A Recent Survey of Production Scheduling

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Abstract —Recent advances in the theory and practice of production scheduling cut across traditional disciplinary boundaries. Different research communities have addressed different aspects of the problem, bringing to bear a variety of research traditions, problem perspectives, and analytical techniques. The authors seek to assess the breadth and practical implications of contemporary work in this field. The authors provide a structured overview, a high-level bibliography, and a limited critique of seven scheduling paradigms. The sense and direction of current developments in each of these seven areas are summarized. The contributions, strengths, and weaknesses of each approach are considered.

I. Introduction

PRODUCTION scheduling concerns the efficient allocation of resources over time for the manufacture of goods. Scheduling problems arise whenever a common set of resources—labor, material, and equipment—must be used to make a variety of different products during the same period of time. The objective of scheduling is to find a way to assign and sequence the use of these shared resources such that production constraints are satisfied and production costs are minimized.

Interest in new approaches to production scheduling has been stimulated by a variety of pragmatic and theoretical considerations. First among these have been the increasingly competitive world markets for manufactured goods. Better production schedules provide a competitive advantage through gains in resource productivity and related efficiencies in operations management. Competition also has motivated the introduction of sophisticated and capital-intensive new manufacturing systems made possible by the declining cost and increasing power of industrial computers and robots. Most notable among the new manufacturing technologies are systems for automated, flexible, and computer-integrated manufacturing. These new systems have created a range of new operational problems, further quickening the pace of scheduling research.

Among theorists the development of complexity theory and maturation of artificial intelligence have begun to redirect the body of scheduling research. Sequencing and scheduling theory long has been preoccupied with the design of constructive solutions and optimization algorithms for highly simplified machine-scheduling problems. Theoretical advances now appear to have legitimized research on innovative heuristic search procedures which are applied to more realistic scheduling problems. These problems and procedures appear to be more robust than optimization-based machine scheduling and for this reason hold greater promise for commercial adaptation. Taken as a whole, current market, technological, and theoretical developments have made solutions to both long-standing and newly emerging scheduling problems the subject of intense applied and theoretical research.

Recent advances in the theory and practice of production scheduling transcend traditional disciplinary boundaries. Different research communities have begun to address different aspects of the problem, bringing to bear a variety of different research traditions, problem perspectives, and analytical techniques. As a consequence, the scheduling literature has escaped its traditional locus in operations research, management science, and industrial engineering. Production research recently has been reported in proceedings and journals principally concerned with control theory, artificial intelligence, system simulation, man–machine interaction, large-scale systems, and other branches of engineering and computer science. The sheer diversity and momentum of activity has made developments in production scheduling increasingly difficult to track and assimilate.

This paper presents a survey that grew out of our desire to assess the breadth and practical implications of contemporary production scheduling research and practice. In this survey we seek to provide a structured overview, a high-level bibliography, and a limited critique of seven production scheduling paradigms that we believe are historically significant or particularly promising. The first purpose of this paper is to provide a means by which researchers working within traditional disciplinary bounds can explore in outline some of the more novel formulations and technical approaches to scheduling problems. A second purpose of this paper is to stimulate researchers new to production research by providing access to a broad spectrum of contemporary production scheduling literature.

The purpose and scope of this survey have required compromise and compression in its presentation. Our claims for success in our purpose are necessarily modest. We have attempted to be comprehensive, although the

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pace of current activities and the limits of space prohibit guarantees against even significant omissions. Wherever possible, we rely on reference to original research papers and reports and to prior surveys and current texts to provide accurate and detailed exposition of the rich substructures within the various paradigms surveyed. Our treatment of specific techniques is necessarily shallow. We attempt neither a critique of specific technical methods nor a definitive comparison of the various areas of research endeavor. Instead, we attempt to convey the sense and direction of research conducted within these areas and to offer our summary observations concerning the overall strengths and weaknesses of the various research paradigms as applied to practical scheduling problems.

In the following section we develop a precise problem definition, describe the important characteristics of the production scheduling environment, and elicit the corresponding research issues. A summary and brief assessment of each of seven alternative approaches to the problem are presented in the third section. These include approaches used in current industrial practice and approaches based on machine sequencing and scheduling theory, resource-constrained project scheduling, control theory, discrete-event simulation, stochastic optimization, and artificial intelligence. The final section offers some concluding thoughts and remarks. The references are categorized as follows: General and problem definition—[1]–[14]; Industrial practice—[15]–[19]; Machine sequencing and scheduling—[20]–[27]; resource-constrained project scheduling—[28]–[31]; Control theory—[32], [33]; Discrete-event simulation—[34]–[43]; Stochastic optimization—[44]–[58]; and Artificial intelligence—[59]–[74].

