Computer Aided Process and Product Engineering
Luis Puigianer and Georges Heyen

1
Resource Planning

Michael C. Georgiadis and Panagiotis Tsiakis

1.1
Introduction

Until recently, resources planning exercises in many companies were based on quantitative, managerial judgements about the future directions of the firms and the markets in which they compete. Complex interactions between the different decision-making levels were often ignored. In the past few years however, important planning decisions, such as those relating to capacity expansion, new product introduction, oil and chemical product distribution and energy planning, have been formally addressed based on recent developments in mixed-integer optimization. Today, most process and energy industries have turned to the use of optimization models in seeking efficient long-term planning use of their resources (Shapiro 2004).

In the last two decades, new techniques have developed to analyze large size planning models, while research in aggregation and decomposition techniques has multiplied. In addition, many managers have begun to recognize the major drawbacks of most current planning systems and the necessity for more intelligent and quantitative decisions tools instead of administrative routine procedures. This comes as a natural continuation of the pioneering work of F. W. Taylor and H. L. Gantt, who in the early 1900s identified the impact on productivity and other key performance indices, of general production planning systems based on scientific approaches (Wilson 2003). Today's computing offers more powerful techniques for modeling and solving planning problems, while Gantt charts still provide an excellent display tool for understanding and acceptance of plans in any type of environment, in addition to other available interfaces.

During the last year, companies have realized that in order to achieve significant competitive advantage within their sector they need to understand the operations hierarchy and solve their problems in a unified framework, a fact that is resulting in the development of corresponding tools. Towards that, the interest in planning and scheduling capabilities has given rise to the providers of solution systems designing, developing and implementing planning systems as part of general supply-chain sup-

Computer Aided Process and Product Engineering. Edited by Luis Puigjaner and Georges Heyen

ISBN: 3-527-30804-0

port systems or with open architecture to allow easy integration. Owing to the inherent complexity and the different scales of integration this has been accepted by the research community as a topic that needs urgent answers, since the planning software industry is in its infancy and under pressure to respond to the demand.

The objective of this chapter is to present a comprehensive review of state-of-the-art models, algorithms, methodologies and tools for the resource planning problem covering a wide range of manufacturing activities. For reasons of presentation, the remaining of this chapter is organized as follows. The long-range planning problem in the process industries is considered in Section 1.2 including a detailed discussion on the effect of uncertainty, the planning of refinery operations and offshore oilfields, the campaign planning problem and the integration of scheduling and planning. Section 1.3 describes the planning problem for new product development with emphasis on pharmaceutical industries. Section 1.4 presents briefly the tactical planning problem, followed by a description of the resource planning problem in the power market and construction projects in Section 1.5. Section 1.6 is a review of recent computational solution approaches to the planning problem are reviewed, while available software tools are outlined in the Section 1.7. Finally, Section 1.8 will make some conclusions and propose future challenges in this area.

1.2 Planning in the Process Industries

1.2.1 Introduction

New environmental regulations, new processing technologies, increasing competition and fluctuating prices and demands in process industries have led to an increasing need for quantitative techniques for planning the selection of new processes, the expansion and shut down of existing processes, and the production of new products. Further decisions also include creation of production, distribution, sales and inventory plans. (Kallrath 2002). It has been recently realized that in a competitive and changing environment the need to plan new output levels and production mixes is likely to arise much more frequently than the need to design new batch plants.

Although the boundaries between planning and scheduling are not very clear we can distinguish the following basic features of the process planning problem:

- multipurpose equipment
- sequence-dependent set-up times and cleaning costs
- combined divergent, convergent and cyclic material flows
- multistage, batch and campaign production using shared intermediates
- multicomponent flow and nonlinear blending for the refinery operations
- finite intermediate storage, dedicated and variable tanks.

Structurally, these features often lead to allocation and sequencing problems and knapsack structures, or to the pooling problem for the petrochemical industries. In production planning we usually consider material flow and balance equations connecting sources and sinks of a production network. Time-indexed models using a relative coarse discretization of time, e.g., a year, quarter, months or weeks are usually accurate enough. linear programming (LP), mixed-integer linear programming (MILP) and mixed-integer nonlinear programming (MINLP) technologies are often appropriate and successful for problems with a clear quantitative objective function, as will become clear in the following sections.

Nowadays, it is possible to find the optimal way to meet business objectives and to fulfil all production, logistics, marketing, financial and customer constraints and especially:

- to accurately model single-site and multisite manufacturing networks;
- to perform capital planning and acquisition analysis, i.e., to have the possibility to change the structure of a manufacturing network through investment and to determine the best investment type, size and location based on user-defined rules related to business objectives and available resources; the results of such analysis can lead to nonintuitive solutions that provide management with scenarios that could dramatically increase profits;
- to produce integrated enterprise solutions and to enable a crossfunctional view of the planning process involving production, distribution and transport, sales, marketing and finance functions;
- to develop new product and introduction strategies along with capacity planning and investment strategies.

The following sections provide a comprehensive review of the above areas.

1.2.2
Long-Range Planning in the Process Industries

Chemical process industries are increasingly concerned with the development of planning techniques for their process operations. The incentive for doing so derives from the interaction of several factors (Reklaitis 1991, 1992). Recognizing the potential benefits of new resources when these are used in conjunction with existing processes is the first. Another major factor is the dynamic nature of the economic environment. Companies must assess the potential impact on their business of important changes in the external environment. Included are changes in product demand, prices, technology, capital market and competition. Hence, due to technology obsolescence, increasing competition, and fluctuating prices of and demands for chemicals, there is an increasing need to develop quantities techniques for planning the selection of new processes, and the production of chemicals (Sahinidis et al. 1989)

The long-range planning problem in process industries has received a lot of attention over the last 20 years and numerous sophisticated models exist in the literature. Sahinidis et al. (1989) consider the long-range planning problem for a chemical complex involving a network of chemical processes that are connected in a finite number of ways. The network also consists of chemicals: raw materials, intermediates and products that may be purchased from and/or sold to different markets. The objective function to be maximized is the net present value (NPV) of the planning problem over a long-range horizon of interest consisting of a number of *NT* time periods during which prices and demands of chemicals, and investment and operating costs of the processes can vary. The problem consists of determining the following items:

- capacity expansion and shut down policy
- selection of new processes and their capacity expansion and shut down policy
- production profiles
- sales and purchase of chemicals at each time period.

It is assumed that the material balance and the operating cost in each process can be expressed linearly in terms of the operating level of the plant. The investment costs of the processes and their expansions are considered to be linear expressions of the capacities with a fixed charge cost to account for economies of scale. This is a multiproduct, multifacility, dynamic, location-allocation problem that has been formulated using MILP modes. Sahinidis and Grossmann (1991) extended the above model to account for production facilities that are flexible manufacturing systems operating in a continuous or in a batch mode. The suggested model provides a unified representation for the different types of processes.

Norton and Grossmann (1994) extended the original model of Sahinidis and Grossmann (1991) for dedicated and flexible processes by incorporating raw materials flexibility in addition to product flexibility. In their model, raw material flexibility is characterized by different chemicals as raw materials or different sources of the same raw material. The model was able to handle any combination of raw material and process flexibility, thus providing a truly unified representation for all types of process flexibility in the long-range planning problem.

The above industrial relevance of the chemical process planning problem motivated the need to develop more efficient solution techniques for large-scale problems. Liu and Sahinidis (1995) presented a comprehensive investigation of the effect of time discretization, data uncertainty and problem size, on the quality of the solution and computational requirements of the above MILP planning models. The importance of detailed time discretization was demonstrated and the effect of uncertainty was critically assessed. An exact branch-and-bound algorithm was also presented along with several heuristic approaches for the solution of larger problems. Extending this work, Liu and Sahinidis (1996a) investigated separation algorithms and cutting plane approaches that were demonstrated to be more robust and faster than conventional solution approaches for large-scale problems with long time-horizons.

Oxe (1997) considered a LP approach to choose an appropriate subset of existing production plants and lines and to optimize allocation, transportation paths and central stock profiles so that the overall costs are minimized while product delivery is ensured within some months (specified for each product) from the order.

McDonald and Karimi (1997) developed production planning and scheduling models for the case of semicontinuous processes, which are assumed to comprise several facilities in distinct geographical locations, each potentially containing multiple parallel lines. The models developed are deterministic in nature and are formulated as mixed-integer linear programs.

Oh and Karimi (2001a) presented a new methodology for determining the optimal campaign numbers for producing multiple products on a single machine with sequence-dependent set-ups. Their methodology is intended mainly for the purpose of capacity planning. In the second part of this work (Oh and Karimi 2001b) they addressed the problem of determining the sequence of these given product campaigns to obtained a detailed schedule of operation. Heuristic algorithms based on a decomposition scheme were investigated for the efficient solution of the underlying optimization problem.

1.2.3
Process Planning under Uncertainty

Decision making in the design and operation of industrial processes is frequently based on parameters of which the values are uncertain. Sources of uncertainty, which tend to imply the means for dealing with them, can be divided into:

- short-term uncertainties such as processing time variations, rush orders, failed batches, equipment breakdowns, etc.;
- long-term uncertainty such as market trends, technology changes, etc.

A detailed classification of different areas of uncertainty is suggested by Subrahmanyam et al. (1994) including uncertainty in prices and demand, equipment reliability and manufacturing uncertainty. An excellent review on the general subject of optimization under uncertainty has recently been presented by Sahinidis (2004).

In the area of process planning, uncertainty is usually associated with product demand fluctuations, which may lead to either unsatisfied customer demands or loss of market share or excessive inventory costs. A number of approaches have been proposed in the process systems engineering literature for the quantitative treatment of uncertainty in the design, planning and scheduling of batch process plants with an emphasis on the design. The most popular one so far has been the scenario-based approach, which attempts to forecast and account for all possible future outcomes through the use of scenarios. The scenario approach was suggested by Shah and Pantelides (1992) for the design of flexible multipurpose batch plants under uncertain production requirements, and was also used by Subrahmanyam et al. (1994). Scenario-based approaches provide a straightforward way to implicitly account for uncertainty (a comprehensive discussion is presented by Liu and Sahinidis (1996b)). Their main drawback is that they typically rely on either the *a priori* forecasting of all possible outcomes of the discretization of a continuous multivariable probability distribution, resulting in an exponential number of scenarios.

Liu and Sahinidis (1996a,b) and Iyer and Grossmann (1998) extended the MILP process and capacity planning model of Sahinidis and Grossmann (1991) to include multiple product demands 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 1996a) or by decomposition and iteration. However, as pointed out by Shah (1998) a major assumption in their formulation is that product inventories are not carried from one period to the next. This has the advantage in ensuring that the problem size is of, $0(np \times ns)$, where np is the number of periods and ns is the number of demand scenarios, rather than $0(ns^{np+1})$. However, if the periods are too short, this compromise the solution from two perspectives:

- All products must be produced in all periods if demand exists for them – this may be suboptimal.
- Plant capacity must be designed for a peak demand period.

