2
Production Scheduling

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2.1
Introduction

The theme of production planning and scheduling has been the subject of great attention in the recent past. Initially, especially from the early 1980s to the early 1990s, this was due to the resurgence in interest in flexible processing either as a means of ensuring responsiveness or of adapting to the trends in chemical processing towards lower volume, higher-value-added materials in the developed economies (Reklaitis 1991, Rippin 1993, Hampel 1997). More recently, the topic has received a new impetus as enterprises attempt to optimize their overall supply chains in response to competitive pressures or to take advantage of recent relaxations in restrictions on global trade, as well as the information storage and retrieval capabilities provided by ERP systems.

It is widely recognized that the complex problem of what to produce and where and how to produce it is best considered through an integrated, hierarchical approach that also acknowledges typical corporate structures and business processes. This type of structure is illustrated in Figure 2.1. In the most general case, the extended supply chain is taken to mean the multienterprise network of manufacturing facilities and distribution points that perform the functions of materials procurement, transformation into intermediate and finished materials and distribution of the finished products to customers.

The most common context for planning at the supply-chain level is the coordination of manufacturing and distribution activities across multiple sites operated by a single enterprise (enterprise-wide or multisite planning). Here, the aim is to make the best use of geographically distributed resources over a certain time period.

The result of the multisite planning problem is typically a set of production targets for each of the individual sites, and rough transportation plans for the network as a whole. The production scheduling activity at each individual site seeks to determine precisely how these targets can be met (or indeed how best to compromise them if they cannot be met in whole). This involves determining the precise details of resource allocation over time.

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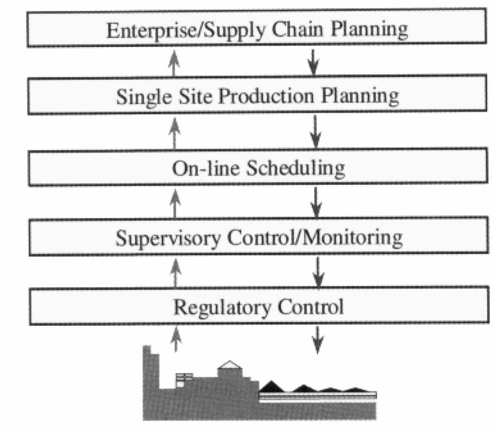

Figure 2.1 Process operations hierarchy

Once a series of activities has been determined, these must be implemented in the plant. The role of the supervisory control system is to initiate the correct sequences of control logic with the correct parameters at the correct time, making sure that conflicts for plant resources are resolved in an orderly manner. It is also useful at this level to create a schedule of planned operations over a short future interval using a model detailed enough to ensure that there are no anticipated resource conflicts. This "online" scheduling allows current estimates of the starting and finishing times of each operation to be known at any time. Although this capability is not essential for the execution of operations in the plant, it is vital if the hierarchical levels are to be integrated so that production scheduling is performed in response to deviations in expected plant operation ("reactive scheduling").

Finally, the lowest levels of the hierarchy relate to execution of individual control phases and ensuring safe and economic operation of the plant.

2.1.1 Why Is Scheduling Important?

The planning function aims to optimize the economic performance of the enterprise as it matches production to demand in the best possible way.

The production scheduling component is of vital importance as it is the layer which translates the economic imperatives of the plan into a sequence of actions to be executed on the plant, so as to deliver the optimized economic performance predicted by the higher-level plan.

2.1.2
Challenges in Scheduling

There is clearly a need for research and development in all the levels of the operations hierarchy. Four previous reviews in this area (Reklaitis 1991, Rippin 1993, Shah 1998, Kallrath 2002a) summarized some of the main challenges as:

- the development of efficient general-purpose solution methods for the mixed-integer optimization problems that arise in planning and scheduling;
- the design of tailored techniques for the solution of specific problem structures, which either arise out of specific types of scheduling problems or are embedded substructures in more general problems;
- the design of algorithms for efficient solution of general resource constrained problems, especially those based on a continuous representation of time;
- the development of hybrid methods based on optimization and constraint propagation methods;
- the development of commercially available software packages for optimization-based scheduling (as distinct from planning);
- the systematic treatment of uncertainty;
- the advancement of online techniques for rapid adaptation of operations;
- the development of methods for the integrated planning and scheduling of multisite systems.

Multisite and supply-chain planning and scheduling is dealt with in section 5.7, and the focus here is on scheduling at a single site. Progress towards these challenges will be described. The remainder of this chapter is organized as follows: Section 2.2 describes the problem in more detail. Sections 2.3–2.9 review research into alternative solution methods for scheduling problems, both with deterministic and uncertain data, and Section 2.10 describes some successful industrial applications of advanced scheduling methods. The remaining sections list some new application domains and describe conclusions drawn.

2.2
The Single-Site Production Scheduling Problem

The scheduling problem at a single site is usually concerned with meeting fairly specific production requirements. Customer orders, stock imperatives or higher-level supply chain or long-term planning would usually set these requirements, as described in subsequent sections. It is concerned with the allocation over time of scarce resources between competing activities to meet these requirements in an efficient fashion. The data required to describe the scheduling problem typically include:

- Production recipes: details of how each product is to be produced, including details of production of intermediates. This will include material balance information, resource requirements, processing times/rates of the process tasks, etc.

- Resource data: for process equipment, storage equipment, utilities (capacities, capabilities, availabilities, costs, etc.)
- Material data: stability, opening inventories, anticipated receipts of raw materials/ intermediates.
- Demand data: time horizon of interest, firm orders, forecasted demands, sales prices.

The key components of the scheduling problem are resources, tasks and time. The resources need not be limited to processing equipment items, but may include material storage equipment, transportation equipment (intra- and interplant), operators, utilities (e.g., steam, electricity, cooling water), auxiliary devices and so on.

The tasks typically comprise processing operations (e.g., reaction, separation, blending, packaging) as well as other activities that change the nature of materials and other resources such as transportation, quality control, cleaning, changeovers, etc.

There are both external and internal elements to the time component. The external element arises out of the need to coordinate manufacturing and inventory with expected product liftings or demands, as well as scheduled raw material receipts and even service outages. The internal element relates to executing the tasks in an appropriate sequence and at the right times, taking account of the external time events and resource availabilities.

Overall, this arrangement of tasks over time and the assignment of appropriate resources to the tasks in a resource-constrained framework must be performed in an efficient fashion, which implies the optimization, as far as possible, of some objective. Typical objectives include the minimization of cost or maximization of profit, maximization of customer satisfaction, minimization of deviation from target performance, etc. Generally speaking, depending on raw material lead times, production lead times, forecast accuracy and other similar factors, production scheduling is driven either by firm customer orders ("make-to-order") or forecasted demands ("make-to-stock").

As noted by Gabow (1983), all but the most trivial scheduling problems belong to the class of NP hard (Non-deterministic Polynomial-time hard) problems; there are no known solution algorithms that are of polynomial complexity in the problem size. This has posed a great challenge to the research community, and a large body of work aiming to develop either tailored algorithms for specific problem instances or efficient general-purpose methods has arisen.

Solving the scheduling problem requires methods that search through the decision space of possible solutions. The search processes can be classified as follows:

- Heuristic: a series of rules (e.g., the sequence of production should be based on order due-dates) are used to generate alternative schedules.
- Metaheuristic: higher level generic search algorithms (e.g., simulated annealing, genetic algorithms) are used to explore the decision space.
- Mathematical programming: the scheduling problem is posed as a formal mathematical optimization problem and solved using general-purpose or tailored methods (see section 4.2).

The research into production scheduling techniques may be further subdivided into specific and general application domains. The latter division is intended to reflect the scope of the technique (in terms of plant structure and process recipes). Rippin (1993) classified different flexible plant structures as follows:

- Multiproduct plants, where each product has the same processing network, i.e., each product requires the same sequence of processing tasks (often known as "stages"). Owing to the historic association between the work on batch plant scheduling and that on discrete parts manufacturing, these plants are sometimes called "flowshops".
- Multipurpose plants ("jobshops"), where the products are manufactured via different processing networks, and there may be more than one way in which to manufacture the same product. In general, a number of products undergo manufacture at any given time.