TABLE I
PROCESSING TIMES AND MACHINE ROUTINGS FOR A DETERMINISTIC THREE-JOB THREE-MACHINE SCHEDULING PROBLEM

Job	Processing Times/Machine Routing Operation 1	2	3
1	$1/M_1$	$8/M_2$	$4/M_3$
2	$6/M_2$	$5/M_1$	$3/M_3$
3	$4/M_1$	$7/M_3$	$9/M_2$

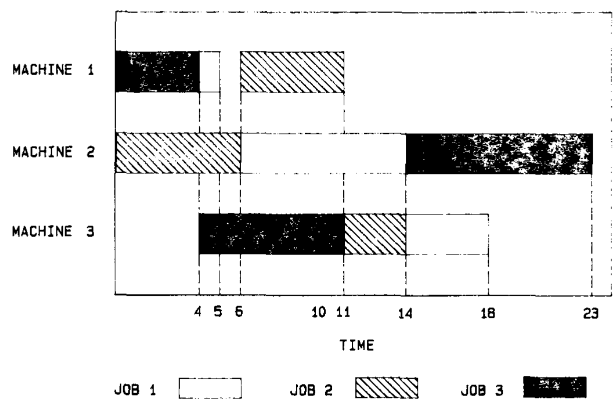

Fig. 1. Minimum-makespan production schedule for scheduling problem defined in Table I.

II. PRODUCTION SCHEDULING

Production scheduling is the allocation of available production resources over time to meet some set of performance criteria [7]. Typically, the scheduling problem involves a set of jobs to be completed, where each job comprises a set of operations to be performed. Operations require machines and material resources and must be performed according to some feasible technological sequence. Schedules are influenced by such diverse factors as job priorities, due-date requirements, release dates, cost restrictions, production levels, lot-size restrictions, machine availabilities, machine capabilities, operation precedences, resource requirements, and resource availabilities. Performance criteria typically involve trade-offs between holding inventory for the task, frequent production changeovers, satisfaction of production-level requirements, and satisfaction of due dates.

Developing a production schedule involves selecting a sequence of operations (or process routing) that will result in the completion of a job, designating the resources needed to execute each operation in the routing, and assigning the times at which each operation in the routing will start and finish execution. Routings and resource assignments typically are the product of process planning. Scheduling generally refers to the activity of timetabling operations [60].

To illustrate the art of production scheduling, consider a specific example of the traditional, single-stage, job-shop, or machine scheduling problem. Table I provides job processing times and machine routing data for three jobs which are to be processed on three machines [14]. Fig. 1 is a Gantt chart that shows one choice for scheduling the jobs. Under the usual assumptions that all jobs are ready at the start and that all operations require the exclusive use of a machine and cannot be split, this schedule represents the sequence of operations that minimizes the total time required to complete the processing of all jobs (the makespan). Note that the required ordering of operations within each job (the technological sequence) is preserved and that the ordering of operations on the machine has been selected so as to achieve the desired objective.

Although the difficulty of determining the optimal machining sequence for problems of this type is well established (the problem is known to be NP-hard, i.e., the time required to solve the problem to optimality increases exponentially with increasing problem size), the formal machine scheduling problem itself is an almost trivial abstraction of the multitude of complex, dynamic, and multiobjective scheduling problems that must be resolved in actual production environments. A given scheduling approach might be classified according to how it represents and deals with these complexities. Since to a greater or lesser degree every production environment is unique, the appropriateness of a given scheduling approach might be assessed by how well its assumptions correlate with the important features of a particular target production environment.

In this survey, we have selected five attributes of typical production scheduling environments that we have found especially useful in distinguishing among the paradigms considered. These attributes follow.

Boundary Stages: A production schedule must be implemented at some given point in time. Except from cold start-up, it is rare (if not undesirable) that all job inventory levels are zero, all machines are idle and ready to process any job, and all required labor and material resources are fully available. It is commonly observed that the scheduling problem encountered in production is really one of rescheduling, i.e., one of modifying an existing production schedule to account for new jobs, new job priorities, or unscheduled disruptions in production. To provide for rescheduling, a scheduling approach must be capable of accommodating all relevant initial states for the production system.