Clay and Grossmann (1994) addressed this issue. They considered the structure of both the two-period and multiperiod problem for LP models and derived an approximate model based on successive repartitioning of the uncertain space, with expectations being applied over partitions. This has the potential to generate solutions to a high degree of accuracy in a much faster time than the full deterministic equivalent model.

Liu and Sahinidis (1997) presented two different formulations for the planning in a fuzzy environment (the forecast model parameters are assumed to be fuzzy). The first considers uncertainty in demands and availabilities, whereas the second accounts for uncertainty of the right hand size of made constraints and objective function coefficient.

The approaches above mainly focus on relatively simple planning models of plant capacity. Petkov and Maranas (1997) considered the multiperiod planning model for multiproduct plants under demand uncertainty. Their planning model embeds the planning/scheduling formulation of Birewar and Grossmann (1990) and therefore calculates accurately the plant capacity. They do use discrete demand scenarios, but assume normal distributions and directly manipulate the functional forms to generate a problem which maximizes the expected profit and meets certain probabilistic bounds on demand satisfaction without the need for numerical integration. Ierapetritou and Pistikopoulos (1994) proposed a two-stage stochastic programming formulation for the long-range planning problem including capacity expansion options. Based on the Gaussian quadrature method for approximating multiple probability integrals, Ierapetritou et al. (1996) considered the operational and production planning problem under varying conditions and changing economic circumstances. The effect of uncertainty on future plant operation was investigated via the incorporation of explicit future plan feasibility constraints into a two-stage stochastic programming formulation, with the objective of maximizing an expected profit over a time horizon, and the use of the value of perfect information. The main drawback of this approach is its high computation cost. To address this issue Bernardo et al. (1999) investigated more efficient integration schemes for the solution of problems with many uncertain parameters. Recently, Ryu et al. (2004) addressed bilevel decision making problems under uncertainty in the context of enterprise-wide supply-chain optimization with one level corresponding to a plant planning problem, and the other to a distribution network problem. The bilevel problem was transformed into a family of single parametric optimization problems solved to global optimality.

Rodera et al. (2002) presented a methodology for addressing investments planning in the process industry using a mixed-integer multiobjective optimization approach. Romero et al. (2003) proposed a modeling framework integrating cash flow and budgeting aspects with an advanced scheduling and planning model. It was illustrated that potential budget limitation can significantly affect scheduling and planning decisions. Recently, Barbaro and Bagajewicz (2004) proposed a new mathematical formulation for problems dealing with planning under design uncertainty that allows management of financial risk according to the decision-maker's preferences.

Sanmarti et al. (1995) define a robust schedule as one which has a high probability of being performed, and it is readily adaptable to plant variations. They define an index of reliability for a unit scheduled in a campaign through its intrinsic reliability, the probability that a standby unit is available during the campaign, and the speed with which it can be repaired. An overall schedule reliability is then the product of the reliabilities of units scheduled in it, and solutions to the planning problem can be driven to achieve a high value of this indicator.

Ahmed and Sahinidis (1998) noted that the resulting two-stage stochastic optimization models in process planning under uncertainty minimize the sum of the costs of the first stage and the expected cost of the second stage. However, a limitation of this approach is that it does not account for the variability of the second-stage costs and might lead to solutions where the actual second-stage costs are unacceptably high. In order to resolve this difficulty they introduced a robustness measure that penalizes second-stage costs that are above the expected cost.

Pistikopoulos et al. (2001) presented a systems effectiveness optimization framework for multipurpose plants that involves a novel preventive maintenance model coupled with a multiperiod planning model. This provides the basis for simultaneously identifying production and maintenance policies, a problem of significant industrial interest. This framework was then extended by Goel et al. (2003) to incorporate the reliability allocation problem at the design stage. Li et al. (2003) employed probabilistic programming approach to plan operations under uncertainty and to identify the impact on profits based on reliability analysis. Recently, Suryadi and Papageorgiou (2004) presented an integrated framework for simultaneous maintenance planning and crew allocation in multipurpose plants.

1.2.4
Integration of Production Planning and Scheduling

The decisions made by planning, scheduling, and control functions have a large economic impact on process industry operations – estimated to be as high as US $10 increased margin per ton of feed for many plants. The current process industry environment places even more of a premium on effective execution of these functions. In spite of these incentives, or perhaps because of them, there exists significant disagreement about the proper organization and integration of these functions, indeed even which decisions are properly considered by the planning, scheduling or control business processes. It has long been recognized that maintaining consistency among the decisions in most process companies continues to be difficult and the lack of consistency has real economic consequences. In their recent work Shobrys and White (2002) presented a critical and comprehensive analysis of several practical aspects that need to be carefully considered when challenges, associated with improving these functions and achieving integration, arise.

The planning and scheduling levels of the operations hierarchy are natural candidates for integration because the structure of these two decision problems is very similar. However, the direct merging of these two levels requires embedding the details of the scheduling level into a super-scheduling-problem defined over the entire planning horizon. The result is a problem that is extremely difficult to solve. Thus, in recent years research has been increasingly interested in the issues around the integration of production and scheduling, in order to provide greater consistency.

The most common approach for the simultaneous treatment of production planning and scheduling is a hierarchical decomposition scheme, where the overall production planning problem is decomposed into two levels (Bitran and Hax 1977). At the upper level, the planning problem, which usually involves a simplistic representation of the scheduling problem, is solved as a multiperiod LP problem in order to maximize the profit and set production targets. At the lower level, the scheduling problem is concerned with the sequencing of tasks that should meet the goals. An alternative integration approach is through the rolling schedule strategy (Hax 1978).

Production planning and scheduling are closely related activities. Ideally these two should be linked, in order that the production goals set at the production plan level should be implementable at the scheduling level. Birewar and Grossmann (1990), based on their initial LP flow-shop scheduling model, proposed aggregate methods that allow tackling longer time-horizons by reducing the combinatorial nature of the problem. The model accounts for inventory costs, sequence-dependent clean-up times and costs, and penalties for not meeting predefined product demands. Using a graph enumeration method, the production goals predicted by the planning model are applied to the actual schedule, with the key point that both problems are solved simultaneously, since the sequencing constraints can be accounted for at the planning level with very little error.

Bassett et al. (1996a), working in the same direction of model-based integrated applications and focused on integrating planning decisions with the actual schedule, proposed an aggregation/disaggregation technique that can be used to provide solutions to otherwise intractable mid-term planning models. The initiative is the exploitation of available enterprise information within the process operational hierarchy tree. A more formal approach to integration of production and scheduling is described based on the previous work of Subrahmanyam et al. (1996), where the planning model, based on an aggregate formulation, is modified to be consistent with detailed scheduling decisions.

Hierarchical production planning algorithms often make use of rolling horizon algorithms as a suboptimal to obtain feasible, but often good, solutions. The disadvantage of the method is reliance on the simplistic or rather poor representation of the scheduling problem within the aggregate part. Wilkinson (1996) derived an accurate aggregate formulation by applying formal aggregation operators to the resource-task network (RTN) formulation, and dividing the horizon into aggregate time periods (ATPs). This allows creating single MILP models that have varying time resolution. The first ATP is modeled in fine detail (scheduling) and the subsequent ATPs are modeled using the aggregate formulation (planning). The problem can then be solved as a single MILP, maintaining consistency between plan and schedule.

Rodrigues et al. (2000) presented a two-level decomposition procedure for integrating scheduling and planning decisions. At the planning level, demands are adjusted, a raw material plan is defined and a capacity analysis is performed. At the scheduling level an MILP model is proposed. Geddes and Kubera (2000) described a practical integration between planning and online optimization with application in olefins production. Das et al. (2000) developed a prototype system by integrating two higher-level hierarchical production planning application programs (aggregated production plan and master production schedule) using a common data model integration approach into an existing planning system for short-term scheduling and supervisory management, which was originally developed by Rickard et al. (1999). Bose and Pekny (2000) presented a similar approach to model predictive control for integrated planning and scheduling problems. Van den Heever and Grossmann (2003) addressed the integration of production planning and reactive scheduling for the optimization of a hydrogen supply network consisting of 5 plants, 4 interconnected pipelines and 20 customers. A multiperiod MINLP model was proposed for both the planning and scheduling levels, along with heuristic solution methods based on Lagrangean decomposition.

During the last Foundations on Computer Aided Process Operations (FOCAPO 2003) event, several contributions presented were on the integration between planning and scheduling decisions. Harjunkoski et al. (2003) provided a comprehensive analysis of different aspects needed for the integration of the planning, scheduling and control levels in the light of ABB's industrial initiative. They presented a framework introducing an approach to integrating all aspects relevant to decision making in a supportive way. An industrial case study was used to illustrate the benefits of the integrated framework. Yin and Liu (2003) developed a problem formulation and solution procedure for production planning and inventory management of systems under uncertainty. The production system is modeled by finite-event continuous-time Markov chains. Kabore (2003) presented a model predictive control formulation for the planning and scheduling problem in process industries. The main idea is to use moving-horizon techniques as well as a feedback control concept to continuously update production schedules. Wu and Ierapetritou (2003) proposed a method for simultaneously solving a planning and scheduling problem. The mathematical formulation of the planning problem involves scheduling decisions and results to a large MINLP problem, intractable to solve directly within reasonable computational time. A nonoptimal solution strategy is selected to provide near-optimal solutions within reasonable computational times.

Tsiakis et al. (2003) applied the algorithm of Wilkinson (1996) to obtain an integrated plan and schedule of the operations of a complex specialty oil refinery, focusing on the downstream products of the oil supply-chain. Operating in an uncertain environment, the company needed to schedule the refinery operations in detail over the next month, while producing plans for the next year that were both reasonably accurate and consistent with the short-term schedule.

1.2.5
Planning of Refinery Operations and Offshore Oilfields

The refinery industry is currently facing a rather difficult situation, typically characterized by decreasing profit margins, due to surplus refinery capacity, and increasing oil prices. Simultaneous market competition and stringent environmental regulations are forcing the industry to perform extensive modifications in its operations. As a result there is no refinery nowadays that does not use advanced process engineering tools to improve its business performance. Such tools range from advanced process control to long-range planning, passing through process optimization, scheduling and short-term planning. Despite their widespread use and the existence of quasi-standard technologies for these applications, their degree of commercial maturity varies greatly and there are many unresolved problems concerning their use. Moro (2003) presents a comprehensive discussion on current approaches to solving these problems and proposes directions for future development in this area.