In addition to the process structure, the storage policies for intermediate materials are critical in production scheduling, especially for batch plants. Any intermediate material can usually be classified as being subject to one of five intermediate storage policies:

- Zero-wait (ZW): the material is not stable and must be processed further upon production.
- No intermediate storage (NIS): the material is stable, but no storage vessels are provided. However, it may reside temporarily in the processing equipment that produced it before being processed further.
- Shared intermediate storage (SIS): the material is stable, and may be stored in one or more storage vessels that may also be used to store other materials (though not at the same time).
- Finite intermediate storage (FIS): the material is stable, and one or more dedicated storage vessels are available.
- Unlimited intermediate storage (UIS): the material is stable, and one or more dedicated storage vessels are available, the total capacity of which is effectively unlimited.

The importance of these is clearly evident from the following example. Consider a process whereby a material C, is made from raw material A, via the following reactions:

$A \rightarrow B$ (reaction 1, duration 3 h)
$B \rightarrow C$ (reaction 2, duration 1 h)

Reaction 1 takes place in reactor 1 (capacity 10.000 kg) and reaction 2 takes place in reactor 2 (capacity 5000 kg). The average production rate of C depends strongly on the storage policy for B. The rates for the ZW, NIS and UIS cases are calculated below.

2.2.1 ZW Case

Here, only 5000 kg of A can be loaded into reactor 1, because once this batch is complete, it must be immediately transferred to reactor 2, which limits the size of the batch. A sample operating schedule is shown in Figure 2.2.

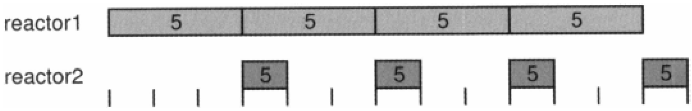

Figure 2.2 Sample schedule for the zero-wait (ZW) case

According to the schedule, 5000 kg of C is produced every 3 h, so the average production rate is 1667 kg h^{-1}.

2.2.2 NIS Case

Here, 10.000 kg of A can be loaded into reactor 1. After the reaction is complete, 5000 kg of B can be transferred to reactor 2, and 5000 is held in reactor 1 for an extra hour before being transferred to reactor 2. A sample operating schedule is shown in Figure 2.3.

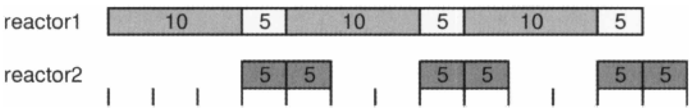

Figure 2.3 Sample schedule for the no intermediate storage (NIS) case

In this case, 10.000 kg of C is produced every 4 h, so the average production rate is 2500 kg h^{-1}.

2.2.3 UIS Case

In this case, there is sufficient storage (e.g., 10.000 kg) to decouple the operation of reactor 1 and reactor 2 completely. The production rate is then limited by the bottleneck stage; in this case reactor 1. A sample operating schedule is shown in Figure 2.4.

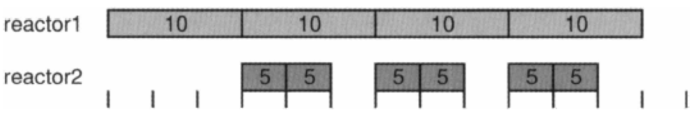

Figure 2.4 Sample schedule for the unlimited intermediate storage (UIS) case

Here, 10.000 kg of C is produced every 3 h; the production rate is 3333 kg h^{-1}.

The above discussion serves to define categories for scheduling techniques and categories for process structures.

The next sections review developments in the solution of scheduling problems and are organized along the categories listed above.

2.3 Heuristics/Metaheuristics: Specific Processes

Most scheduling heuristics are concerned with formulating rules for determining sequences of activities. They are therefore best suited to processes where the production of a product involves a prespecified sequence of tasks with fixed batch sizes; in other words, variants of multiproduct processes. Often, it is assumed that fixing the front-end product sequence will fix the sequence of activities in the plant (the so-called permutation schedule assumption; see Figure 2.5). Generally, the processing of a product is broken down into a sequence of jobs that queue for machines, and the rules dictate the priority order of the jobs.

Dannebring (1977), Kuriyan and Reklaitis (1985, 1989) and Pinedo (1995) give a good exposition on the kinds of heuristics (dispatching rules) that may be used for different plant structures. Typical rules involve ordering products (see, e.g., Hasebe et al. 1991) by processing time (either shortest or longest), due dates and so on.

Most of the heuristic methods originated in the discrete manufacturing industries, and might be expected not to perform as well in process industry problems, because in the latter material is infinitely divisible and batch sizes are variable (unlike discrete "jobs"). Furthermore, batch splitting and mixing are allowed and are becoming increasingly popular as a means of effecting late product differentiation.

Stochastic search approaches ("metaheuristics") are based on continual improvement of trial solutions by the application of an evolutionary algorithm which modifies solutions and prioritizes solutions from a list for further consideration. The two main evolutionary algorithms applied to this area are simulated annealing and genetic algorithms. An early application of simulated annealing to batch process scheduling problems was undertaken by Ku and Karimi (1991), where they applied the algorithm to multiproduct plant scheduling. They concluded that such algorithms are easy to implement and tended to perform better than conventional heuristics, but often required significant computational effort.

Xia and Macchietto (1997) described the application of simulated annealing and genetic algorithm techniques to the scheduling of multiproduct plants with complex material transfer policies. More recently, Murakami et al. (1997) described a repetitive simulated annealing procedure which avoids local minima by using many starting points with fewer evolutionary iterations per starting point.

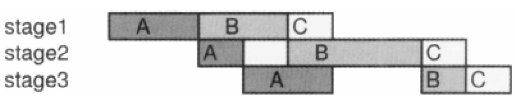

Figure 2.5 Permutation schedule

Sunol et al. (1992) described the application of a genetic algorithm approach to a simple flowshop sequencing problem, and found the technique to be superior to explicit enumeration. As noted by Hasebe et al. (1996), the performance of a genetic algorithm depends on the operators used to modify trial solutions. They applied a technique that selects appropriate operators during the solution procedure for the scheduling of a parallel-unit process.

Overall, the stochastic search processes are best applied to problems of an entirely discrete nature, where an objective function can be evaluated quickly. The classic example is the sequencing and timing of batches in a multiproduct plant, where the decision variables are the sequence of product batches, and the completion time of any candidate solution is easily evaluated through recurrence relations or minimax algebra. The main disadvantages are that it is difficult to consider general processes, and inequality constraints and continuous decisions, although some recent work (e.g., Wang et al. 2000) aims at addressing this.

2.4
Heuristics/Metaheuristics: General Processes

The problem of scheduling in general multipurpose plants is complicated by the additional decisions (beyond the sequencing of product batches) of assignment of equipment items to processing tasks, task batch sizes and intermediate storage utilization. It is difficult to devise a series of rules to resolve these, and there are therefore few heuristic approaches reported for the solution of this problem.

Kudva et al. (1994) consider the special case of "linear" multipurpose plants, where products flow through the plant in a similar fashion, but potentially using different stages and with no recycling of material. A rule-based constructive heuristic is used, which requires the maintenance of a status sheet on each unit and material type for each time instance on a discrete-time grid. The algorithm uses this status sheet with a sorted list of orders and develops a schedule for each order by backwards recursive propagation. The schedule derived depends strongly on the order sequence. Solutions were found to be within acceptable bounds of optimality when compared with those derived through formal optimization procedures.

Graells et al. (1996) presented a heuristic strategy for the scheduling of multipurpose batch plants with mixed intermediate storage policies. A decomposition procedure is employed where subschedules are generated for the production of intermediate materials. Each subschedule consists of a mini production path determined through a branch-and-cut enumeration of possible unit-to-task allocations. The mini-paths are then combined to form the overall schedule. The overall schedule is checked for feasibility with respect to material balances and storage capacities. Improvements to the schedules may be effected manually through an electronic Gantt chart or through a simulated annealing procedure.

Lee and Malone (2000) describe the application of a simulated annealing metaheuristic to a variety of batch process planning problems. Here, intermediate products, inventory costs and a variety of process flow networks can be represented.