Similarly, a production schedule generally spans some finite time horizon. For a cyclical production environment, where the same or similar sets of jobs are repeated in a regular cycle, this time horizon typically is keyed to the calendar, with weekly or monthly production levels adjusted to account for available capacity. For a job shop, where the number and composition of future orders are unknown, this time horizon might correspond to the latest due date for any current job or to the makespan for all current jobs. Except for long-term shutdown, it is unlikely that either type of production system (or any combination of these) actually will be empty and idle at the end of the scheduling horizon. The ability to accommodate or even specify final system states can be a desirable attribute of a scheduling approach.

Batch Sizes and Setup Costs: Discrete parts are grouped into one or more batches for processing. Larger batches reduce the number of setups and changeovers required during the scheduling horizon, while smaller batches decrease in-process inventories and increase the number of scheduling options. Minimum batch sizes typically are established by management decisions based on the products, technologies, and resources involved (down to single part batches for flexible manufacturing systems). Maximum batch sizes typically are governed by performance needs and the amount of work to be done. The most general and flexible scheduler would need to determine batch sizes as a product of scheduling constraints and objectives, would accommodate both fixed and variable batch sizes, would represent setups and changeovers explicitly, and would account for sequence-dependent setup times and costs.

Process Routings: In the classical machine-scheduling problem, every job is processed on every machine exactly once, in a strict technological (within job) sequence. In actual manufacturing environments, process routings can be far more complex and even dynamic. Rarely is every job processed on every machine. Frequently, the technological sequence is a semiorder with some limited choices among which operation of a job can be processed next. The process routing can change dynamically given the state of the plant (e.g., the availability of resources) or the condition of the job (e.g., the need for rework).

Typically, there also exists a choice of machines on which certain operations can be performed. These machines may be identical with identical processing times for a given operation, as in a common machine bank. Alternatively, machines may be nonidentical with widely varying processing times and even processing characteristics and resource requirements. Examples include choices between newer and older equipment, between automated and manual equipment, and between special-purpose and general-purpose equipment (e.g., robots). The process routing and even the technological sequence of operations may change depending on the choice of machines. Ideally, a general scheduler would need to be highly flexible with respect to the types of process routings it could capture.

Random Events and Disturbances: In the classical machine-scheduling formulation, process times, release times, and due dates are deterministic. Jobs, machines, labor, and material resources are available at all times. This can be far from the case in actual production environments. A general scheduler would need to be capable of representing the stochastic scheduling environment. This includes random events and disturbances such as the timing of hot jobs, machine failures, operator unavailabilities, and material stockouts, as well as variable job process times, release times, and due dates.

Performance Criteria and Multiple Objectives: The classical machine-scheduling formulation usually specifies a single optimality criterion, such as minimum makespan or minimum tardiness. Such criteria tend implicitly to maximize machine utilization over the (unspecified) scheduling time horizon. Actual production environments clearly embrace multiple, conflicting, and sometimes noncommensurate constraints and performance objectives. While management typically seeks to minimize costs and maximize the utilization of high-ticket machines and resources, scheduling objectives also frequently include objectives directed toward minimizing operating stresses. Examples include improving schedule stability, reducing confusion, and placating a demanding customer. Related objectives actually can imply deliberate underutilization of machines to reduce queues and inventories or to ensure reliability. A completely general scheduler would need to capture and balance a great variety of performance criteria.

It is unlikely that a single scheduling technique can usefully represent all of these complex problem attributes in their full richness. Attempts to develop general-purpose scheduling tools probably are destined to fall from their own weight, inhibited by massive data requirements, cumbersome output, and slow execution. Useful tools are most likely to capture only the most important features of a given environment, ignoring the least important entirely, and dealing with those of intermediate importance in an aggregate way. For the most part, each scheduling paradigm considered in the following section addresses only a subset of these attributes. Selecting a specific paradigm to use in the development of a scheduling aid most likely depends upon how the production scheduling problem of interest can best be structured.

III. Scheduling Approaches

A. Industrial Practice

Production scheduling in discrete-parts manufacturing is generally acknowledged to be skilled craft practiced by experienced human schedulers. Despite the comparatively recent emergence of a number of industrial database and software tools for automated scheduling, it is perhaps still accurate to say that actual production schedules are largely generated by hand, using paper, pencil, and graphical aids (such as the familiar Gantt chart). Knowledge and intuition gained through years of first-hand experience are the principal tools employed by the scheduler in generating and maintaining satisfactory production schedules.

To assist the human scheduler and improve the quality and consistency of production schedules, major manufacturers have developed or purchased database systems which track raw-materials and work-in-process (WIP) inventories. Many of these database systems also incorporate software tools which, to a greater or lesser degree, automate some aspect of schedule generation. These commercial tools are generally classified by the scheduling technique or the underlying scheduling philosophy employed. Among the most current of the scheduling philosophies and associated software packages are manufacturing resource planning (MRP—formerly materials requirements planning), just-in-time (JIT) production, and optimized production timetables (OPT) [18].