Traditionally, planning and scheduling decisions in refinery plants have been addressed using LP techniques and several tools exist such as the Integrated System for Production Planning (SIPP) and the Refinery and Petrochemical Modelling System (RPMS). An excellent review has recently been presented by Pinto et al. (2000). These tools allow the development of general production plans of the whole refinery. As pointed out by Pelham and Pharris (1996), the planning technology in the refinery operations can be considered well-developed and the margins for further improvement are very tight. The major advances in this area should be expected in the form of more detailed and accurate modeling of the underlying processes, notably through the use of nonlinear programming (NLP) as illustrated by Moro et al. (1998) using a real-world application. Ballintjin (1993) compared continuous and mixed-integer linear formulations and emphasized the low applicability of models based solely on continuous variables.

In the literature, the first mathematical programming (MP) approaches utilizing advances in mixed-integer optimization are focused on specific applications such as gasoline blending (Rigby et al. 1995) and crude oil unloading. Shah (1996) presented a MP approach for scheduling the crude oil supply to a refinery, whereas Lee et al. (1996) developed a MILP model for short-term refinery scheduling of crude oil unloading with optimal inventory management decisions. Gothe-Lundgren (2002) proposed a planning and scheduling model which seems to be limited to the specific industrial problem to which it has been applied, whereas Jia and Ierapetritou (2004) addressed the optimal operation of gasoline blending and distribution, the transfer to product stock tanks and the delivery schedule to satisfy all of the orders.

Recent work by Pinto et al. (2000) is a key contribution in this area. A nonlinear planning model for refinery production was developed that is able to represent a general refinery topology. The model relies on a general representation for refinery processing units in which nonlinear equations are considered. The unit modes are composed of blending relations and process equations. Certain constraints are imposed to ensure product specifications, maximum and minimum unit feed flow rates, and limits on operating variables. Real-world industrial case studies for the planning of diesel production were used to illustrate the applicability and usefulness of the overall approach. In the second part of their work scheduling problems in oil refineries were studied in detail. Discrete time representations were employed to model scheduling decisions in important areas of the refinery such as crude oil inventory management and fuel oil, asphalt, and liquefied petroleum gas (LPG) production. Several real-world refinery problems were presented and solved using the developed models.

Based on the above work, Neiro and Pinto (2004) proposed a general mathematical framework for modeling petroleum supply chains. A set of crude oil suppliers, refineries that can be interconnected by intermediate and final product streams and a set of distribution centres form the basis for this work.

The scheduling of well and facility operations is a very relevant problem in offshore oil field development and represents a key subsystem of the petroleum supply-chain. The problem is characterized by long planning horizons (typically 10 years) and a large number of choices of platforms, wells, and fields and their interconnecting pipeline infrastructure. Resource constraints such as availability of the drilling rings make the requirement for proper scheduling more imperative to utilize resources efficiency. The sequencing of installation of well and production platforms is essential to ensure their availability before drilling wells. The operational design of the well and production platforms and the time of installation are critical, as they involve significant investment costs, these decisions must be optimized to maximize the return on investment. Thus, oil field development represents a complex and expensive undertaking in the oil industry. The process systems engineering community has recently made several key contributions in this area based on advances in mixed-integer optimization. Iyer et al. (1998) developed a multiperiod MILP formulation for the planning and scheduling of investments and operations in offshore oil field facilities. For a given time-horizon, the decision variables in their model are the choice of reservoir to develop, selection from among candidate well sites, and the well-drilling and platform installation planning, the capacities of well and production platforms and the fluid production rates from wells for each time period. The nonlinear reservoir behavior is handled with piecewise linear approximation functions.

Van den Heever and Grossmann (2000) presented a mixed-integer nonlinear model for oilfield infrastructure that involves design and planning decisions. The nonlinear reservoir behavior is directly incorporated into the formulation. For the solution of this model an iterative aggregation/disaggregation algorithm is proposed according to which time periods are aggregated for the design problem, and subsequently disaggregated for the planning subproblem. Van den Heever et al. (2000) addressed the design and planning of offshore oilfield infrastructure focusing on business rules and complex economic objectives. A specialized heuristic algorithm that relies on the concept of Lagrangean decomposition was proposed by Van den Heever et al. (2001) for the efficient solution of this problem. Ierapetritou et al. (1999) studied the optimal location of vertical wells for a given reservoir property map. The problem is formulated as a large-scale MILP and solved by a decomposition technique that relies on quality cut constraints. Kosmidis et al. (2002) described a MILP formulation for the well allocation and operation of integrated gas-oil systems, whereas Barnes et al. (2002) focused on the production design of offshore platforms. Kosmidis (2003) presented a MINLP model for the daily well-scheduling, where the nonlinear reservoir behavior, the multiphase flow in the well, and constraints from the surface facilities are simultaneously considered. An efficient solution strategy is also proposed. Lin and Floudas (2003) presented a continuous-time modeling and optimization approach for the long-term planning problem for integrated gas-field development. They proposed a two-level formulation and solution framework taking into account complicated economic calculations. I.E. Goel, V. Grossmann Comput. Chem. Eng. 28 (2004), 1409 considered the optimal investment and operational planning of gas-field development under uncertainty in gas reserves. A novel stochastic programming model that incorporates the decision-dependence of the scenario was presented. Aseeri et al. (2004) discussed the financial risk management in the planning and scheduling of offshore oil infrastructures. They added budgeting constraints to the model of Iyer et al. (1998) by following the cash flow of the project, taking care of the distribution of proceeds and considering the possibility of taking loans.

1.2.6
The Campaign Planning Problem

The campaign planning problem has received rather limited attention in the past 20 years, yet it is considered a key problem in chemical batch production. If reliable long-term demand predictions are available, it is often preferable to partition the planning horizon into a smaller number of relatively long periods of time ("campaigns"), each dedicated to the production of single product. The campaign mode of operations may result in important benefits such as minimizing the number and costs of changeovers when switching production from one product to another. The complexity of management and control of the plant operation is further reduced by operating the plant in a more regular fashion, such as in a cyclic mode within each campaign, with the same pattern of operations being repeated at a constant frequency. Typical campaign lengths are from weeks to several months, with cycle times ranging from a few hours to a few days. The campaign mode of operations is often used for the manufacture of "generic" materials (e.g., base pharmaceuticals) which are produced in relatively large amounts and are then used as feedstocks for downstream processes producing various more specialized final products (Papageorgiou 1994, Grunow, et al. 2002).

Mauderli and Rippin (1979) studied the combined production planning and scheduling problem, developing a hierarchical procedure suitable for serial processing networks operated in a zero-wait mode. First, they consider each product individually, generating alternative production lines of a single product by assembling the available processing equipment in groups in order to achieve maximum path capacity. A LP-based screening procedure is used to determine a set of dominant campaigns. Finally, the production plan is generated by solving a LP or MILP problem, allocating the available production time to the various dominant campaigns for a given set of production requirements.

The generation of alternative production lines in the Mauderli and Rippin (1979) algorithm is based on an exhaustive enumeration procedure. A more efficient generation procedure is described by Wellons and Reklaitis (1989a), who formulated the optimal scheduling of a single-product production line as a MINLP model. However, this approach has several limitations, including high degeneracy, as many path assignments result in equivalent schedules. The elimination of this degeneracy was considered by Wellons and Reklaitis (1989b) who identified a set of dominant unique path sequences and hence improved the solution efficiency of the original formulation. A further improvement from the single-product production line scheduling to the single-product campaign formulation problem has been presented by Wellons and Reklaitis (1991a), including the automatic assignment of different equipment items to groups, and also the assignment of these groups to production stages. This work was extended by Wellons and Reklaitis (1991b) to the multiproduct campaign formulation problem for multipurpose batch plants. Finally, a multiperiod planning model is proposed, allocating the production time among the dominant campaigns while considering simultaneously profit from sales, changeover, inventory costs and campaign set-ups.

Papageorgiou and Pantelides (1993) presented a hierarchical approach attempting to exploit the inherent flexibility of multipurpose plants by removing various restrictions regarding the intermediate storage policies between successive processing steps, the utilization of multiple equipment items in parallel and also the use of the same item of equipment for more than one task within the same campaign. A three-step procedure was proposed. First, a feasible solution to the campaign planning problem is obtained to determine the number of campaigns and the active parts of the original processing network involved within each campaign. Secondly, the production rate in each campaign is improved by removing some assumptions and applying the cyclic scheduling algorithm of Shah et al. (1993). Finally, the timing of the campaigns is revised to take advantage of the improved production rates. An interesting feature of this approach is that any existing campaign planning algorithm can be used for its first step. However, this approach relies on several restricted assumptions, including limited flexibility in the utilization of processing equipment and limited operating modes, while multiple production routes or material recycles are not taken into account.

The algorithms described above are hierarchical in nature, and therefore relatively easy to implement given the reduction in the size of the problem solved at each step. On the other hand it is difficult to relate the exact objective for each individual step in the hierarchy to the overall campaign and planning objective function, and therefore it is very difficult to assess the quality of the final solution obtained.

Shah and Pantelides (1991) proposed a single-level mathematical (MILP) formulation for the simultaneous campaign formation and planning problem. Their algorithm simultaneously determines the number and the length of the campaigns and the products and/or stable intermediates manufactured within each campaign. They consider serial processing networks operating in a mixed Zero-Wait/Unlimited Intermediate Storage (ZW/UIS) mode, and nonidentical parallel equipment items operating in phase.

Voudouris and Grossmann (1993) extended the work originally presented by Birewar and Grossmann (1989a,b, 1990) to campaign planning problems for multiproduct plants. They introduced cyclic scheduling, location and sizing of intermediate storage, and inventory considerations along with novel linearization schemes transforming the resulting MINLP formulation.

Tsiroukis et al. (1993) considered the optimal operation of multipurpose plants operating in campaign mode to fulfil outstanding orders. Resource constraints are explicitly taken into account while the limited availability of resource levels affects the operation of the plant. To deal with the complexity, nonconvexity and nonlinearity of the MINLP formulation, more efficient formulations along with a problem-specific two-level decomposition strategy were proposed.

Papageorgiou and Pantelides (1996a) presented a general MP formulation for multiple campaigns planning/scheduling of multipurpose batch/semicontinuous plants. In contrast to hierarchical approaches presented above, a *single-level* formulation was developed, encompassing both overall planning considerations pertaining to the campaign structure and scheduling constraints describing the detailed operating of the plant during each campaign. The problem involves the simultaneous determination of the campaigns (i.e., duration and constituent products) and for every campaign the unit-task allocations, the tasks' timings and the flow of material through the plant. A cyclic operating schedule is repeated at a fixed frequency within each campaign, thus significantly simplifying the management and control of the plant operation. A rigorous decomposition approach to the solution of this problem is presented by Papageorgiou and Pantelides (1996b) and its effectiveness was demonstrated by applying it to a number of examples. Ways in which the special structure of the constituent mathematical models of the decomposition scheme can be exploited to reduce the size and associated integrality gaps are also considered.