As mentioned earlier, the application of heuristics to such problems is not straightforward. Although this effectively represents current industrial practice, most academic research has been directed towards the development of mathematical programming approaches for multipurpose plant scheduling. As will be described later, these approaches are capable of representing all the complex interactions present.

2.5 Mathematical Programming: Specific Processes

Here, we shall first outline some of the features of mathematical programming approaches in general, and then consider their application to processes other than the general multipurpose one. The latter will be considered in the Section 2.6. Mathematical programming approaches to production scheduling in the process industries have received a large amount of attention recently. This is because they bring the promise of generality (i.e., ability to deal with a wide variety of problems), rigor (the avoidance of approximations) and the possibility of achieving optimal or near-optimal solutions.

The application of mathematical programming approaches implies the development of a mathematical model and an optimization algorithm. Most approaches aim to develop models that are of a standard form (from linear programming (LP) models for refinery planning to mixed-integer nonlinear programming (MINLP) models for multipurpose batch plant scheduling). These may then be solved by standard software or specialized algorithms that take account of problem structure.

The variables of the mathematical models will tend to include some or all of the following choices, depending on the complexity considered:

- sequence of products or individual tasks
- timing of individual tasks in the process
- selection of resources to execute tasks at the appropriate times
- amounts processed in each task
- inventory levels of all materials over time.

The discrete nature of some of the variables (sequencing and resource selection) implies that binary or integer-valued variables will be required.

The selection of values for all the variables will be subject to some or all of the following constraints:

- nonpreemptive processing: once started, processing activities must proceed until completion;
- resource constraints: at any time, the utilization of a resource must not exceed its availability;
- material balances;
- capacity constraints: processing and storage;
- orders being met in full by their due dates.

Finally, optimization methods dictate that an objective function be defined. This is usually of an economic form, involving terms such as production, transition and inventory costs and possibly revenues from product sales.

A very good review of mathematical programming techniques applied to scheduling and an associated classification of methods and models is provided by Pinto and Grossmann (1998).

A critical feature of mathematical programming approaches is the representation of the time horizon. This is important because activities interact through the use of resources; therefore, the discontinuities in the overall resource utilization profiles must be tracked with time, to be compared with resource availabilities to ensure feasibility. The complexity arises because these discontinuities (unlike discontinuities in availabilities) are functions of any schedule proposed and are not known in advance. The two approaches for dealing with this are:

- Discrete-time (or "uniform discretization"): the horizon is divided into a number of equally spaced intervals so that any event that introduces such discontinuities (e.g., the starting of a task or a due date for an order) can only take place at an interval boundary. This implies a relatively fine division of the time grid, so as to capture all the possible event times, and in the solution to the problem it is likely that many grid points will not actually exhibit resource utilization discontinuities.
- Continuous time (or "nonuniform discretization"): here, the horizon is divided into fewer intervals, the spacing of which will be determined as part of the solution to the problem. The number of intervals will correspond more closely to the number of resource utilization discontinuities in the solution.

In addition to the above, another attribute of time representation is whether the same grid is used for all major equipment items in the plant (the "common grid" approach) or whether each major equipment item operates on its own grid (the "individual resource grid", only used with continuous-time models). Generally speaking, the former approach is more suitable for processes in which activities on the major equipment items also interact with common resources (materials, services, etc.) and the latter where activities on the major equipment items are quite independent in their interactions with common resources. These distinctions will become clearer when individual pieces of research are discussed. The distinctions between these representations are shown in Figures 2.6 and 2.7.

The simplest specific scheduling process is probably a single production line which produces one product at time in a continuous fashion. Work in this area has been directed towards deriving cyclic schedules (where the production pattern is

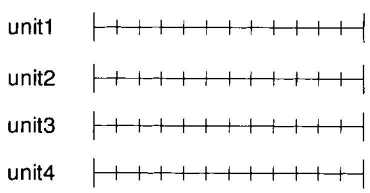

Figure 2.6 Discrete-time representation

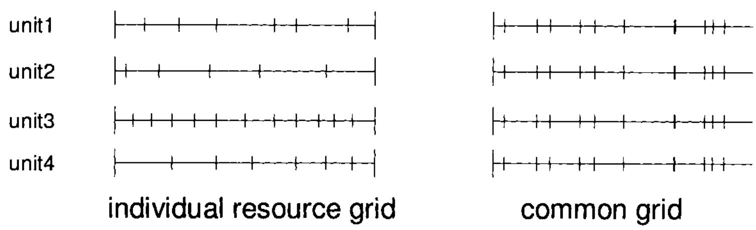

Figure 2.7 Continuous-time representations

repeated at a fixed frequency) that balance inventory and transition costs by determining the best sequence of products and their associated run-lengths or lot-sizes. A review of this so-called economic lot scheduling problem is given by Elmaghraby (1978).

Sahinidis and Grossmann (1991) consider the more general problem of the cyclic scheduling of a number of parallel multiproduct lines, where each product may in principle be produced on more than one line and production rates and costs vary between lines. They utilize a continuous-time individual resource grid model, which turns out to be a MINLP. This includes an objective function that includes combined production, product transition and inventory costs for a constant demand rate for all products. Their work was extended by Pinto and Grossmann (1994), who considered the case of multiple production lines, each consisting of a series of stages decoupled by intermediate storage and operating in a cyclic mode. Each product is processed through all stages, and each product is processed only once at each stage. The model again uses a continuous-time model, and it is possible to use the independent grid approach despite the fact that stages interact through material balances; this is due to the special structure of the problem.

A number of mathematical programming approaches have been developed for the scheduling of multiproduct batch plants. All are based (either explicitly or implicitly) on a continuous representation of time.

Pekny et al. (1988) considered the special case of a multiproduct plant with no storage (zero wait (ZW)) between operations. They show that the scheduling problem has the same structure as the asymmetric traveling salesman problem, and apply an exact parallel computation technique employing a tailored branch-and-bound procedure which uses an assignment problem to provide problem relaxations. The work was extended to cover the case of product transition costs, where the problem structure is equivalent to the prize-collecting traveling salesman problem (Pekny et al. 1990), and LP relaxations are used. For both cases, problems of very large magnitude were solved to optimality with modest computational effort. Gooding et al. (1994) augmented this work to cover the case of multiple units at each stage (the so-called "parallel flowshop" stage).

A more complete overview of the development of algorithms for classes of problems ("algorithm engineering") is given by Applequist et al. (1997) and a commercial development in this area is described by Bunch (1997).

Birewar and Grossmann (1989) developed a mixed-integer programming model for a similar type of plant. They show that through careful modeling of slack times, and by exploiting the fact that relatively large numbers of batches of relatively few products will be produced (which allows end-effects to be ignored), a straightforward LP model can be used to minimize the makespan. The result is a family of schedules from which an individual schedule may be extracted. They extend the work to cover simultaneous long-term planning and scheduling, where the planning function takes account of scheduling limitations (Birewar and Grossmann 1990).

Pinto and Grossmann (1995) describe a mixed-integer linear programming (MILP) model for the minimization of earliness of orders for a multiproduct plant with multiple equipment items at each stage. The only resources required for production are the processing units. Pinto and Grossmann (1997) then augmented the model to take account of interactions between processing stages and common resources (e.g., steam). Rather than utilize a common grid, they retained individual grids, and accounted for the resource discontinuities through complex mixed-integer constraints which weakened the model and resulted in large computational times. They therefore proposed a hybrid logic-based/MILP algorithm where the disjunctions relate to the relative timing of orders. This dramatically reduces the computational effort expended.

Moon et al. (1996) also developed a MILP model for ZW multiproduct plants. The objective was to assign tasks to sequence positions so as to minimize the makespan, with nonzero transfer and set-up times being included.

The extension of the work to more general intermediate storage policies was described by Kim et al. (1996), who proposed several MINLP formulations based on completion time relations.

The case of single-stage processes with multiple units per stage has been considered by Cerda et al. (1997) and McDonald and Karimi (McDonald and Karimi, 1997; Karimi and McDonald, 1997). Both describe continuous-time-based MILP models. Cerda et al. focus on changeovers and order fulfilment, while Karimi and McDonald focus on semicontinuous processes and total cost (transition, shortage and inventory) with the complication of minimum run lengths. A characteristic of both approaches is that discrete demands must be captured on the continuous-time grid.