MRP systems are perhaps the most widely installed in industry today. For a fixed planning horizon, MRP systems determine 1) the quantities of each item that will be used in the production of a prescribed volume of end products and 2) the times at which each of these items must be purchased or manufactured to meet prescribed due dates for the end products. MRP works approximately as follows [15]. First, for each end product the quantities of all components and subassemblies which are used in the manufacture of that product are determined. Using prescribed processing times and working backwards from the date for final assembly, MRP next determines the latest time at which these components and subassemblies should be made or ordered. Finally, MRP performs a more detailed capacity requirements analysis, determines an operation sequence, and sizes production lots.

MRP systems are highly detailed and an excellent means for determining and tracking materials requirements. As a means for production scheduling, however, MRP systems leave a good deal to be desired. The principal shortcoming of MRP is that it determines capacity *requirements* based on prescribed product volumes, release (starting) dates, and due dates. Actual *installed* or *available* production capacity is ignored, with the result that MRP schedules can prescribe machine loadings in excess of 100-percent utilization. Production volumes and due dates must be adjusted manually to achieve feasible schedules. A second and perhaps lesser shortcoming of MRP is that it is entirely deterministic and cannot anticipate the impact on schedules of variable processing times and random events.

JIT production is a scheduling philosophy that dictates reduced materials inventories and minimum WIP inventories to aid process improvement and reduce process variability [19]. The obvious benefit of JIT schedules is the reduced capital cost associated with holding inventories, both in terms of reduced inventory storage requirements and reduced investment in raw materials and intermediate goods on hand. The more subtle benefits reside in associated improvements in process flow and floor control, particularly with respect to the early detection of rejects and immediate isolation of the associated culprit operation.

As a scheduling philosophy, the success of JIT production demands highly reliable suppliers, workforce, and repair facilities, since buffer stocks are essentially eliminated. In the present context, however, JIT has the singular disadvantage that it is purely descriptive. While JIT is commonly misclassified as a "method" that achieves minimal WIP with a lot size of one, in fact, there is no prescriptive theory or method for deriving JIT schedules or achieving JIT goals.

OPT is a proprietary software (and hardware) package that recently has generated considerable interest as a production planning and scheduling tool [16], [17]. OPT can be viewed as an alternative to a comprehensive MRP system for production planning, materials planning, and resource scheduling. While the details of the finite scheduling portion of OPT have not been disclosed, promotional literature and an examination of OPT schedules suggests the following general strategy. OPT works by sequentially considering, at fixed intervals of time, how production resources should be used to meet requirements. OPT first selects a candidate production schedule and then simulates this schedule to determine bottleneck machines (critical resources). Next, operations are scheduled from the critical resources using heuristic procedures to feed the bottleneck during periods when it is starved. This basic process apparently is repeated until an "optimal" schedule is produced or until some stopping rule is invoked.

While there has not been a comprehensive comparison of OPT schedules to those produced using conventional scheduling logic, the underlying philosophy has considerable intuitive appeal and, by accounts, OPT customers are generally pleased with the quality of schedules produced. The primary disadvantages of OPT appear to derive from its proprietary status: licenses and maintenance agreements are expensive and custom installation and maintenance must be performed by the vendor. Also, there may be hidden costs associated with set-up/tear-down on non-bottleneck machines (labor, wear, and tear) and excessive work-in-process inventory. OPT also can require significant time to generate schedules and therefore may be inappropriate as a real-time scheduling tool where production is highly variable.

MRP, OPT, and JIT are not distinct scheduling models and were not designed specifically to address the scheduling problem. It is common in comparative analyses of the MRP, JIT, and OPT scheduling philosophies to note that it may not be feasible to develop a schedule for arbitrary combinations of due dates and resource constraints. In such cases, solving the problem requires relaxing one of three conditions: the initial state, the final state, or the state-trajectory constraints. The initial state corresponds to initial inventory levels and schedules of incoming parts and materials. The final state corresponds to production volumes of finished goods with prescribed due dates as well as desired final material and WIP inventories. The trajectory and control constraints correspond to limitations on maximum WIP inventories and maximum productive capacity. To guarantee a feasible schedule will be found, each of the commercial philosophies employs a different relaxation technique: MRP systems relax trajectory constraints, OPT ignores the final state, and JIT ignores the initial conditions.