1.3
Planning for New Product Development

Pharmaceutical industries are undergoing major changes to cope with the new challenges of the modern economy. The internationalization of the business, the diversity and complexity of new drugs, and the diminishing protection provided by patents are some of the factors driving these challenges. Market pressures are also forcing pharmaceutical industries to take a more holistic view of their product portfolio. The typical life cycles of new drugs are becoming shorter making it harder to recover the investments, especially with the expiry of short-life patents and the arrival of generic substitutes that can later appear in the market, reducing its profitability. It becomes necessary that the industry protects itself against these pressures while considering the limited physical and financial resources available. Several important issues and strategies for the solution of problems concerning pharmaceutical supply-chains are critically reviewed by Shah, (2004).

A large number of candidate new products in the agricultural and pharmaceutical industry must undergo a set of steps related to safety, efficacy, and environmental impact prior to commercialization. If a product fails any of the tests then all the remaining work of that product is halted and the investment in the previous tests is wasted. Depending on the nature of the products, testing may last up to 10 years and the problem of scheduling of tests should be made with the goal of minimizing the time-to-market and the expected cost of the testing. Another important challenge that the pharmaceutical and agrochemical industry faces today is how, then, to configure its product portfolio in order to obtain the highest possible profit, including any capacity investments, in a rapid and reliable way. These decisions have to be taken in the face of considerable uncertainty as demands, sales prices, outcomes of clinical tests, etc. may not turn out as expected.

These problems have recently received attention from the process systems engineering community utilizing advances from the process planning and scheduling area. The first approach appeared in the literature by Schmidt and Grossmann (1996), who considered the problem of optimal sequencing of testing tasks for new product development, assuming that unlimited resources are available. For a product involving a set of testing tasks with given costs, durations and probabilities of success, these authors formulated a MILP model based on a continuous-time representation to determine the sequence of those tasks. The objective of the model is to maximize the expected net present value (NPV) associated with a product, while a special case considers the minimization of cost, subject to a time completion constraint. Even though there may be a number of new products under consideration, the assumption of unlimited resources allows the problem, with either of the two objectives, to be decomposed by each product. Extending this work, Jain and Grossmann (1999) developed an MILP model that performs the sequencing and scheduling of testing tasks for new product development under resources constraints. It was shown that it is critical to incorporate resource constraints along with the sequencing of testing tasks to obtain a globally optimal solution. Blau et al. (2000) developed a simulation model for risk management in the new product development process andSubramanian et al. (2001) proposed a simulation-based framework for the management of the research and development (R&D) pipeline. The focus of these works, however, is the new products development processes and not the planning and design of manufacturing facilities. In most of these references it is assumed that there are no capacity limitations or that the production level of a new product is not affected by the production levels of other products. Furthermore, investments costs are not explicitly included in the calculation of the NPV of the projects.

The problem of simultaneous new product development and planning of manufacturing facilities has received rather limited attention. Papageorgiou et al. (2001) developed a novel optimization-based approach to selecting a product development and introduction strategy, as well as capacity planning and investment strategies. The overall problem is formulated as a MILP model that takes account of both the particular features of pharmaceutical active ingredient manufacturing and the global trading structures. Maravelias and Grossmann (2001) considered the simultaneous optimization of resource-constrained scheduling of testing tasks in new product development and design/planning of batch manufacturing facilities. A multiperiod MILP model was proposed that takes into account multiple tradeoffs and predicts which products should be tested, the detailed test schedule that satisfy design decisions for the process network, and production profiles for the different scenarios defined by the various testing outcomes. A heuristic algorithm based on Lagrange decomposition was investigated for the solution of larger problem instances. Roger et al. (2002) have addressed a similar problem.

In most of the above approaches it is assumed that the resources available for testing, such as laboratories and scientists, are constant throughout the testing horizon, and that all testing tasks have fixed costs, duration and resources requirements. Another common assumption in all the above approaches is that the cost of one test does not depend on the amount of resources allocated to one test. However, as noted in the recent contribution by Maravelias and Grossmann (2004) a company may decide to hire more scientists or build more laboratories to handle more efficiently a great number of potential new products in the R&D pipeline. As another option the company may have to outsource the tests, often at a high cost. All these issues have been addressed by proposing a MILP model that is efficiently solved with a heuristic decomposition algorithm.

In most of the above approaches uncertainty aspects have been neglected although clinical tests are highly uncertain in practice. The recent work by Gatica et al. (2003) explicitly considers uncertainty in clinical trial outcomes. A multistage, multiperiod stochastic problem was developed that was reformulated as a multiscenario MILP model. For this model, a performance measure that takes appropriate account of risk and potential returns has also been formulated. Levis and Papageorgiou (2004) extended the work of Papageorgiou et al. (2001) and proposed a two-stage multiscenario MILP model determining both the product portfolio and the multisite capacity planning in the face of uncertain clinical outcomes, while taking into account the trading structure of the company. They proposed a novel hierarchical algorithm to reduce the computational effort needed for the solution of the resulting large-scale MILP models.

1.4 Tactical Planning

Planning and scheduling is usually part of a company-wide logistics and supply-chain management platform. However, to distinguish between those topics, or even to distinguish further between planning and scheduling is often an artificial rather than a pragmatic approach. In reality, the borderline between all these areas is diffuse, due to the strong overlaps between scheduling and planning in production, distribution or supply-chain management and strategic planning.

Planning and scheduling considerations are very closely related and often confused. The most common distinction between the two concepts is based on the time horizon they consider. While scheduling considers problems that may be of some hours to a few weeks, planning problems may consider time horizons that are of a few weeks up to a few months, and in many applications can even be of years. Tactical planning aims to set the targets for the scheduling applications that will follow in order to determine the operational policy of the plant in the short term. Owing to its nature of involving longer time horizons, planning decisions are often subject to uncertainty that might arise from many sources.

The planning operation in the process industry is focused on analyzing the supply-chain operations as they are defined by strategic planning (see Fig. 1.1). Competitive environment and technological advances have resulted in enterprise resource planning (ERP) systems to be widely used within the process sector; they are considered to be software suites that help organizations to integrate their information flow and business processes (Abdinour-Helm et al. 2003).

The fundamental benefits of ERP systems do not in fact come from their planning capabilities but rather from their abilities to process transactions efficiently and to provide organized structured data bases (Jacobs 2003). Planning and decision support applications represent optional additions to this basic transactional, query and report capability. ERP has been designed to supersede the earlier concepts of material requirement planning (MRP) and manufacturing resource planning (MRP-II) that were designed to assist planners at a local level, by linking various pieces of information, especially in manufacturing. The advantage of a successful ERP implementation is the integration between different levels of the enterprise, such as financial, controlling, project management, human resources, plant maintenance and material flow logistics (Mandal and Gunasekaran 2003). The planning functions at a tactical level benefit from the existence in-place of an ERP system; the two systems do not replace each other but their relationship can be described as complementary. ERP systems play the role of an information highway that connects all planning levels and links various decision support systems to the same data.

MRP systems were designed to work backwards from the sales orders to determine the raw material required for production (Orlicky 1975). MRP-II was introduced as a follow-up to resolve obvious operational problems usually associated with the absence of capacity considerations from MRP that resulted in poor schedules (Wight 1984). The weakness of both approaches is that they were targeting and devel-

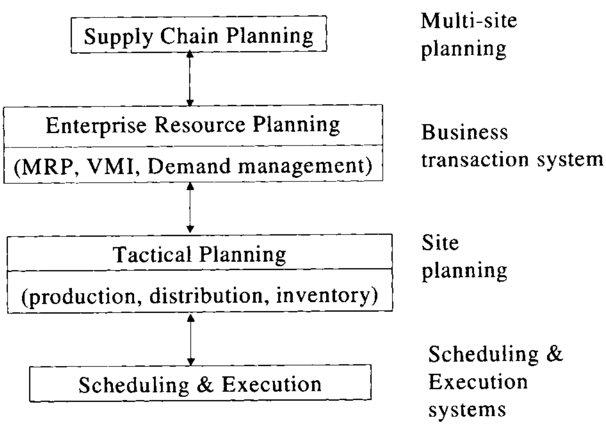

Fig. 1.1 Operations planning decision hierarchy.

oped for the manufacturing environment, and very often ignored the complexities of the process world. ERP on the other hand, is not limited only to manufacturing companies, but is useful for any company with the need to integrate their information across many functional areas.

Planning in the process industry is used to create production, distribution, order satisfaction and inventory plans, based on the information that can be extracted from ERP systems, while satisfying several constraints. In particular, operational plans have to be determined that are aimed to set targets for future production, plan the distribution of materials and allocate other related activities according to the business expectations. Business expectations are the product of strategic resource planning. A successful strategic resource planning, which can be performed either by activity-based cost (ABC), MP, resource-based view (RBV), or a combined approach, is sent to the ERP (Shapiro 1999). It is common practice that, based on these tactical plans, detailed schedules may be produced that define the exact sequence of operations, and determine the utilization of the available resources. Tactical planning is called on to address a number of decisions: the manufacturing policy (what shall we make?), the procurement policy (what do we need?), the inventory or stock policy (what stock already exists?), the resources utilization policy (what do I need to make it?).

Tactical planning supports different short- to medium-term objectives for the business by using different objective functions. By using different objective functions we can create several operational plans to support the various strategic supply-chain decisions. Its differentiation from other planning approaches is that it requires a more detailed representation of the resources in a system. These resources are tied with a number of constraints that might need to be satisfied.

A common approach to tactical planning in the process industry is to describe the problem using a MP model, and then to optimize towards a desired objective. The objective can be maximization of profit, customer order satisfaction, minimization of cost, minimization of tardiness, minimization of common resource utilization, etc. The production environment is a rather complex network and most standard heuristic production planning tools fail to address this complexity. This situation gave rise to the idea of employing MP-based models to provide planning systems with a higher degree of flexibility by considering both product demands as a function of the marketing and sales departments of an organization, and the plant capacity in terms of equipment, material, manpower and utility resources. The problem has been modeled using a number of approaches.

Bassett et al. (1996b) proposed a higher level planning model based on formal aggregation techniques and using uniform time discretization. The model contains aggregate material balance constraints and equipment allocation constraints similar to those of the state-task network (STN) description of a process. This planning model forms part of a decomposition strategy where production is allocated to different time zones, thus creating a set of scheduling problems that can then be solved independently.

Wilkinson (1995) presented a generic mathematical technique to derive aggregate planning models of high accuracy based on the resource-task network (RTN) representation. The proposed formulations allow a large number of the complicating features of multipurpose, multiproduct plant operation to be taken into account in a unified manner. Sequence-dependent changeovers, task utility requirements and limited intermediate storage are some of the additional features included. Also the use of linking variables allows the planning model to take into account inventory levels more accurately.

These two formulations are fairly generic and include most of the important features regarding the planning in process industries where fixed recipes are employed. Prior to them, most of the planning models contained complicated sets of constraints which had been tailored to a specific problem type.

1.5
Resource Planning in the Power Market and Construction Projects

The area of resources planning in the energy and power market and construction projects is worthy of a review in its own right; it will be considered somewhat briefly here, mainly due to its strong similarities with the process planning problem.