Méndez and Cerdá (2000) developed a MILP model for a process with a single production stage with parallel units followed by a storage stage with multiple units, with restricted connectivity between the stages. This was extended to the multistage case with general production resources by Méndez et al. (2001). In common with other models, there are no explicit time slots in the model; the key variables are allocations of activities to units and the relative orderings of activities.

The work described above all relates to special process structures, which means that mathematical models can be designed specifically for the problem class. This ensures that, despite the typical concerns about computational complexity of discrete optimization problems, solutions are available with reasonable effort. The drawback of the work is its limited applicability. Nevertheless, several models appear to have been developed with specific industrial applications in mind (e.g., Sahinidis and Grossmann (1991a), Pinto and Grossmann (1995) and Karimi and McDonald (1997)).

2.6
Mathematical Programming: Multipurpose Plants

A large portion of the most recent research in planning and scheduling undertaken by the process systems community relates to the development of mathematical programming approaches applied to multipurpose plants. As intimated earlier, in this case the application domain tends to imply the solution approach: mathematical models are the best way of representing the complex interactions between resource allocations, task timings, material flows and equipment capacities. Much of the recent work reported in the literature deals with this class of problem.

The work in this are can be characterized by three different assumptions about plant operation:

- The unique assignment case: each task can only be performed by a unique piece of equipment, and there are no optional tasks in the process recipe and batch sizes are usually fixed.
- The campaign mode of operation: the horizon is divided into relatively long campaigns, and each campaign is dedicated to one or a few products.
- Short-term operation: products are produced as required and no particular scheduling pattern may be assumed.

The first assumption is particularly restrictive. The second relates to a mode of operation that is becoming relatively scarce, as it implies a low level of responsiveness. One sector in which campaign operation is still prevalent is in the manufacture of active ingredients for pharmaceuticals and agrochemicals. The short-term mode of operation is tending to become the most prevalent elsewhere, as it best exploits operational flexibility to meet changing external circumstances.

Mauderli and Rippin (1979) developed a procedure for campaign planning which attempts to optimize the allocation of equipment to tasks. An enumerative procedure (based on different equipment-to-task allocations) is used to generate possible single-product campaigns which are then screened by LP techniques to select the dominant ones. A production plan is then developed by the solution of a MILP that sequences the dominant campaigns and fixes their lengths. The disadvantages of this work are the inefficiency of the generation procedure and the lower level of resource utilization implied by single-product campaigns. Wellons and Reklaitis (1991a,b) addressed this through a formal MINLP method to generate campaigns and production plans in a two-stage procedure, as did Shah and Pantelides (1991) who solved a simultaneous campaign generation and production planning problem.

An early application of mathematical programming techniques for short-term multipurpose plant scheduling was the MILP approach of Kondili et al. (1988). They used a discrete representation of time, and introduced the state-task network (STN) representation of the process (see Figure 2.8).

The STN representation has three main advantages:

- It distinguishes the process operations from the resources that may be used to execute them, and therefore provides a conceptual platform from which to relax the unique assignment assumption and optimize unit-to-task allocation.

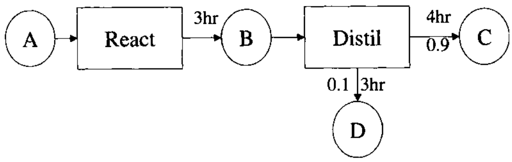

Figure 2.8 Example of a state-task network. *Circles*: material states, *rectangles*: tasks

- It avoids the use of task precedence relations, which become very complicated in multipurpose plants: a task can be scheduled to start if its input materials are available in the correct amounts and other resources (processing equipment and utilities) are also available, regardless of the plant history.
- It provides a means of describing very general process recipes, involving batch splitting and mixing and material recycles, and storage policies including ZW, NIS, SIS and so on.

The formulation of Kondili et al. (1988) (described in more detail in Kondili et al. (1993)) is based on the definition of binary variables that indicate whether tasks start in specific pieces of equipment at the start of each time period, together with associated continuous batch sizes. Other key variables are the amount of material in each state held in dedicated storage over each time interval, and the amount of each utility required for processing tasks over each time interval.

Their key constraints related to equipment and utility usage, material balances and capacity constraints. The common, discrete-time grid captures all the plant resource utilizations in a straightforward manner; discontinuities in these are forced to occur at the predefined interval boundaries. Their approach was hindered in its ability to handle large problems by the weakness of the allocation constraints and the general limitations of discrete-time approaches, such as the need for relatively large numbers of grid points to represent activities with significantly different durations.

Their work formed the basis of several other pieces of research aiming to take advantage of the representational capabilities of the formulation while improving its numerical performance. Sahinidis and Grossmann (1991b) disaggregated the allocation constraints and also exploited the embedded lot-sizing nature of the model where relatively small demands are distributed throughout the horizon. They disaggregate the model in a fashion similar to that of Krarup and Bilde (1977), who were able to improve the solution efficiency despite the larger nature of the disaggregated model. This was due to a feature particular to mixed-integer problems: other things being equal, the computational effort for problem solution through standard procedures is dictated mainly by the difference between the optimal objective function and the value of the objective function obtained by solving the continuous relaxation where bound constraints rather than integrality restrictions are imposed on the integer variables (the so-called "integrality gap"). The formulation of Sahinidis and Grossmann (1991b) was demonstrated to have a much smaller integrality gap than the original.

Shah et al. (1993a) modified the allocation constraints even further to generate the smallest possible integrality gap for the type of formulation. They also devised a tailored branch-and-bound solution procedure which utilizes a much smaller LP relaxation and solution processing to improve integrality at each node. The same authors (Shah et al. 1993b) considered the extension to cyclic scheduling, where the same schedule is repeated at a frequency to be determined as part of the optimization. This was augmented by Papageorgiou and Pantelides (1996a,b) to cover the case of multiple campaigns, each with a cyclic schedule to be determined.

Elkamel (1993) also proposed a number of measures to improve the performance of the STN-based discrete-time scheduling model. A heuristic decomposition method was proposed, which solves separate scheduling problems for parts of the overall scheduling problem. The decomposition may be based on the resources ("longitudinal decomposition") or on time ("axial decomposition"). In the former, the recipes and suitable equipment for each task are examined for the possible formation of unique task-unit subgroups which can be scheduled separately. Axial decomposition is based on grouping products by due dates and decomposing the horizon into a series of smaller time periods, each concerned with the satisfaction of demands falling due within it. He also described a perturbation heuristic, which is a form of local search around the relaxation. Elkamel and Al-Enezi (1998) describe valid inequalities that tighten the MILP relaxations of this class of model.

Yee and Shah (1997, 1998) and Yee (1998) also considered various manipulations to improve the performance of general discrete-time scheduling models. A major feature of their work is variable elimination. They recognize that in such models, only about 5–15 % of the variables reflecting task-to-unit allocations are active at the integer solution, and it would be beneficial to identify as far as possible inactive variables prior to solution. They describe a LP-based heuristic, a flexibility and sequence reduction technique and a formal branch-and-price method. They also recognize that some problem instances result in poor relaxations and propose valid inequalities and a disaggregation procedure similar to that of Sahinidis and Grossmann (1991b) for particular data instances (Romero and Puigjaner (2004)). Bassett et al. (1996) and Dimitriadis et al. (1997a, 1997b) describe decompostion-based approaches which solve the problems in stages, eventually generating a complete solution.

Blömer and Günther (1998) also introduced a series of LP-based heuristics that can reduce solution times considerably, without compromising the quality of the solution obtained.

Grunow et al. (2002) show how the STN tasks can be aggregated into higher level processes for the purposes of longer-term campaign planning.

Gooding (1994) considers a special case of the problem with firm demands and dedicated storage only. The scheduling model is described in a digraph form where nodes correspond to possible task-unit-time allocations and arcs the possible sequences of the activities. The explicit description of the sequence in this form addresses one of the weaknesses of the discrete-time formulation of Kondili et al. (1988, 1993), which was that it did not model sequence-dependent changeovers very well. Gooding's (1994) model therefore performed relatively well in problems with a strong sequencing component, but suffers from model complexity in that all possible sequences must be accounted for directly.