B. Machine Sequencing and Scheduling Theory

The formal job-shop or machine-scheduling problem has been studied extensively over the past several decades [2], [3], [5], [9], [10]. The problem may be stated as follows [4], [6], [20], [24]: N jobs are to be processed on M machines. Each job consists of a set of M operations, one operation uniquely associated with each of the M machines. The processing time for an operation cannot be split. Technological constraints demand that the operations within each job must be processed in a unique order. The scheduling problem involves determining the sequence and timing of each operation on each machine such that some given performance criterion is maximized or minimized. Typical performance criteria include minimizing the makespan (i.e., minimizing the time required to complete all of the jobs) and minimizing maximum tardiness (i.e., minimizing the largest difference between completion times and due dates).

The machine-scheduling problem is a highly simplified formalism for the production scheduling problem encountered in practice. The problem is of particular interest, however, precisely because it captures the fundamental computational complexity of the central problem of sequencing jobs on machines, divorced of any side issues. This general problem has been shown to be NP-hard for instances larger than two jobs and two machines [6], [11]. The time required to compute an optimal schedule increases exponentially with the size of the problem. The standard ten-job, ten-machine benchmark problem first posed by Muth and Thompson [9] in 1963 has only recently been solved to optimality, requiring the generation of 22000 nodes in five hours on a Prime 2655 computer [8]. Problems of larger than modest size cannot generally be solved to optimality, even with computing power that far exceeds the capacities of modern supercomputers.

From a practical vantage, work on the machine-scheduling problem clearly has demonstrated the need for heuristic (nonoptimizing) approaches to commercial scheduling problems. A large number of single-stage heuristics have been advanced and tested in this context. In general, single-stage heuristics select the next operation to be processed based upon some easily computed parameter of the jobs, operations, or machines. These parameters can include processing times, due dates, operation counts, costs, setup times, arrival times, and machine loadings [6], [21], [22], [23], [25], [27]. Examples are SPT (shortest processing time first), LPT (longest processing time first), FIFO (first-in, first-out), LPR (longest processing time remaining), EDD (earliest due date), and pure random (Monte Carlo) selection. More complicated heuristics are generally built up from simpler rules. Panwalkar and Iskander [26], for example, cite some 113 scheduling heuristics that have been proposed or actually applied.

Work on the machine-scheduling problem has also provided a wealth of information on solution strategies and approximation algorithms that exploit single-stage heuristics and that may ultimately form the basis for commercially viable tools. For example, partial enumeration techniques which combine heuristics and neighborhood search strategies have been shown to work reasonably well under various conditions [6]. These strategies involve the use of a heuristic to find a good seed or starting schedule, modify the seed, and then evaluate the resulting schedule. A cycle of adjustment and evaluation is repeated until no further progress relative to the performance measure is achieved.

Although these contributions are significant, the machine-scheduling problem itself is perhaps too restrictive a formulation to provide results that are anything more than suggestive for actual production scheduling. There is a great need for better scheduling algorithms and heuristics, more realistic models of the scheduling setting, and better understanding of the dynamics inherent in the scheduling environment [7]. Developing an appropriate model for direct use in solving production scheduling problems will require a significant relaxation of the basic assumptions of the classical formulation of the machine-scheduling model. Mathematical formulations that exploit the special structure of the scheduling problem offer a readily accessible starting point for research into new areas concerning machine scheduling and algorithm development [12], [14].

C. Resource-Constrained Project Scheduling

The machine-scheduling problem is a special case of resource-constrained project scheduling. The conceptual similarity of the machine- and project-scheduling problems has stimulated interest in the reciprocal applicability of solution approaches [29]. These similarities are emphasized when both problems are modeled as networks. When viewed this way, traditional machine sequencing rules are tested on project networks and certain forms of the machine scheduling problems are treated as project scheduling problems.

As with the machine scheduling problem, determining the best resource-constrained project schedule requires the solution of a combinatorial optimization problem. Any approach which seeks an exact solution to a resource-constrained project scheduling problem is really just a different way to formulate and solve this optimization problem. Among the approaches most commonly studied are branch-and bound methods, branch-and-dominate methods, cutting planes, dynamic programming, zero–one integer programming, and Lagrange multiplier methods [28]–[31].

The resource-constrained project scheduling paradigm is fundamentally more pragmatic than machine scheduling and takes into account many more of the complexities of the scheduling environment. More complex technological sequences and multiple resource requirements are considered and a range of ingenious heuristics have been developed. In addition, there is a large body of commercial software available for project scheduling. The heuristic algorithms embodied within this software might well be adapted to production scheduling.