1.5.1
Resource Planning in the Power Market

In a traditional electric power system, a utility company is responsible for generating and delivering power to its industrial, commercial and residential customers in its service area. It owns generation facilities and transmission and distribution networks, and obtains necessary information for the economical and reliable operation of its system. For instance, an important problem faced daily by a traditional utility company is to determine which and when generating units should be committed, and how they should be dispatched to meet the system-wide demand and reserve requirements. The centralized resource planning problem involves discrete states (e.g., on/off of units) and continuous variables (e.g., units' generation levels), with the objective being to minimize the total generation costs. A 1 % reduction in costs can result in more than US$10 million dollars savings per year for a large utility company. Various methods have been presented in the literature and impressive results have been obtained (Wang et al. 1995, Guan et al. 1997, Li et al. 1997).

Today, the deregulation and reconstruction of the electric power industry worldwide have raised many challenging issues for the economic and reliable operation of electric power systems. Traditional unit commitment of hydrothermal scheduling/planning problems are integrated with resource bidding, and the development of optimization-based bidding strategies is a preliminary stage. Ordinal optimization approaches seek "good enough" binding strategies with high probabilities, and will turn out to be effective in handling market uncertainties with much reduced computational cost. Under this new structure, resource planning is intertwined with bidding in the market, and power suppliers and system operators are facing a new spectrum of issues and challenges (Guan and Luh 1999).

Many approaches have been presented in the literature to address resources planning in the deregulated power markets. In this context, modeling and solving the bid selection problem has recently received significant attention. In Hao et al. (1998), bids are selected to minimize the total system cost, and the energy clearing price is determining as the highest accepted price for each hour. In Alvey et al. (1998), a bid clearing system in New Zealand is presented. Detailed models are used, including network constraints, reserve constraints, and ramp-rate constraints, and LP is used to solve the problem.

Another very popular way to model the bidding process is to model the competitors' behavior as uncertainties. Therefore, the bidding problem can be converted to a stochastic optimization problem. One of the widely used approaches in stochastic optimization to address this problem is stochastic dynamic programming (Contaxis 1990, Li et al. 1990). The basic idea is to extend the backward dynamic programming procedure by having probabilistic input and probabilities state transmissions in place of determining input and transitions and by using expected costs to calculate deterministic costs-to-go. The direct consequence is increased computational cost due to the significant increase in the input space and the number of possible transitions. For example, when stochastic dynamic programming is used to solve a hydroscheduling problem with uncertain inflows, one more dimension is needed to consider probable inflows in addition to reservoir levels, which significantly worsens the dimension of the problem. Another approach is scenario analysis (Carpentier et al. 1998, Takriti et al. 1996). Each scenario (or a possible realization of random events) is associated with a weight representing the probability of its occurrence. The objective is to minimize the expected costs over all possible scenarios. Since the number of possible scenarios and consequently the computational requirements increase drastically as the number of uncertain factors and the number of possibilities per factor increase, this approach can only handle problems with a limited number of uncertainties. Recently, stochastic dynamic programming has been embedded within the Lagrangean relaxation framework for energy scheduling problems, where stochastic dynamic programming is used to solve uncertain subproblems after system-wide coupling constraints are relaxed. Since dynamic programming for each subproblem can be effectively solved without encountering the curse of dimensionality, good schedules are obtained without a major increase in computational requirements (Luh et al. 1999).

Among alternatives that are being investigated for the generation of electricity are a number of unconventional sources including solar energy and wind energy. In recent decades photovoltaic (PV) energy found its first commercial use in space. In many parts of the globe, PV systems are being considered as a viable alternative for generating electricity. Achieving this goal requires PV systems to enter the utility market, whereby electric utilities evaluate the potentials of each PV system corresponding to its impact on the electric utility expansion planning, and requirements for backup generating capacity to ensure a reliable supply of electricity. Abdul-Rahman (1996) presented a model for the short-term resource scheduling in power systems. An augmented Lagrangean relaxation was used to overcome difficulties with the solution convergence as realistic constraints were introduced (i.e., transmission flows, fuel emissions, ramp-rate limits, etc.) in the formulation of unit commitment. Marwali et al. (1998) presented an efficient approach to short-term resource planning for an integrated thermal and PV battery generation. The proposed model incorporates battery storage for peak loads. Several constraints including battery capacity, minimum up/down time and ramp-rates for thermal units as well as natural PV capacity are considered in the proposed model.

1.5.2
Resource Planning in Construction Projects

Traditionally, resource planning problems in construction projects have been solved either as resources-leveling or as a resource-constrained scheduling problem. The resources-constrained scheduling problem constitutes one of the most challenging facing the construction industry, due to the limited availability of skilled labor, and the increasing need for productivity and cost-effectiveness. These challenges have been discussed by many practitioners and have led researchers to investigate various avenues. One of the most promising solutions to the problem of the shortage of skilled labor has been to develop methods that optimize or better utilize the skilled workers already in the industry (Burleson et al. 1998). The resource-leveling problem arises when there are sufficient resources available and it is necessary to reduce the fluctuations in the resource usage over the project duration. These resource fluctuations are undesirable because they often require a short-term hiring and firing policy. The short-term hiring and firing presents labor, utilization, and financial difficulties because (a) the clerical costs for employee processing are increased, (b) top-notch journeymen are reluctant to join a company with a reputation of doing this and (c) new, less experienced employees require long periods of training. The scheduling objective of the resource-leveling problem is to make the resource requirements as uniform as possible or to make them match a particular nonuniform resource distribution in order to meet the needs of a given project. Resource usage usually varies over the project duration because different types of resources are needed in varying amounts over the life of the project. In construction projects, for example, operators are needed in the beginning of the project to dig the foundations, but they are not needed at the end of the project for the interior finish work. In resource-leveling, the project duration of the original critical path remains unchanged.

MILP models have been used to formulate the resource-constrained scheduling problem (Nutdtasomboon and Randhawa 1996). The efficiency of these models usually decreases due to the high combinatorial nature of the problem, and special algorithms have been developed as an attempt to reduce computational costs and improve the quality of the solution. Most of these algorithms rely on special branch-and-bound and implicit enumeration approaches (Sung and Lim 1996, Demeulemeester and Herroelen 1997). An alternative approach to improving the computational efficiency is the use of heuristic methods that produce feasible, but not necessarily optimal, solutions (Padilla and Carr 1991, Seibert and Evans 1991).

Savin et al. (1998) presented a neural network application for construction resource-leveling using an augmented Lagrangian multiplier. The formulation objective is to make the resource requirements as uniform as possible. Thus, the formulation does not consider the case of nonuniform resource usage. Also, it only allows for one precedence relationship (finish-start) and one resource type, and does not perform cost optimization.

Chan et al. (1996) proposed a resource scheduling method based on genetic algorithms (GAs). The method considers both resource-leveling and resource-constrained scheduling. It can minimize the project duration, but it does not consider the case of nonuniform resource usage, neither does it minimize the construction cost. Adeli and Karim (1997) presented a general mathematical formulation for project scheduling. Multiple crew strategies, work continuity considerations, and the effect of varying job conditions on the crew performance could be modeled. They developed an optimization framework for minimizing the direct construction cost. However, the resource-leveling and resource-constrained scheduling problems were not addressed. Recently, Senousi and Adeli (2001) presented a new formulation including project scheduling characteristics such as precedence relationships, multiple crew strategies, and time-cost tradeoff. The formulation can handle minimization of the total construction cost or duration while resource-leveling and resource-constrained scheduling are performed simultaneously.

An important problem that has received rather limited attention in the literature is related to the optimal allocation of multiskilled labor resources in construction projects. This strategy is commonly found in the manufacturing and process industries where some of the labor force is trained to be multiskilled. Various studies have demonstrated the benefits of multiskilled resources. Nilikari (1995) presented a study involving Finnish shipbuilding facilities, based on a multiskilled work team strategy and found savings of up to 50% in production time.

Burleson et al. (1998) explored several multiskill strategies such as a dual-skill strategy, a four-skill strategy and an unlimited-skill strategy. The study compared the economic benefits in a huge construction project to prove the benefits of multiskilling but did not develop a mechanism for selecting the best strategy for a given project. The work of Brusco and Johns (1998) presented an integer goal-programming model for investigating cross-training multiskilled resource policies to determine the number of employees in each skill category so as to satisfy the demand for labor while minimizing staff costs. The model was applied to the maintenance operations of a large paper mill in the USA. Hegazy et al. (2000) presented an approach for modifying existing resource scheduling heuristics that deal with limited resources, to incorporate the multiskills of available labor and accordingly to improve the schedule. The performance of the proposed approach was demonstrated using a case study and the solution is compared with that of a high-end software system that considers multiskilled resources.

1.6 Solution Approaches to the Planning Problem

Most of the planning problems in the process industry result in an LP/MILP or NLP/MINLP model. Planning problems are usually NP-hard and data-driven; no standard solution techniques are therefore available, and in many cases we are actually searching for a feasible solution to the problem rather than an optimal one. The solution approaches found in the literature may be categorized as:

- *exact* and *deterministic methods* such as mathematical optimization including MILP and MINLP, graph theory (GT) or constraint programming (CP), or *hybrid approaches* in which MILP and CP are integrated;
- *metaheuristics* (evolutionary strategies, tabu search, simulated annealing (SA), various decomposition schemes, etc.).

In this section we are going to focus on general solution approaches applied to planning problems, in addition to those that are mentioned in other sections and are problem-dependent. We are not going to describe extensively how these methods have been employed by a variety of authors, but we are going to describe the algorithms and the classes of problem to which they have been applied. Despite the extensive research work that exists for the solution of long-term planning and short-term scheduling problems, the interest in medium-term planning problem is limited. While the benefits of integrating tactical planning into strategic planning and production scheduling are becoming clear, interest in research into more effective methods has increased. Applequist et al. (1997) provide an excellent review on planning technology and the approaches available for solving planning and scheduling problems. Despite substantial efforts over the last 40 years, no algorithm, either exact or heuristic, has been found that can provide a solution to all planning problems.

1.6.1 Exact and Deterministic Methods

In real life applications we rarely see any NLP/MINLP planning models, except in pooling or refinery planning. The rest of the models proposed, despite their complexity, in term of features they include and mathematical terms, they remain or are transformed to be linear regarding their variables and constraints. Therefore, using state-of-the-art commercial solvers, such as, XPRESS-MP (Dash Optimization, http://www.dashoptimization.com<urle>), CPLEX (ILOG, http://www.ilog.com), or OSL (IBM, http://www.ibm.com), LP/MILP problems can be solved efficiently and at a reasonable computational cost.

In the case of NLP/MINLP, the solution efficiency depends strongly on the individual problem and the model formulation. Thus, in many cases the structure of the problem is exploited in order to provide valid cuts, or identify special structures in order to reduce computational times and increase the quality of the solution.