Pantelides et al. (1995) reported a STN-based approach to the scheduling of pipeless plants, where material is conveyed between processing stations in movable vessels. This requires the simultaneous scheduling of the movement and processing operations.

Pantelides (1994) presented a critique of the STN and associated scheduling formulations. He argued that despite its advantages, it suffers from a number of drawbacks:

- The model of plant operation is somewhat restricted: each operation is assumed to use exactly one major item of equipment throughout its operation.
- Tasks are always assumed to be processing activities which change material states: changeovers or transportation activities have to be treated as special cases.
- Each item of equipment is treated as a distinct entity: this introduces solution degeneracy if multiple equivalent items exist.
- Different resources (materials, units, utilities) are treated differently, giving rise to many different types of constraints, each of which must be formulated carefully to avoid unnecessarily increasing the integrality gap.

He then proposed an alternative representation, the resource-task network (RTN), based on a uniform description of all resources (Figure 2.9). In contrast to the STN approach, where a task consumes and produces materials while using equipment and utilities during its execution, in this representation, a task is assumed only to consume and produce resources. Processing items are treated as though consumed at the start of a task and produced at the end. Furthermore, processing equipment in different conditions (e.g., "clean" or "dirty") can be treated as different resources, with different activities (e.g., "processing" or "cleaning") consuming and generating them › this enables a simple representation of changeover activities.

Pantelides (1994) also proposed a discrete-time scheduling formulation based on the RTN that, due to the uniform treatment of resources, only requires the description of three types of constraint, and does not distinguish between identical equipment items (which results in more compact and less degenerate optimization

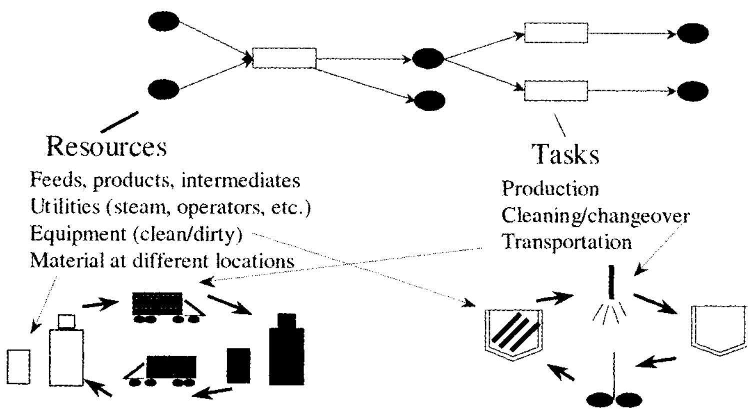

Figure 2.9 The resource-task network representation

models). He illustrated that the integrality gap could not be worse than the most efficient form of STN formulation, but that the ability to capture additional problem features in a straightforward fashion made it an ideal framework for future research.

The review above has mainly considered the development of discrete-time models. As argued by Schilling (1997), discrete-time models have been able to solve a large number of industrially relevant problems (see, e.g., Tahmassebi 1996), but suffer from a number of inherent drawbacks:

- The discretization interval must be fine enough to capture all significant events; this may result in a very large model.
- It is difficult to model operations where the processing time is dependent on the batch size.
- The modeling of continuous and semicontinuous operations must be approximated, and minimum run-lengths give rise to complicated constraints.

A number of researchers have therefore attempted to develop scheduling models for multipurpose plants which are based on a continuous representation of time, where fewer grid points are required as they will be placed at the appropriate resource utilization discontinuities during problem solution.

Zentner and Reklaitis (1992) described a formulation based on the unique assignment case and fixed batch sizes. The sequence of activities as well as any external effects can be used to infer the discontinuities and therefore the interval boundaries. A MILP optimization is then used to determine the exact task starting times.

Reklaitis and Mockus (1995) detailed a continuous-time formulation based on the STN formulation, and exploiting its generality. A common resource grid is used, with the timing of the grid points ("event orders" in their terminology) determined by the optimization. The model is a MINLP, which may be simplified to a mixed-integer bilinear problem by linearizing terms involving binary variables. This is solved using an outer-approximation algorithm. Only very preliminary findings were reported, but the promise of such models is evident.

Mockus and Reklaitis (1996) then reported an alternative solution procedure. They introduce the concept of Bayesian heuristics, which are heuristics that can be described through parameterized functions. The Bayesian technique iteratively modifies the parameters to develop a heuristic that is expected to perform well across a class of problem parameters. They illustrate the procedure using a material requirements planning (MRP) backward-scheduling heuristic which outperforms a standard discrete-time MILP formulation solved using branch-and-bound. They extend this work (Mockus and Reklaitis 1999a,b) to the case where a variety of heuristics are used in combination with optimization).

Zhang and Sargent (1994, 1996) presented a continuous-time formulation based on the RTN representation for both batch and continuous operations, with the possibility of batch-size-dependent processing times for batch operations. Again, the interval durations are determined as part of the optimization. A MINLP model ensues; this is solved using a local linearization procedure combined with what is effectively a column generation algorithm.

A problem with continuous-time models of the form described above arises from the inclusion of products of binary variables and interval durations or absolute starting times in the constraints. The linearization of these products gives rise to terms involving products of binary variables and maximum predicted interval durations or starting times. The looser these upper bounds, the worse the integrality gap of the formulation and, in general, the more difficult it becomes to solve the scheduling problem. Furthermore, it is difficult to predict good duration bounds *a priori*. The poor relaxation performance of the continuous-time models is the main obstacle to their more widespread application.

Schilling and Pantelides (1996) and Schilling (1997) attempted to address this deficiency. They developed a continuous-time scheduling model based on the RTN. They proposed a number of modifications to the formulation of Zhang and Sargent (1996) ,which simplify the model and improve its general solution characteristics. A global linearization gives rise to a MILP. They then developed a hybrid branch-and-bound solution procedure which branches in the space of the interval durations as well as in the space of the integer variables. For a given problem instance, this can be viewed as generating a number of problem instances, each with tighter interval duration bounds. The independence of these new instances was recognized by Schilling (1997), who implemented a parallel solution procedure based on a distributed computing environment. The combination of the hybrid and parallel aspects of the solution procedure resulted in a much improved computational performance on a wide class of problems. Their model and solution procedure was then extended to the cyclic scheduling case (Schilling and Pantelides 1999). Castro et al. (2001) made some adjustments to the model to account for stable materials that can be held temporarily in processing units; these improve the computational performance considerably.

Ierapetritou and Floudas (1998a–c) and Ierapetritou et al. (1999) introduced a new continuous-time model where the task and unit events are not directly coordinated against the same grid, but have their own grids (i.e., individual resource grids). Sequencing and timing constraints are then introduced to ensure feasibility. This has the effect of reducing the model size and reducing the associated computational effort required to find a solution. Their model is able to deal with semicontinuous processes and products with due dates falling arbitrarily within the horizon. Lin and Floudas (2001) extended this work to cover simultaneous design and scheduling.

Wu and Ierapetritou (2003) employed time-, recipe- and resource-based decomposition procedures to this class of model. They indicated that near-optimal solutions may be obtained with modest effort. The work was generalized further by Janak et al. (2004) who included mixed storage policies, batch-size-dependent processing times, general resource constraints and sequence-dependent changeover constraints.

Lee et al. (2001) extended this body of work with a formulation that uses binary variables to represent the start, process and end components of a process task. The computational performance of their model is similar to that of Castro et al. (2001).

Orcun et al. (2001) used the concept of operations through which batches flow to develop a continuous-time model. Each batch has a prespecified alternative set of recipes for its manufacture; each recipe defines the flow through the operations. One of the major decisions is then the choice of recipe for each batch. The complicating constraints are those that ensure the timing and sequence of batches and operations are feasible.

Majozi and Zhu (2001) modified the STN concept by removing tasks and units; thereby generating a state-sequence network (SSN); essentially a state-transition network. They developed a continuous-time model based on this, which relies on specialized sequencing constraints to ensure feasibility. Resources other than processing units cannot be treated.

Giannelos and Georgiadis (2002) described a very straightforward continuous-time model for multipurpose plant scheduling based on the STN process representation. In their work, they introduced "buffer times", which means that although all tasks must start at event points, they do not need to finish on event points. This reduced synchronization improves the computational performance considerably when compared to similar mathematical models.