D. Control Theory

Gershwin *et al.* [33] present an excellent interpretation of recent progress in manufacturing systems from the perspective of control theory. A control-systems framework for manufacturing systems issues is provided that includes production scheduling issues. Current practice and research applied to the general manufacturing environment also are summarized.

Control theory seeks scheduling methods that either explicitly reflect the uncertain nature of the available information or give some guarantee as to the insensitivity of the schedule to future information. This modeling paradigm attempts to limit the effect of machine failures, operator absences, material unavailability, surges in demand, or other disruptions upon the scheduling process [32], [33]. Schedules are sought that are robust to disruptions, robust to the absence or inaccuracy of status information, and flexible to change [1]. Control theory views scheduling as a dynamic activity, where the scheduling problem is really one of understanding how to reschedule.

Although control theory has only recently been applied to discrete production scheduling, the underlying problem and fundamental issues are perhaps most naturally described as problems in control. Consider the standard control paradigm that is depicted in Fig. 2 as the control system model for the scheduling problem.

The system under control operates on a sequence of inputs $u(t)$, yielding a sequence of outputs $y(t)$. The outputs at any time are a function of the state of the system $x(t)$. The system state at time t is defined as the set of variables such that knowledge of the state at some initial time, together with knowledge of the inputs to the system at this and all future times, is sufficient to determine (given an adequate model) all of the future states of the system. A general statement of the control problem is to determine a means to guide the system state (and thus the system output) through time according to some trajectory that satisfies the constraints imposed by the system model and that simultaneously satisfies some set of performance criteria.

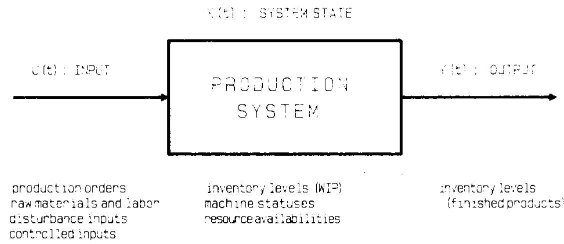

Fig. 2. Production scheduling as control system.

For a manufacturing facility, inputs to the system include production orders, raw material and labor, disturbance inputs, and controlled inputs. Production orders specify the quantities of various jobs to be processed and the dates at which these quantities are due for delivery. Raw material and labor are used in production and without these production is impaired. Disturbance inputs include machine failures or labor outages, which alter the productive capacity of the plant over some period of time, but over which the scheduler has little influence. Controlled inputs include scheduling, maintenance, and overtime decisions, which alter the productive capacity of the plant but which the scheduler can regulate within certain bounds.

The state of a manufacturing facility defines the levels of inventory for all completed and partially completed jobs, the status of all machines (whether idle, active on job, in setup for job, or in repair), availability of labor, and the levels of inventory for all materials. Outputs from the manufacturing facility can be any appropriate combination of the state, for example, the inventory levels of all jobs ready for shipment on a specified due date.

The scheduling problem is then to determine the control, i.e., the sequencing of the operations of each job, the scheduling of overtime and maintenance, and the timing of materials orders, which yields a desired state trajectory. The control must also satisfy constraints imposed by limited manufacturing resources and must simultaneously satisfy performance measures. These performance measures may include minimum tardiness of finished jobs, minimum and maximum in-process inventory levels, and minimum production and holding costs.

Merits of the control paradigm are numerous. First, this modeling paradigm recognizes the need to integrate the scheduling activity with the planning activity. Second, the paradigm accepts the dynamic environment of the scheduling problem as a given and attempts to find schedules which are robust, flexible, and adaptable to this dynamic environment. The control theory modeling paradigm also provides a wealth of knowledge in defining the scheduling problem and the corresponding scheduling objectives.

While the control paradigm appears to be especially well suited to defining the fundamental problem qualitatively, control theory has yet to develop a set of techniques adequate to scheduling model formulation, analysis, or design. The mathematics and techniques of control theory apply to continuous- and discrete-time systems, but are not well-adapted to discrete-event systems. Those aspects of the manufacturing problem that can be usefully approximated by continuous- or discrete-time systems are the areas most likely to benefit from traditional quantitative applications of control theory, at least in the short run. The recent emergence of discrete-event dynamic systems (DEDS) as a principal thrust of control research, however, offers considerable promise for future developments [37], [42].

E. Discrete-Event Simulation

Most manufacturing systems are too complex to allow realistic models to be evaluated analytically. Simulation models provide the desired realism [39] and can be evaluated numerically over a time period of interest. Data are gathered as the model is running to estimate the characteristics and throughput of the simulation model.