However, as both MILP and MINLP are NP-hard problems, it is recommended that the full mathematical structure of a problem to be exploited. Software packages may also differ with respect to their ability in presolving techniques, default strategies for the branch-and-bound algorithm, cut generation within the branch-and-cut algorithm, and last but not least, diagnosing and tracing infeasibilities, which is an important issue in practice. Kallrath (2000) provides an extensive review of mixed-integer optimization in the process industry by describing solution methods, algorithms, and applications.

Taking advantage of the special structure of mathematically formulated problems either as MILPs or MINLPs, several decomposition methods have been proposed and implemented in various types of problems.

Bassett et al. (1996a), focusing on chemical process industries, examined a number of time-based decomposition approaches along with their associated strengths and weaknesses. It is shown that the most promising of the approaches utilizes a reverse rolling window in conjunction with a disaggregation heuristic, applied to an aggregate production plan as part of their approach to integrate hierarchically related decisions. Resource- and task-based decompositions are also examined as possible approaches to reduce the problem to manageable proportions. To validate their proposed schemes a number of examples are presented.

Gupta, A. Maranas, C. D. Ind. Eng. chem. Res. 38 (1999) 1937 utilized an efficient decomposition procedure to solve mid-term planning problems based on Lagrangean relaxation. Having tried commercial MILP solvers, they found that the employed solution strategy is more efficient. The basic idea of the proposed solution technique is the successive partitioning of the original problem into smaller, more computationally tractable subproblems by hierarchical relaxation of key complicating constraints. Alongside with the hierarchical Lagrangean relaxation they employ a heuristic algorithm to obtain valid upper bounds. Two examples are used to demonstrate the capabilities of the proposed algorithm.

The size of the actual planning problem may be prohibitive for standard commercial solvers. Therefore, rigorous decomposition techniques that benefit from the special structure of MILP problems is exploited. Dimitriadis (2001), identified that block-diagonal MILP problems may be decomposed to simpler ones and introduced the concept of decomposable MILP (D-MILP). An algorithm based on the idea of "key variables", which break the problem down into a number of smaller partial MILPs that can be solved independently and in parallel, was implemented based on a standard branch-and-bound scheme. The decomposition branch-and-bound (dBB) as the algorithm is called, achieves better performance by obtaining quick upper bounds to the problem and assisting the solver to find an optimal solution within reasonable computational time. One of the advantages of the approach is that is can guarantee the optimality of the solution. Tsiakis et al. (2000) improved the algorithm by providing an automated method to decompose the problem and implementing a more generic solution scheme applicable to all MILP problems that have a similar structure.

1.6.2
Metaheuristics

In addition to the so called optimization methods we have techniques described as heuristics. These techniques differ in the sense that cannot guarantee an *optimal* solution; instead they aim to find reasonably good solutions in a relatively short time. Heuristics tend to be fairly generic and easily adaptable to a large variety of planning problems. There are a number of heuristic general-purpose approaches that can be applied to planning and scheduling problems (Pinedo 2003).

SA and *tabu search*are described as improvement algorithms. Algorithms of the improvement type are conceptually completely different from the constructive type algorithms. The algorithm starts by obtaining a complete plan that can be selected arbitrarily, and then tries to obtain a better plan by manipulating the current solution. The procedure is described as local search. A local search procedure does not guarantee an optimal solution, but aims to obtain a better solution in the neighborhood of the current one. They very often employ a probabilistic acceptance-rejection criterion with the hope it will lead to better solution. Reeves (1995) describes extensively the methods and applications in production planning systems.

*GAs*are more general than SA and tabu search and they can be classified as a generalization of the previously mentioned techniques. In this case a number of feasible solutions are initially found. Then, local search based on an evolution criterion is employed to select the most promising solution for further exploitation. The rest of the solutions are fathomed (Reeves 1995).

Heuristics are widely employed in industry to provide solutions to production planning problems. Stockton and Quinn (1995) describe how a GA based on aggregate planning techniques is used to develop a production plan that allows a strategic business objective to be implemented in short- and mid-term operational plans.

LeBlanc et al. (1999) utilize an extension of the multiresource generalized assignment problem (MRGAP) in order to provide an implementable solution to production planning problems. The model considers splitting of individual batches across multiple machines, while considering the effect of set-up times and set-up costs, features that the standard assignment problem (AP) fails to capture. The proposed formulations are solved using adaptations of a GA and SA.

A multiobjective GA (MOGA) approach was employed by Morad and Zalzada (1999) for the planning of multiple machines, taking into account their processing capabilities and the process costs incurred. The formulation is based on multiobjective weighted-sums optimization, which is to minimize makespan, to minimize total rejects produced and to minimize the total cost of production.

Tabu search is employed by Baykasoglu (2001) to solve multiobjective aggregate production planning (APP) problems based on a mathematically formulated problem. The model by Masud and Hawng was selected as the basis due to its extensibility characteristics.

1.7
Software Tools for the Resource Planning Problem

Enterprise resource planning (ERP) is a software-driven business management system which integrates all facets of the business, including planning, manufacturing, sales and marketing. Increasingly complex business environments require better and more accurate resource planning. Furthermore, management is under constant pressure to improve competitiveness by lowering operating costs and improving logistics, thus increasing the level of control within the operating environment. Organizations therefore have to be more responsive to the customer and competition. Resource planning as a business solution aims to help the management by setting up better business practices and equipping them with the right information to take timely decisions.

Production planning as a later business function is considered to be part of the supply-chain planning and scheduling suite, alongside other functions such as demand forecasting, supply-chain planning, production scheduling, distribution and transportation planning. Tactical production planning includes those software modules responsible for production planning within a single manufacturing facility. These solutions normally address tactical activities, although they may also be used to support both strategic and operational decisions and are very often integrated with them.

1.7.1
Enterprise Resource Planning

A big share of the software and services provided worldwide is targeting the integration of ERP and supply-chain operations. Most of the information needed by production planning software tools resides within ERP systems. Most of the ERP software providers already have developed their own fully integrated planning applications, have acquired smaller companies with production planning software or have been in partnership with such providers. The standard object-oriented approach to the implementation of ERP systems has contributed towards an easy integration. The leading suppliers and systems integrators to the worldwide ERP market across all industry sectors are alphabetically: Oracle (http://www.oracle.com), Manugistics (http://www.manugistics.com), PeopleSoft (http://www.peoplesoft.com), and SAP (http://www.sap.com) according to the latest market share studies. In small-medium enterprises (SMEs) the leading provider of ERP systems is Microsoft Business Solutions with its Navision system (http://www.microsoft.com/businessSolutions).

1.7.2
Production Planning

Production planning deals in medium-range time horizons, where decisions about incremental adjustments to the capacity or customer service levels are made.

Changes to supplier delivery dates, swings in raw materials purchases, and outsourcing agreements may require 3-5 months. Thus, production planning deals with what will be done, and when, in a factory over longer time frames. Tactical plans are updated frequently based on the operational plan and the actual schedule. This section provides the profiles of production planning software suppliers with main focus on the process industry, again in alphabetical order.

1.7.2.1
Advanced Process Combinatorics (http://www.combination.com)

The company's modular supply-chain product VirtECS contains a module, called Scheduler, with production planning capability. The package handles complex production planning models with multiple input/output bills of material, multiple routings, resource constraints and set-up times. Their algorithms used for production planning are based on a MILP formulation, with a number of techniques applied for their solution. Additionally, a set of Gantt-chart-based interactive tools provides the user with manipulating capabilities on the actual plan. A key strength of APC revolves around the research on optimization since the company was generated from an industrial research consortium at Purdue University.

1.7.2.2
Aspen Technologies (http://www.aspentech.com)

Aspen Technology's supply-chain capabilities are based largely on the company's acquisition of the Process Industry Modelling Systems (PIMS) from Bechtel and Manager for Interactive Modelling Interfaces (MIMI) of Chesapeake Decision Sciences. Aspen PIMS is a tactical level refinery planning package that is widely used in over 170 refineries worldwide. The Aspen MIMI production planner is focused on models that include material flows, set-up times, labor constraints and other resource restrictions. In addition to the standard heuristics and simulation employed for production planning and scheduling, the advanced planning offers LP-based optimization capabilities. Users can interact with the Gantt chart in order to develop "what-if" analysis cases and add constraints. Aspen has one of the larger installed bases of MIMI products for over 300 customers around the globe.

1.7.2.3
i2 Technologies (http://www.i2.com)

As part of its supply-chain platform, i2's Factory Planner manages material and capacity constraints to develop feasible operating plans for production plants. The tool aims to be a decision support system in the areas of production planning and scheduling, taking into account material and capacity requirements. It utilizes a number of heuristic algorithms and basic optimization to obtain feasible plans, and to answer capable-to-promise delivery-date quoting.

1.7.2.4
Manugistics (http://www.manugistics.com)

Manufacturing Planning and Scheduling, integrated within the Constraint-Based Master Planning supply-chain system of Manugistics, provides the detailed operational plan. It is based on a flow-oriented model, and uses the theory of constraints to solve the production planning problems. It takes into account throughput of equipment, determines the bill of materials, and allows what-if scenario analysis.

1.7.2.5
Process System Enterprise (PSE) (http://www.psenterprise.com)

PSE's ModelEnterprise has been designed as a modular supply-chain modeling platform that allows the construction and maintenance of complex enterprise models, and supports a wide range of tools applied to these models for solving different types of problem. The Optimal Single Site Planner and Scheduler (OSS Planner Scheduler) determines an optimal schedule for a plant producing multiple products. It is especially suited to multipurpose plant where products can be made on a selection of equipment units, via different routes and in different sizes. The plans produced are finite capacity and rigorously optimal. The objective of the optimization problem can be configured according to the economic requirements of the operation – for example, to deliver maximum profit, maximum output or on-time in-full. The OSS Planner Scheduler uses state-of-the-art MILP optimization algorithms that allow complex systems to be modeled. Utilizing comprehensive costing all costs may be accounted such as processing, storage, utilities, cleaning, supplies and penalties for late delivery. PSE originated at Imperial College, London, in the 1990s. and ModelEnterprise has been developed based on knowledge and research found there.

1.7.2.6
SAP AG (http://www.sap.com)

The APO Production Planning and Detailed Scheduling (PP/DS) tool comes under the umbrella of SAP APO supply-chain solutions. The software can be used to generate production plans and sequence schedules. A variety of approaches is included in this solution for theory of constraints and mathematical optimization, but in principle it is a heuristics-based tool, where the user-developed rules are employed. Other features of the tool include forward and backwards scheduling, simultaneous capacity and material planning in detail, what-if analysis to simulate effects of changes in constraints, and interactive scheduling via a Gantt chart interface.