Giannelos and Georgiadis (2003) applied their continuous-time model to the scheduling of consumer goods factories. The latter are characterized by sequence-dependent changeovers and flexible intermediate storage. By preprocessing the data, good upper bounds on the number of changeover tasks can be estimated and used to tighten the MILP model. Good solutions were found for the case of a medium-size industrial study.

Maravelias and Grossmann (2003) used a mixed time representation, where tasks which produce ZW states must start and finish at slot boundaries, while others are only anchored at the start, as per Giannelos and Georgiadis (2002). A different set of binary variables and assignment constraints is used from other works in this area. General resource constraints, sequence-dependent cleaning, and variable processing times are also included. Good computational performance is observed.

Castro et al. (2003) investigated both discrete- and continuous-time RTN models for periodic scheduling applied to a pulp and paper case study. A coarse and then a fine grid is used with the discrete-time model to optimize the cycle time, and an iterative search on the number of event points is used in the continuous-time model. The discrete-time model allowed more flexibility in the statement of the objective function and is easier to solve, while the continuous-time model in principle allows more accurate modeling of the operations.

Castro et al. (2004) presented a simple model for both batch and continuous processes which has an improved LP relaxation compared to that of Castro et al. (2001), due to a different set of timing constraints; this model generally outperforms other continuous-time models proposed in the literature.

Overall, considerable progress has been made towards the development of general-purpose mathematical programming-based methods for process scheduling. At least two commercial packages ModelEnterprise (see http://www.psenterprise.com/products-me.html) and Verdict (see http://www.combination.com) have resulted from these academic endeavours.

2.7
Hybrid Solution Approaches

So far, we have described individual solution approaches. A new class of solution methods has arisen out of the recognition that mathematical programming approaches are very effective when the scheduling problems are dominated by flow-type decisions, but often struggle when sequencing decisions dominate. Hybrid approaches decompose the problem into flow and sequence-based components and then apply different algorithms to these components. An example of this is described by Neumann et al. (2002), who solve separate batching and scheduling problems. The batching problem is a mixed-integer optimization problem which determines the number of instances of each task on each unit. The scheduling problem then determines the sequence and timing of the batches. A tailored algorithm based on project scheduling concepts is used for the scheduling/sequencing problem (Schwindt and Trautmann 2000).

Most of the other hybrid methods are based on the same decomposition principle, but recognize that constrained logic programming (CLP) (also called constraint programming) is a powerful technique for the solution of sequencing problems. It is based on the concept of domain reduction and constraint propagation (van Hentenryck 1989).

Jain and Grossmann (2001) use a single, hybrid model where different degrees of freedom are determined by the two solvers. Effectively, this requires an iteration between MILP and CLP solvers which proceeds until an optimal and feasible solution is found. A specific (parallel flowshop), rather than general process is studied.

Harjunkoski et al. (2000) extend this work by developing a solution procedure which starts with the relaxed MILP and then iterates through different CLP solutions, each with a different objective function target. This approach performed better on a trim-loss problem than a traditional jobshop scheduling problem as tackled by Jain and Grossmann (2001).

Huang and Chung (2000) explained how CLP can be used on its own (along with some dispatching rules) for the scheduling of a simple pipeless batch plant.

Maravelias and Grossmann (2004) and Roe et al. (2003, 2004) also recognized that mixed-integer optimization techniques are appropriate for the batching problem, and constrained logic programming (CLP) approaches may be appropriate for the scheduling problem.

Roe et al. (2003, 2005) developed an algorithm appropriate to all types of processes. A STN-based description is used. A "batching" optimization is solved to determine the number of allocations of STN tasks to units and the average batch sizes, and then a tailored algorithm based on the ECLiPse framework (Wallace et al. 1997) is used to derive the schedule which aims to ensure completion of all tasks in the minimum possible time. A series of constraints are introduced in the batching problem (as per Maravelias and Grossmann 2004) to try to ensure schedule feasibility. Their approach has a single pass, while that of Maravelias and Grossmann (2004) is more sophisticated in that the algorithm iterates between MILP and CLP levels, and the two solution methods deal with different parts of a single model (essentially that of

Maravelias and Grossmann 2003), which allows for variable batch sizes. The CLP level, rather than just adding simple integer cuts, adds a more general type of cut that excludes similar permutations of the solution to be excluded.

Romero et al. (2004) used a graph theoretical framework to tackle scheduling problems which involve complex shared intermediate storage systems. Their representation is based on two types of graph: the recipe graph which depicts possible material flow routes, and the schedule graph which shows a unique solution to the scheduling problem. A branch-and-bound algorithm is used to search for optimal solutions.

2.8
Combined Scheduling and Process Operation

A feature of scheduling problems is that the representation of the production process depends on the gross margin of the business. Businesses with reasonable to large gross margins (e.g., consumer goods, specialties) tend to use "recipe-based" representations, where processes are operated at fixed conditions and to fixed recipes. Recipes may also be fixed by regulation (e.g., pharmaceuticals) or because of poor process knowledge (e.g., food processing). On the other hand, businesses with slimmer margins (e.g., refining, petrochemicals) are moving towards "property-based" representations, where process conditions and (crude) process models are used in the process representation, and stream properties are inferred from process conditions and mixing rules. Hence some degrees of freedom associated with process operation are optimized during production scheduling. Some examples of this type of process are described below.

Castro et al. (2002) described the use of both dynamic simulation and scheduling for the improved operation of the digester part of a pulp mill. A dynamic model is used to determine task durations and an RTN-based model is used for scheduling. The schedule optimization indicated that steam availability limits throughput. Alternative task combinations based on different steam sharing options were generated through the detailed modeling, and these were made available to the scheduling model. This then (approximately) enables the scheduling model to optimize the details of process operation.

Glismann and Gruhn (2001) describe a model which combines scheduling with nonlinear recipe blend optimization. Here, a long-range planning problem using nonlinear programming identifies products to be produced and different blending recipes to produce them. A short-term RTN-based scheduling model then schedules the blending activities in detail. Deviations between plan and schedule can then be reduced in a further step.

Alle and Pinto (2002) developed a model for the cyclic scheduling of continuous plants including operational variables such as processing rates and yields. This enables the optimization procedure to trade off time and material efficiencies. A tailored algorithm is used to find the global optimum of this mixed-integer nonconvex optimization problem.

A different type of operational consideration is performance degradation over time. Jain and Grossmann (1998) describe the cyclic scheduling of an ethylene cracking process. Here, the conversion falls with time, until a cleaning activity is undertaken to restore the cracker to peak performance. There is a tradeoff between frequent cleaning (and high downtime) and high average performance and infrequent cleaning (and lower downtime) and lower average performance. The problem is complicated by the presence of multiple furnaces and model nonlinearity.

Joly and Pinto (2003) describe a discrete-time MINLP model for the scheduling of fuel oil and asphalt production at a large Brazilian refinery. The nonlinear operational component comes from the calculation of the viscosity through variable flow rates rather than through fixed recipes. Because the viscosity specifications are fixed, a linear model can be derived from the MINLP and solved to global optimality.

Pinto et al. (2000) and Joly et al. (2002) described a refinery planning model with nonlinear process models and blending relations. They demonstrated that industrial scale problems can in principle be solved using commercially available MINLP solvers.

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

Moro (2003), in his review of technology in the refining industry, indicates that scheduling tools that include details of process operation are still not available, but their application should results in benefits of US$10 million per year for a typical refinery.

2.9 Uncertainty in Planning and Scheduling

As with any other industrially relevant optimization problem, production scheduling requires a considerable amount of data. This is often subject to uncertainty (e.g., task processing times, yields, market demands, etc.). Sources of uncertainty (which tend to imply the means for dealing with them) can crudely be divided into:

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

Traditionally, short-term uncertainties have been treated through online or reactive scheduling, where schedules are adjusted to take account of new information. Longer-term uncertainties have been tackled through the solution of some form of stochastic programming problem. These two areas are considered below.

2.9.1 Reactive Scheduling

A major requirement of reactive scheduling systems is the ability to generate feasible updated schedules relatively quickly. A secondary objective is often to minimize deviations from the original schedule. As plants become more automated, this may become less important.