Discrete-event simulation has been used primarily as a vehicle for testing fixed scheduling heuristics and dispatching rules. In contrast to this approach, there appears to be a consensus that a combination of simple priority rules, or a combination of heuristics with a simple priority rule, works better than individual priority rules. This supports the concept of a flexible interactive simulation tool that can be used to schedule the manufacturing facility. The user of the simulation tool reviews the status of the job-shop model which is dynamically displayed before him. He can use his knowledge and practical experience to stop, interact with the model, and try alternative scheduling approachs [34], [38]–[40], [43].

Scheduling simulation is designed to provide the user with the capability of performing "what if" analysis on the current scheduling problem. The scheduling options that can be explored experimentally are only limited by the time constraints and resources available to the user. Since the simulation process provides dynamic output, the user can identify long queues within the model and attempt to eliminate the bottlenecks that may exist for priority jobs [36].

Perturbation analysis is a recent development which offers efficient optimization of parameters in simulation [37], [42]. This technique is related to dynamic systems linearization. Observing only one sample path, the technique enables the gradient vector of system (simulation) output to be estimated with respect to a variety of parameters. Recent studies of perturbation analysis have shown that it is better than repeated simulation in many situations.

An advantage of the simulation approach to scheduling is that it can model the effects of such factors as policy changes, which cannot be accounted for in an analytic model [41]. Another advantage of discrete-event simulation is that it can provide the user with the opportunity of performing exploratory tests upon the schedules being produced [35]. The experimental nature of simulation is also its principal disadvantage, however. Simulation studies are difficult to generalize beyond the specific experimental setting employed and, as such, contribute little to the theory of production scheduling. Using simulation to produce schedules is costly, both in the computer time used to generate schedules and in the human modeling effort required to design and run the simulation model. The accuracy of a simulation is limited by the judgment and skill of a programmer [33] and even highly accurate modeling does not guarantee that optimal or even good schedules will be found experimentally.

F. Stochastic Optimization

Stochastic optimization addresses a number of types of manufacturing systems problems by applying the research practices of queueing theory, reliability theory, lot-sizing techniques, and inventory theory. A common failing of stochastic optimization models, however, is that these require highly simplified models to pursue analytical solutions.

Queueing theory pictures each machine center as a set of servers, with each machine a server and each job a customer. The wide variety of jobs and the complex routing of jobs is represented by assuming that processing times and arrival of jobs at a center are governed by probability distributions [51]. The application of queueing theory to manufacturing was considerably enhanced by the development of network-of-queues theory [46]. However, only the more recent development of efficient computational algorithms and good approximation methods has enabled the implementation of reasonable "first-cut" evaluative models of fairly complex manufacturing systems [33], [50], [56].

An important reason for the increasing popularity of queueing models in manufacturing is their proven usefulness in the area of computer/communication systems modeling. Queueing models tend to give reasonable estimates of system performance, require relatively little input data and do not use much computer time. For these reasons, queueing models can be used interactively to arrive quickly at preliminary decisions. More detailed models can then refine these decisions [33].

The disadvantages of queueing network models are that these must represent certain aspects of the system in an aggregate way and fail to represent certain other features at all (such as limited buffer space). Also, the output measures produced are average values, based on a steady-state operation of the system. Thus queueing network models are not useful for modeling transient effects which result from infrequent but severe disruptions such as machine failures [33]. Also, there are many queueing situations in which potentially useful queueing models are mathematically intractable or in which mathematical models are difficult or impossible to derive [45], [51].

Reliability theory is concerned with maintaining a stable schedule in the face of machine failures [53], [54]. Reliability is the probability that a machine performs adequately over an interval. Knowing the reliability of machines may help to limit the disruptions caused by machine failures.

Determining the reliability of machines requires knowledge of the time-varying failure rate, however. The assumption of constant failure rate, which appears to be used frequently in practice, may lead to crude results [45].

Lot-sizing techniques [44], [47], [49], [52], [57] and inventory theory [48], [58] attempt to determine lot sizes which will maximize production throughput and assure that due dates are met and production and inventory costs are minimized. Traditional lot-sizing models trade-off the cost of setting up a machine against the cost of holding inventory, on an individual machine basis [33]. Lot-size decisions are frequently required for many different products and demand quantities, which creates the need for a practical efficient decision rule [55]. Finding the optimal lot size which minimizes the total of production, setup, holding, shortage, and scrap costs, however, is not currently feasible. Most techniques either cannot guarantee the generation of a feasible solution or are computationally prohibitive [51].