1.8
Conclusions

The impact of accurate resource planning on the productivity and performance of both manufacturing and service organizations are tremendous. Researchers have found that organizations that had no resource planning information technology infrastructure in place performed poorly most of the time compared to those who had a specific plan. The successful implementation of planning capabilities means reduction in cost, increased productivity and improved customer services. The importance of resource planning models and systems therefore becomes significant. Moreover, the solution to the problems associated with that poses further challenges.

Despite many years of study in resource planning models, plus numerous examples of successful modeling systems implementations and industrial applications, there is still a great potential for applying them in a pervasive and enduring manner to a wider range of real-life industrial applications.

Several researchers have tackled the resource planning problem under uncertainty using different approaches. However, in most cases they have skirted around the problem of multiperiod, multiscenario planning with detailed production capacity models (i.e., embedding some scheduling information). Here, issues that must be addressed mainly relate to problem scale. Combined mixed-integer programming and stochastic optimization techniques seem to offer a promising solution alternative to this problem.

One of the major challenges will be to develop planning approaches that are consistent with detailed resource scheduling as part of the overall supply-chain integration. An obvious drawback is the problem size. This poses the need for rigorous decomposition algorithms and techniques that will enable handling problems of greater size without compromising the quality of the solution.

Over the last few years a trend has developed bringing MP and constrained programming techniques closer to each other. This results in hybrid approaches (i.e., in algorithms combining elements from both areas) that may have a great impact on reducing computational requirements for solving large-scale planning problems.

In addition to new techniques and solution approaches, advances in computational power in terms of hardware and software allow the exploitation of parallel algorithm optimization techniques. The tree structure in mixed-integer optimization, and the time- or scenario-dependent structures, indicates that more benefits are to be expected from parallelizing the combinatorial part. Dealing with large-scale NP-hard problems may lead to the implementation of distributed planning, where the computational effort and time is divided over a number of computers or clusters. Time-based or spatial decomposition methods will be exploited more and more.

Resource planning is a fundamental business process that exists in every production environment. It has long been recognized that in the process industries there are very large financial incentives for planning, scheduling and control decisions to function in a coordinated fashion. Nevertheless, many companies have not achieved integration in spite of multiple initiatives. An important challenge thus relates to the development of efficient theoretical methodologies, algorithms and tools to achieve this integration in a formal way, allowing process industries to take steps to practically improve the integration activities at different levels.

The planning problem of refinery operations and offshore oilfields has been recently attacked by several researchers. However, the practical implementation of most of the developed approaches is usually limited to subsystems of a plant with considerable simplifications. Here, the trend is to expand the planning process to include larger systems, such as a group of refineries instead of a single one. Another area that deserves further attention is the inclusion of scheduling decisions in planning processes. Furthermore, there is a lot of scope for developing commercial tools to serve refineries to cope with daily operational problems.

In the area of product planning, the integration of development management and capacity and production planning seems to be very important. Currently, capacity issues are often not considered at the development stage. The development of integrated models of the life cycle, from the discovery through to consumption would greatly facilitate strategic decision making.

Demand for advanced planning systems (APS) is expected to grow with the solutions being increasingly industry- and supply-chain-specific. The standards are specified by the large software suppliers, such as i2 and Manugistics. The scope for smaller suppliers is to have a more specific focus in segments of the industry. There is a clear trend for industry-specific solutions, this being due to the different operating environments and the detail required in order to generate a meaningful plan. The development of resource planning systems very much depends on the industry segment (industrial or nonindustrial) and the manufacturing type (process or discrete industries). While segmentation based on the type of industry is common, it is important to be able to segment the operational environment based on the supply-chain type. In this case we have distribution, manufacturing or source intensive supply chains, each one with their own needs. Many companies are competing as software providers for planning systems. However, they have realized that they need to be able to communicate with other libraries and software modules as part of supply-chain solutions, and at minimum cost. Systems with open architecture and ease of integration are in demand. Initiatives such as CAPE-OPEN aim to define industry-wide standards (CO-LaN 2001).

References

1 *Abdinour-Helm S. Lengnick-Hall M. L. Lengnick-Hill C. A.* Eur. J. Oper. Res. 146 (2003) p. 258
2 *Abdul-Rahman K. H. Shahidehpour S. M. Aganagic M. Mokhtari S.* IEEE Trans. Power Syst. 11 (1996) p. 254
3 *Adeli H. Karim A.*J. Constr. Eng. Manage. 123 (1997) p. 450
4 *Ahmed S. Sahinidis N. V.* Ind. Eng. Chem. Res. 37 (1998) p. 1883
5 *Alvey T. Goodwin D. Ma X. Streiffert D. Sun D.* IEEE Trans. Power Syst. 13 (1998) p. 986
6 *Applequist G. Samikog|u O. Pekny J. Reklaitis G.* ISA Trans. 36 (1997) p. 81
7 *Aseeri A. Gorman P. Bagajewicz M. J.* Ind. Eng. chem. Res. 43 2004, 3063
8 *Ballintjin K.* 1993 In: Ciriani T. A. Leachman R. C. (eds.), Vol. 3, Wiley, New York
9 *Barbaro A. Bagajewicz AICH Journal*, 50 (2004) 963
10 *Barnes R. Linke P. Kokossis A.* 2002 In: Proceedings of ESCAPE-12, The Hague, The Netherlands, p 631
11 *Bassett M. H. Dave P. Doyle F. J. Kudva G. K. Pekny J. F. Reklaitis G. V. Subrahmanyam S. Miller D. L. Zentner M. G.* Comput. Chem. Eng. 20 (1996a) p 821
12 *Bassett M. H. Pekny J. F. Reklaitis G. V.* AICHE J. 42 (1996b) p 3373
13 *Bassett M. H. Pekny J. F. Reklaitis G. V.* Comput. Chem. Eng. 21 (1997) p. S1203
14 *Baykasoglou A.* Int. J. Prod. Res. 39 (2001) p. 3685
15 *Bernardo F. P. Pistikopoulos E. N. Saraiva P.* Ind. Eng. Chem. Res. 38 (1999) p. 3056
16 *Birewar D. B. Grossmann I. E.* Comput. ChemM. Eng. 13 (1989a) p. 141

17 *Birewar D. B. Grossmann I. E.* Ind. Eng. Chem. Process Des. Dev. 28 (1989b) p. 1333

18 *Birewar D. B. Grossmann I. E.* Ind. Eng. Chem. Res. 29 (1990) p. 570

19 *Bitran G. R. Hax A. C.* Decision Sci. 8 (1977) p. 28

20 *Blau G. Metha B. Bose S. Pekny J. Sinclair G. Keunker K. Bunch P.* Comput. Chem. Eng. 24 (2000) p. 659

21 *Bose S. Pekny J. F.* Comput. Chem. Eng. 24 (2000) p. 329

22 *Brusco M. J. Johns T. R.* Decision Sci. J. 29 (1998) p. 499

23 *Burleson R. C. Hass C. T. Tucher R. L. Stanley A. J.* Constr. Eng. Manage. 124 (1998) p. 480

24 *Carpentier P. Woodwin D. Ma X. Streiffert D. Sun D.* IEEE Trans. Power Syst. 13 (1998) p. 986

25 *Chan W. T. Chua D. K. H. Kannan G.* J. Constr. Eng. Manage. 122 (1996) p. 125

26 *Clay R.L. Grossmann I. E.* Chem. Eng. Res. Des. 72 (1994) p. 415

27 *CO-LaN:* The CAPE-OPEN Laboratories Network (http://zann.informatik.rwth-aachen.de:8080/opencms/opencms/COLAN-gamma/index.html)

28 *Contaxis G. Kavantza S.* IEEE Trans. Power Syst. 5 (1990) p. 766

29 *Das B. P. Rickard J. G. Shah N. Macchietto S.* Comput. Chem. Eng. 24 (2000) p. 1625

30 *Demeulemeester E. Herroelen W.* Manage. Sci. 43 (1997) p. 1485

31 *A. D. Dimitriadis 2001 PhD thesis Title: Algorithms for the solution of Large-scale Scheduling problems. Imperial College of science, Technology and Medicine*

32 *Gatica G. Papageorgiou L. G. Shah N.* Chem. Eng. Res. Des. 81 (2003) p. 665

33 *Geddes D. Kubera T.* Comput. Chem. Eng. 24 (2000) p. 1645

34 *Goel H. D. Grievink J. Weijnen M. P. C.* Comput. Chem. Eng. 27 (2003) p. 1543

35 *Gothe-Lundgren M. Lundgren J. T. Persson J. A.* Int. J. Prod. Econ. 78 (2002) p. 255

36 *Grunow M. Gunther H. Lehmann M.* OR Spectrum 24 (2002) p. 281

37 *Guan X.. Luh P. B.* Discrete Event Dyn. Syst. Theor Appl. 9 (1999) p. 331

38 *Guan X. Ni E. Li R. Luh P. B.* IEEE Trans. Power Syst. 12 (1997) p. 1775

39 *Hao S. Angelidis G. A. Singh H. Papalexopoulos A. D.* IEEE Trans. Power Syst. 13 (1998) p. 986

40 *Harjunkoski I. Grossmann I. E. Friedrich M. Holmes R.* 2003. FOCAPO 2003 p. 315

41 *Hax A. C.* 1978 Handbook of Operations Research Models and Applications

42 *Hegazy B. T. Shabeeb A. K. Elbeltagi E. Cheema T.* J. Constr. Eng. Manage. 126 (2000) p. 414

43 *Ierapetritou M. G. Floudas C. A. Vasantharajan S. Cullick A. S.* AIChE J. 45 (1999) p. 844

44 *Ierapetritou M. G. Pistikopoulos E. N.* Ind. Eng. Chem. Res. 33 (1994) p. 1930

45 *Ierapetritou M. G. Pistikopoulos E. N. Floudas C. A.* Comput. Chem. Eng. 20 (1996) p. 1499

46 *Iyer R. R. Grossmann I. E.* Ind. Eng. Chem. Res. 37 (1998) p. 474

47 *Iyer R. R. Grossmann I. E. Vasantharajan S. Cullick A. S.* Ind. Eng. Chem. Res. 37 (1998) p. 1380

48 *Jacobs R. F. Bendoly E.* Eur. J. Oper. Res. 146 (2003) p. 233

49 *Jain V. Grossmann I. E.* Ind. Eng. Chem. Res. 38 (1999) p. 3013

50 *Jia Z. Ierapetritou M. G.* Ind. Eng. Chem. Res. 43 (2004), p. 3782

51 *Kabore P.* FOCAPO 2003 p. 285

52 *Kallrath J.* Trans. IChemE 78 (2000) p. 809

53 *Kallrath J.* OR Spectrum 24 (2002) p. 219

54 *Kosmidis V. D.* 2003 Ph.D. Thesis University of London U.K

55 *Kosmidis V. D. Perkins J. D. Pistikopoulos E. N.* 2002 In: Proceedings of ESCAPE-12 The Hague The Netherlands p 327.

56 *LeBlanc L. J. Shtub A. Anandnalingham G.* Eur. J. Oper. Res. 112 (1999) p. 54

57 *Lee H. Pinto J. M. Grossmann I. E. Park S.* Ind. Eng. Chem. Res. 35 (1996) p. 1630

58 *Levis A. A. Papageorgiou L. G.* 28 (2004), p. 707 Comput. Chem. Eng.

59 *Li C. Johnson R. B. Svaboda A. J.* IEEE Trans. Power Syst. 12 (1997) p. 1834

60 *Li C. Yan R. Zhou J.* IEEE Trans. Power Syst. 5 (1990) p. 1487

61 *Li P. Wendt M. Wozny G.* 2003 FOCAPO 2003 p. 289

62 *Lin X. Floudas C. A.* Optimisation Eng. 4 (2003) p. 65

63 *Liu M.L. Sahinidis N. V.* Ind. Eng. Chem. Res. 34 (1995) p. 1662

64 *Liu M.L. Sahinidis N. V.* Comput. Oper. Res. 23 (1996a) p. 237

65 *Liu M.L. Sahinidis N. V.* Ind. Eng. Chem. Res. 35 (1996b) p.4154

66 *Liu L. Sahinidis N. V.* Eur. J. Oper. Res. 100 (1997) p. 142

67 *Luh P. B. Chen D. Tahur L. S.* IEEE Trans. Robot. Autom. 15 (1999) p. 328

68 *Mandal P. Gunasekaran A.* Eur. J. Oper. Res. 146 (2003) p. 274

69 *Maravelias C. T. Grossmann I. E.* Ind. Eng. Chem. Res. 40 (2001) p. 6147

70 *Maravelias C. T. Grossmann I. E.* 28 (2004), p. 1921 Comput. Chem. Eng. in press
71 *Marwali M. K. C. Ma H. Shahidehpour S. M. Abdul-Rahman H.* IEEE Trans. Power Syst. 13 (1998) p. 1057
72 *Mauderli A. Rippin D. W. T.* Comput. Chem. Eng. 3 (1979) p. 199
73 *McDonald C. M. Karimi I. A.* Ind. Eng. Chem. Res. 36 (1997) p. 2691
74 *Morad N. Zalzada A.* J. Intell Manuf. 10 (1999) p. 169
75 *Moro L. F. L.* Comput. Chem. Eng. 27 (2003) p. 1303
76 *Moro L. F. L. Zanin A. C. Pinto J. M.* Comput. Chem. Eng. S22 (1998) p. S1039
77 *Neiro S. M. S. Pinto J. M.* Comput. Chem. Eng. 28 (2004), p. 871
78 *Nilikari M.* J. Ship Prod. 11 (1995) p. 239
79 *Norton L. C. Grossmann I. E.* Ind. Eng. Chem. Res. 33 (1994) p. 69
80 *Nutdtasomboon N. Randhawa S.* Comput. Ind. Eng. 32 (1996) p. 227
81 *Oh H. Karimi I. A.* Comput. Chem. Eng. 25 (2001a) p. 1021
82 *Oh H. Karimi I. A.* Comput. Chem. Eng. 25 (2001b) p. 1031
83 *Orlicky J.* 1975 Material Requirements Planning. McGraw Hill. New York
84 *Oxe G.* Eur. J. Oper. Res. 97 (1997) p. 337
85 *Padilla E. M. Carr R. L.* J. Constr. Eng. Manage. 117 (1991) p. 279
86 *Papageorgiou L. G.* 1994; Ph.D. Thesis University of London
87 *Papageorgiou L. G. Pantelides C. C.* Comput. Chem. Eng. 17S (1993) p. S27
88 *Papageorgiou L. G. Pantelides C. C.* Ind. Eng. Chem. Res. 35 (1996a) p. 488
89 *Papageorgiou L. G. Pantelides C. C.* Ind. Eng. Chem. Res. 35 (1996b) p. 510
90 *Papageorgiou L. G. Rotstein G. E. Shah N.* Ind. Eng. Chem. Res. 40 (2001) p. 275
91 *Pelham R. Pharris C.* Hydrocarb. Process. 75 (1996) p. 89
92 *Petkov S. B. Maranas C. D.* Ind. Eng. Chem. Res. 36 (1997) p. 4864
93 *Pinedo M.* 2003 Scheduling: Theory Algorithms and Systems 2nd Edn. Prentice Hall, New Jersey
94 *Pinto J. M. Joly M. Moro L. F. L.* Comput. Chem. Eng. 24 (2000) p. 2259
95 *Pistikopoulos E. N. Vassiliadis C. G. Arvela J. A. Papageorgiou L. G.* Ind. Eng. Chem. Res. 40 (2001) p. 3195
96 *Reeves C. R.* 1995 Modern Heuristic Techniques for Combinatorial Problems Wiley
97 *Reklaitis G. V.* 1991 Proceedings of the 4th International Symposium on Process Systems Engineering Montebello Canada
98 *Reklaitis G. V.* 1992 NATO Advanced Study Institute on Batch Processing Systems Eng. Antalya Turkey
99 *Rickard J. G. Macchietto S. Shah N.* Comput. Chem. Eng. S23 (1999) p. S539
100 *Rigby B. Lasdon L. S. Waren A. D.* Interfaces 25 (1995) p. 64
101 *Rodera H. Bagajewicz M. J. Tsafalis T. B.* Ind. Eng. Chem. Res. 41 (2002) p. 4075
102 *Rodrigues M. M. Latre L. G. Rodrigues L. A.* Comput. Chem. Eng. 24 (2000) p. 2247
103 *Roger M. J. Gupta A. Maranas C. D.* Ind. Eng. Chem. Res. 41 (2002) p. 6607
104 *Romero J. Badell M. Bagajewicz M. Puigjaner L.* Ind. Eng. Chem. Res. 42 (2003) p. 6125
105 *Ryu J.-H. Dua V. Pistikopoulos E. N.* Comput. Chem. Eng. 28 (2004), p. 1121
106 *Sahinidis N. V.* Comput. Chem. Eng. 28 (2004), p. 971
107 *Sahinidis N. V. Grossmann I. E.* Ind. Eng. Chem. Res. 30 (1991) p. 1165
108 *Sahinidis N. V. Grossmann I. E. Fornari R. E. Chathrathi C.* Comput. Chem. Eng. 13 (1989) p. 1049
109 *Sanmarti E. Espuna A. Puigjaner L.* Comput. Chem. Eng. S19 (1995) p. S565
110 *Savin D. Alkass S. Fazio P.* J. Comput. Civ. Eng. 12 (1998) p. 241
111 *Schmidt C.W. Grossmann I. E.* Ind. Eng. Chem. Res. 35 (1996) p. 3498
112 *Seibert J. E. Evans G. W.* J. Constr. Eng. Manage. 117 (1991) p. 503
113 *Senousi A. B. Adeli H.* J. Constr. Eng. Manage. 127 (2001) p. 28
114 *Shah N.* Comput. Chem. Eng. S20 (1996) p. S1227
115 *Shah N.* AIChE Symp Ser. 1998 No. 320 94 75
116 *Shah N.* Comput. Chem. Eng. 28 (2004), p. 929
117 *Shah N. Pantelides C. C.* Ind. Eng. Chem. Res. 30 (1991) p. 2308
118 *Shah N. Pantelides C. C.* Ind. Eng. Chem. Res. 31 (1992) p. 1325
119 *Shah N. Pantelides C. C. Sargent R. W. H.* Ann. Oper. Res. 42 (1993) p. 193
120 *Shapiro J.F.* Eur. J. Oper. Res. 118 (1999) p. 295
121 *Shapiro J. F.* Comput. Chem. Eng. 28 (2004), p. 855
122 *Shobrys D. E. White D. C.* Comput. Chem. Eng. 26 (2002) p. 149

123 *Stockton D. J. Quinn L.* Proc. Inst. Mech. Eng. 209(3) (1995) p. 201

124 *Subrahmanyam S. Pekny J. F. Reklaitis G. V.* Ind. Eng. Chem. Res. 33 (1994) p. 2668

125 *Subrahmanyam S. Pekny J. F. Reklaitis G. V.* Ind. Eng. Chem. Res. 35 (1996) p. 1866

126 *Subramanian D. Pekny J. F. Reklaitis G. V.* AIChE J. 47 (2001) p. 2226

127 *Sung C. S. Lim S. K.* Comput. Ind. Eng. 12 (1996) p. 227

128 *Suryadi H. Papageorgiou L. G.* Int. J. Prod. Res. 42 (2004) p. 355

129 *Takriti S. Birge J. Long E.* IEEE Trans. Power Syst. 11 (1996) p. 1497

130 *Tsiakis P. Rickard J. G. Shah N. Pantelides C. C.* 2003 AIChE Annual Conference San Francisco California USA

131 *Tsiakis P. Dimitriadis A. D. Shah N. Pantelides C. C.* 2000 AIChE Annual Conference Los Angeles California USA

132 *Tsiroukis A.G. Papageorgaki S. Reklaitis G. V.* Eng. Chem. Res. 32 (1993) p. 3037

133 *van den Heever S. A. Grossmann I. E.* Ind. Eng. Chem. Res. 39 (2000) p. 1955

134 *van den Heever S. A. Grossmann I. E.* Comput. Chem. Eng. 27 (2003) p. 1813

135 *van den Heever S. A. Grossmann I. E. Vasantharajan S. Edwards K.* Comput. Chem. Eng. 24 (2000) p. 1049

136 *van den Heever S. A. Grossmann I. E. Vasantharajan S. Edwards K.* Ind. Eng. Chem. Res. 40 (2001) p. 2857

137 *Voudouris T. V. Grossmann I. E.* Ind. Eng. Chem. Res. 32 (1993) p. 1962

138 *Wang S. J. Shahidehpour S. M. Kirschem D. S. Mokhtari S. Irissari G. D.* IEEE Trans. Power Syst. 10 (1995) p. 1294

139 *Wellons M. C. Reklaitis G. V.* Comput. Chem. Eng. 13 (1989a) p. 201

140 *Wellons M. C. Reklaitis G. V.* Comput. Chem. Eng. 13 (1989b) p. 213

141 *Wellons M. C. Reklaitis G. V.* Ind. Eng. Chem. Res. 30 (1991a) p. 671

142 *Wellons M. C. Reklaitis G. V.* Ind. Eng. Chem. Res. 30 (1991b) p. 688

143 *Wight O.* 1984 Manufacturing Resource Planning: MRP-II Wight Williston

144 *Wilkinson S. J.* 1996 PhD Thesis University of London

145 *Wilkinson S. J. Shah N. Pantelides C. C.* Comput. Chem. Eng. 19 (1995) p. S583

146 *Wilson J. M.* Eur. J. Oper. Res. 149 (2003) p. 430

147 *Wu D. Ierapetritou M. G.* 2003. FOCAPO 2003 p. 257

148 *Yin K. K. Liu H.* 2003. FOCAPO 2003 p. 261