Cott (1989) presented some schedule modification algorithms to be used in conjunction with online monitoring, in particular to deal with processing-time variations and batch-size variations.

Kanakamedala et al. (1994) presented a least-impact heuristic beam search for reactive schedule modification in the face of unexpected deviations in processing times and resource availability. This is based on evaluating possible product reroutings and selecting that which has least overall impact on the schedule.

Rodrigues et al. (1996) modified the discrete-time STN formulation to take account of due-date changes and equipment unavailability. They use a rolling horizon (rolling out a predefined schedule) approach which aims to look ahead for a short time to resolve infeasibilities. This implies a very small problem size and fast solution times.

Schilling (1997) adapted his RTN-based continuous-time formulation to create a hierarchical family of MILP-based reactive scheduling formulations. At the lowest level, the sequence of operations is fixed as in the original schedule and only the timing can vary. At the topmost level, a full original scheduling problem is solved. The intermediate levels all trade off degrees-of-freedom with computational effort. This allows the best solution in the time available to be implemented on the plant.

Bael (1999) combined constraint satisfaction and iterative improvement (based on local perturbations) in his rescheduling strategy for jobshop environments. A trade-off between computational time and solution quality was identified.

Castillo and Roberts (2001) described a real-time scheduling approach for batch plants, based on model predictive control methods. The future allocation of orders to machines can be investigated using a fast tree-search algorithm, and robust solutions are generated in real time. This works due to the assumption of batch integrity throughout the process (i.e., there is no mixing or splitting of material).

Wang et al. (2000) described a genetic algorithm for online scheduling of a complex multiproduct polymer plant with many conflicting constraints. They describe how this technique may be successfully applied to scheduling problems and give guidance on appropriate mutation and crossover operations.

Henning and Cerdá (2000) described a knowledge-based framework which aims to support a human scheduler performing both offline and reactive scheduling. They argue that purely automated scheduling is difficult because plant circumstances change regularly. An object-oriented, knowledge-based framework is used to capture problem information and a scheduling support system developed (within which a variety of scheduling algorithms can be encoded) that enhances the capabilities of the human domain expert via an interactive front end. Because schedules can be generated very quickly using this approach, it is suitable for reactive scheduling.

One reason for reactive scheduling is the need to rework batches when quality criteria are not met. Flapper et al. (2002) provide a review of methods for planning and control of rework.

2.9.2
Planning and Scheduling under Uncertainty

Most of the work in this area is based on models in which product demands are assumed to be uncertain and to differ between a number of time periods. Usually, a simple representation of the plant capacity is assumed, and the sophistication of the work relates to the implementation of stochastic planning algorithms to select amounts for production in the first period (here and now) and potential production amounts in different possible demand realizations in different periods (see, e.g., Ierapetritou et al. (1996)).

In relatively long-term planning, it is reasonable to introduce additional degrees of freedom associated with potential capacity expansions. Liu and Sahinidis (1996a,b) and Iyer and Grossmann (1998) extended the MILP process and capacity planning model of Sahinidis and Grossmann (1991b) to include multiple product-demand scenarios in each period. They then proposed 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 (Iyer and Grossmann 1998). A major assumption in their formulation is that product inventories are not carried over from one period to the next.

Clay and Grossmann (1994) also addressed this issue. They considered the structure of both the two-period and multiperiod problem for LP models and derived an approximation method 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-scale deterministic equivalent model.

The approaches above are based on relatively simple models of plant capacity. Petkov and Maranas (1997) treat 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 accurately calculates the plant capacity. They do not use discrete demand scenarios but assume normal distributions and directly manipulate the functional forms to generate a problem which maximizes expected profit and meets certain probabilistic bounds on demand satisfaction without the need for numerical integration. They also make the no-inventory-carryover assumption, but show how this can be remedied to a certain extent at the lower level scheduling stage. Sand and Engell (2004) use a rolling horizon, two-stage stochastic programming approach to schedule an expandable polystyrene plant that is subject to uncertainty in processing times, yields, capacities and demands. The former two sources of uncertainty are considered short-term and the latter two medium-term. A hierarchical scheduling technique is used where a master schedule deals with medium-term uncertainties and a detailed schedule with the short-term ones. The uncertainties are represented through discrete scenarios and the two-stage problem solved using a decomposition technique.

Alternative approaches have attempted to characterize the effects of some sources of uncertainty on detailed schedules.

Rotstein et al. (1994) defined flexibility and reliability indices for detailed schedules. These are based on data for equipment reliability and demand distributions. Given a schedule (described in network flow form), these indices can be calculated to assess its performance.

Dedopoulos and Shah (1995) used a multistage stochastic programming formulation to solve short-term scheduling problems with possibilities of equipment failure at each discrete time instant. The technique can be used to assess the impact of different failure characteristics of the equipment on expected profit, but suffers from the very large computational effort required even for small problems.

Sanmarti et al. (1995) define a robust schedule as one which has a high probability of being performed, and 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.

Mignon et al. (1995) assess schedules obtained from deterministic data for performance under variability by Monte Carlo simulation. Although a number of parameters may be uncertain, they focus on processing time. Performance and robustness (predictability) metrics are defined and features of schedules with good indicators are summarized (e.g., introducing an element of conservatism when fixing due dates).

Honkomp et al. (1997) build on this to compare schedules generated by discrete-time and continuous-time algorithms and two means of ensuring robustness in the face of processing time uncertainties, namely increasing the processing times of bottleneck stages and increasing all processing times at the deterministic scheduling level. They found that the latter heuristic was better, and that the rounding effect of the discrete-time model results in marginally better robustness. Robustness is defined with respect to variance in the objective function. Strictly speaking, penalizing the variance of a metric to ensure robustness assumes that the metric is two-sided (i.e., "the closer to nominal the better" in the Taguchi sense). Since economic objective functions are one-sided ("the more the better"), robustness indicators such as these should be used with caution. This has been noted recently by Ahmed and Sahinidis (1998).

Gonzalez and Realff (1998a) analyze MILP solutions for pipeless plants that generated by assuming lower level controls for detailed vehicle movements and fixed, nominal transfer times. The analysis performed using stochastic simulation with variabilities in the transfer times. The system performance was found not to degrade considerably from its nominal value. They extended the work (Gonzalez and Realff 1998b) to consider the development of dispatching rules based on both general flexible manufacturing principles and properties of the MILP solutions. They found that rules abstracted from the MILP solutions were superior, and could be used in realtime.

A similar "multimodel" technique that combines optimization, expert systems and discrete-event simulation is described by Artiba and Riane (1998), although their focus is on a robust package for an industrial environment rather than uncertainty *per se*.

Bassett et al. (1997) contrasted aggregate planning and detailed scheduling under uncertainties in processing times and equipment failure. They argue that aggregate models that take these into account miss critical interactions due to the complex short-term interactions. They therefore propose the use of detailed scheduling to study the effects of such uncertainties on aggregate indicators such as average probabilities in meeting due dates and makespans. They also use Monte Carlo simulation, but use each set of sampled data to generate a detailed scheduling problem instance, solved using a reverse rolling horizon algorithm. Once enough instances have been solved for statistical significance, a number of comparisons can be made. For example, they conclude that long, infrequent breakdowns are more desirable, with obvious implications for maintenance policies.

Lee and Malone (2001a, 2001b) developed a hybrid Monte Carlo simulation-simulated annealing approach to planning and scheduling under uncertainty. They treat uncertainties in demands, due dates, processing times, product prices and raw material costs. An expected NPV objective is chosen; this is calculated through simultaneous Monte Carlo simulation and simulated annealing. This can also be used to devise strategies to ensure flexibility and robustness, for example by including enforced idle times in the schedule to allow for adjustments or rush orders.

Ivanescu et al. (2002) describe an approach for makespan estimation and order acceptance in multipurpose plants with uncertain task processing times (following an Erlang distribution). Instead of using a large mathematical model, regression analysis is used instead, based on a family of problem classes.

Balasubramanian and Grossmann (2003) presented an alternative approach to scheduling under uncertainty, arguing that probabilistic data on the uncertainties (e.g., in processing times) are unlikely to be available, and instead proposing a fuzzy set and interval theory approach. A rigorous MILP that can provide bounds on the makespan is developed for the flowshop case, based on the evaluation of a fuzzy, rather than crisp, makespan, and rules for comparing alternative makespans in order to determine optimality.

Kuroda et al. (2002) use the simple concept of due-date buffers to allow for flexibility in adjusting schedules in an operational environment. Here, orders further out in the horizon are allowed to move around within the buffer, while those near the current time remain fixed. This facilitates responsiveness to unforeseen orders.

2.10
Industrial Applications of Planning and Scheduling

Honkomp et al. (2000) give a list of reasons why the practical implementation of scheduling tools based on optimization is fraught with difficulty. These include:

- The large amount of user-defined input for testing purposes.

- The difficulty in capturing all the different types of operational constraints within a general framework, and the associated difficulty in defining an appropriate objective function.
- The large amounts of data required; Book and Bhatnagar (2000) list some of the issues that must be faced if generic data models are to be developed for planning/ scheduling applications.
- Computational difficulties associated with the large problem sizes found in practice.
- Optimality gaps arising out of many shared resources.
- Intermediate storage and material stability constraints.
- Nonproductive activities (e.g., set-up times, cleaning, etc.)
- Effective treatment of uncertainties in demands and equipment effectiveness.

Nevertheless, there have been several success stories in the application of state-of-the-art scheduling methods in industry.

Schnelle (2000) applied MILP-based scheduling and design techniques to an agrochemical facility. The results indicated that sharing of equipment items between different products was a good idea, and the process reduced the number of alternatives to consider to a manageable number.

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

Kallrath (2002b) presented a successful application of MILP methods for planning and scheduling in BASF. He describes a tool for simultaneous strategic and operational planning in a multisite production network. The aim was to optimize the total net profit of a global network, where key decisions include: operating modes of equipment in each time period, production and supply of products, minor changes to the infrastructure (e.g., addition and removal of equipment from sites), and raw material purchases and contracts. A multiperiod model is formulated where equipment may undergo one mode change per period. The standard material balance equations are adjusted to account for the fact that transportation times are much shorter than the period durations. Counterintuitive but credible plans were developed that resulted in cost savings of several millions of dollars. Sensitivity analyses showed that the key decisions were not too sensitive to demand uncertainty.

Keskinocak et al. (2002) describe the application of a combined agent- and optimization-based framework for the scheduling of paper products manufacturing. The framework solves the problems of order allocation, run formation, trimming and trim-loss minimization and load planning. The deployment of the system is claimed to save millions of dollars per year. The "asynchronous agent-based team" approach uses constructor and improver agents to generate candidate solutions that are evaluated against multiple criteria.

2.11 New Application Domains

The scheduling techniques described above have in the main been applied to batch chemical production, particularly fine and specialty chemicals and pharmaceuticals. They are also appropriate to the wider and emerging process industries, and have started to find application in other domains, some of which are reviewed below.

Kim et al. (2001) tackle the problem of semiconductor wafer fabrication scheduling involving multiple products with different due dates. A series of dispatching ("lot release") and lot scheduling rules are evaluated.

Bhushan and Karimi (2003) describe the application of scheduling techniques to the wet-etching component of a semiconductor manufacturing process. This process is complicated by its "re-entrant" nature, where a product revisits stages of manufacture, and therefore does not fit the classical flowshop structure. A MILP formulation combined with a heuristic is used to minimize the makespan required to complete an outstanding set of jobs.

Pearn et al. (2004) describe the challenges associated with the scheduling of the final testing stage of integrated circuit manufacture and compare the performance of alternative heuristic algorithms.

El-Halwagi et al. (2003) describe a system for efficient design and scheduling of recovery of nutrients from plant wastes and reuse of the nutrients, with a view to developing a strategy for future planetary habitation.

Lee and Malone (2000b) show how planning can be useful in waste minimization. They combine scheduling with the main process and scheduling of the solvent recovery system. They show that such simultaneous scheduling can reduce waste disposal costs significantly.

Pilot plant facilities can become very scarce resources in the modern chemical industry, with many more short-run processes. Mockus et al. (2002) describe the integrated planning and scheduling of such a facility. The long-term planning problem is primarily concerned with skilled human resource allocation while the short-term scheduling problem deals with production operations.

Röslof et al. (2001) describe the application of production scheduling techniques to the paper manufacturing industry. In this sector, large numbers of orders, some of which are for custom products, are the norm.

Van den Heever and Grossmann (2003) describe the production planning and scheduling of a complex of plants producing hydrogen. This requires the description of the behavior of a pipeline and its associated compressors, which adds complexity and nonlinearity. The combination of longer-term planning and short-term reactive scheduling enables the decision-makers to deal effectively with uncertainty.

2.12 Conclusions and Future Challenges

Production scheduling has been a fertile area for CAPE research and the development of technology. Revisiting the challenges posed by Reklaitis (1991), Rippin (1993), Shah (1998) and Kallrath (2002a), it is clear that considerable progress has been made towards meeting them.

Overall, the emerging trend in the area of short-term scheduling is the development of techniques for the solution of the general, resource-constrained multipurpose plant scheduling problem. The recent research is all about solution efficiency and techniques to render ever-larger problems tractable. There remains work to be done on both model enhancements and improvements in solution algorithms if industrially relevant problems are to be tackled routinely, and software based on these are to be used on a regular basis by practitioners in the field.

Many algorithms have been developed to exploit the tight relaxation characteristics of discrete-time formulations. There remains work to be done in this area, in particular to exploit the sparsity of the solutions. Direct intervention at the LP level during branch-and-bound procedures (e.g., column generation and branch-and-price) seems a promising way of solving very large problems without ever considering the full variable space. Decomposition techniques (e.g., rolling horizon methods) will also find application here.

Much of the more recent research has focussed on continuous-time formulations, but little technology has been developed based on these. The main challenge here is in continual improvement in problem formulation and preprocessing to improve relaxation characteristics, and tailored solution procedures (e.g., branch-and-cut, and hybrid logic-continuous variable-integer variable branching) for problems with relatively large integrality gaps.

Probably the most promising recent development is the implementation of hybrid MILP/CLP solution methods which recognize that different algorithms are suitable for different components of the scheduling problem.

An important contrast between early and recent work is that the early algorithms tended to be tested on "motivating" examples (e.g., to find the best sequence of a few products), while recent algorithms are almost always tested on (and often motivated by) industrial or industrially based studies.

The multisite problem has received relatively little attention, and is likely to be a candidate for significant research in the near future. A major challenge is to develop planning approaches that are consistent with detailed production scheduling at each site and distribution scheduling across sites. An obvious stumbling block is problem size, and a resource-task-based decomposition based on identifying weak connections should find promise here as the problems tend to be highly structured. As scheduling and planning become integrated, the financial aspects will require more rigorous treatment. For example, Romero and Puigjaner (2004) describe the integration of cash flow modeling with production scheduling. This facilitates an accurate forward prediction of cash flow and even allows the enterprise to optimize treasury management simultaneously with decisions on purchasing, production and sales, and can be used to enforce upper and lower bounds on cash balances.

Researchers have attacked the problem of planning and scheduling under uncertainty from a number of angles, but have tended to skirt around the fundamental problem of multiperiod, multiscenario planning with realistic production capacity models (i.e., embedding some scheduling information) in the case of longer-term uncertainties. Issues that must be resolved relate mainly to problem scale. A sensible way forward is to try to capture the problem in all its complexity and then to explore rigorous or approximate solution procedures, rather than develop exact solutions to somewhat idealized problems. Process industry models are complicated by having multiple stages (periods) and integer variables in the second and subsequent stages, so most of the classical algorithms devised for large scale stochastic planning problems are not readily applicable.

The treatment of short-term uncertainties through the determination of characteristics of resilient schedules and then to use online monitoring and rescheduling seems eminently sensible. Further work is required in such characterization and in the design of rescheduling algorithms with guaranteed real-time performance.

A final challenge relates to the seamless integration of the activities at different levels – this is of a much broader and more interdisciplinary nature. Shobrys and White (2002) describe some of the difficult challenges to be faced here, including data and functional fragmentation, inconsistencies between activities and datasets, different tools being used for different activities, time and material buffers at each function for protection, slow responses and information flow.

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