Inventory theory models and analyzes the effects of uncertainty to derive optimal stock policies. Inventory stocking policies assume that each item stocked has an exogenous demand, modeled by some stochastic process, and attempt to find the best stocking policy for each item [33]. There are many inventory situations that possess complications which must still be taken into account, e.g., interaction between products. Several complex models have been formulated in an attempt to fit such situations, but even these efforts leave a large gap between practice and theory [45].

G. Artificial Intelligence

Artificial intelligence (AI) approaches typically depict the scheduling problem as the determination and satisfaction of the large number and variety of hard and soft constraints that are found in the scheduling domain [60]. AI is used to extend knowledge representation techniques to capture these constraints, to integrate constraints into a search process, to relax constraints when a conflict occurs, and to diagnose poor solutions to the scheduling problem.

AI search methods hold promise for scheduling applications. These methods employ heuristic rules to guide the search and may offer efficient search procedures for finding good solutions to computationally complex problems [61]. Ow and Morton [68], for example, describe how a beam-search strategy can be used as an efficient search method and discuss the importance of heuristics in obtaining maximum advantage from the search technique and limited knowledge about the problem. Similarly, current research on genetic algorithms, simulated annealing, and learning systems may hold potential for improving the speed and accuracy of various production scheduling approaches.

Production scheduling may benefit from other research areas within AI, perhaps including rule-based and knowledge-based (expert) systems [59], [60], [62]–[64], [66], [67], [69]–[74]. The scheduling problem appears appropriate for expert systems work because it is heuristic in nature, that is, it requires the use of rules of thumb to achieve acceptable solutions [73]. Expert systems, however, appear to be best suited to developing a diagnosis within a slowly evolving knowledge domain. This may result in poor adaptation of the scheduling problem to the expert system domain. Because each production plant is different, the expert systems approach may not be sufficiently robust to handle new production and scheduling situations [66].

Other difficulties exist as well. First, expert systems are expensive and time consuming to develop. The costs of developing expert schedulers tailored to specific production environments may well be prohibitive. Second, expert systems for reasonably sized problems may result in very slow computational speeds [65]. The costs of using expert schedulers, therefore, may also be prohibitive. Finally, expert systems strive to automate decisions that are made by genuine human experts. To reach this goal, it is necessary to capture the high level of expertise of individuals currently involved in the solution of scheduling problems [72]. Unfortunately, the quality of human performance in many scheduling tasks is suspect and expert human schedulers frequently do not exist in the production scheduling environment [65].

One may conclude that AI and conventional operations research techniques need to be appropriately combined to alleviate some of the difficulties discussed above [63]. Bruno *et al.* [59] provide an example of one such combination, which uses expert systems techniques for knowledge representation and heuristic problem solving, an activity-scanning scheduler adapted from discrete-event simulation, and a closed queueing-network algorithm for schedule analysis and performance evaluation. The authors report that this system is currently in use in a plant that produces several different types of air compressors.

Other specific AI projects reported in the literature are ISA, Deviser, Isis, Isis-2, Opis, Gensched, Fixer, and Plannet. ISA (intelligent scheduling assistant) was developed for master planning and scheduling at Digital Equipment Corporation [66]. The ISA system loads orders for the assembly of computers, sequentially, one job at a time. Approximately 300 rules are employed to build and modify the evolving schedule, relaxing scheduling constants as required.

Deviser is a general purpose planner/scheduler that generates a scheduling network, specifying nominal starting times for operations [74]. Discrete events are defined and schedules are tailored around those events which are fixed in time. A "start-time window" for each operation is updated dynamically, as the schedule evolves, in order to maintain consistency with the windows and processing times of adjacent operations. The system is goal directed, adjusting windows to achieve production milestones within imposed time constraints, while respecting fixed events. Deviser was developed specifically to plan and schedule those actions on-board an unmanned spacecraft (such as the Voyager) that are required to return pictures of objects in deep space.

The best known AI production scheduler is the intelligent scheduling and information system (Isis), a prototype system which uses "constraint-directed reasoning" to construct shop schedules [62]. The system selects a sequence of operations needed to complete an order, determines start and end times, and assigns resources to each operation. Although very much larger than ISA (the knowledge base occupies over 10 megabytes of disk space), Isis also can act as an intelligent assistant, using its expertise to help plant schedulers maintain schedule consistency and identify decisions that result in unsatisfied constraints [73]. Developed for scheduling production at a Westinghouse facility manufacturing turbine blades, the prototype system was not implemented, in part because of difficulties in integrating the scheduling system with existing databases and information systems. