and strategies for optimisation, *Proc.4th Intl. Conf. on Foundations of Computer-Aided Process Operations*, 73-85.
Shapiro, J., 2003, Challenges of strategic supply chain planning and modelling, *Proceedings of 4th Intl. Conference on Foundations of Computer-Aided Process Operations*, 27-34.
Subramanian, D., J.F. Pekny and G.V. Reklaitis, 2001, A simulation-optimization framework for Research and Development Pipeline management, *AIChE Journal*, **47**, 2226-2242.
Subramanian, D., J.R. Pekny, G.V. Reklaitis and G.E. Blau, 2003, Simulation-optimization framework for stochastic optimization of R&D pipeline management, *AIChE* J*ournal*, **49** , 96-112.
Timpe, C.H. and J. Kallrath, 2000, Optimal planning in large multi-site production networks, *EJOR*, **126**, 422-435.
Tsiakis, P., N. Shah, and C. C. Pantelides, 2001a, Design of multi-echelon supply chain networks under demand uncertainty, *Ind. Eng. Chem. Res.* **40**, 3585-3604.
Tsiakis, P., N. Shah and C.C. Pantelides, 2001b, "Optimal Structures for Supply Chain Networks", presented at AIChE Annual Meeting, November.
Vidal, C.J. and M. Goetschalckx, 1997, Strategic production-distribution models: A critical review with emphasis on global supply chain models, *EJOR*, **98**, 1-18.
Wang, B., 2000, Advanced manufacturing in the 21st Century, *Proc. 5th Annual International Conference on Industrial Engineering – Theory, Applications and Practice.*
Wenkai, L., C.-W. Hui, B. Hua and Z. Tong, 2003, Plant-wide scheduling and marginal value analysis for a refinery, *Proceedings of Fourth International Conference on Foundations of Computer-Aided Process Operations*, 339-342.
Wilkinson, S.J., A. Cortier, N. Shah and C.C. Pantelides, 1996, Integrated production and distribution scheduling on a Europe-wide basis", *Computers and Chemical Engineering.*, **S20**, S1275-S1280.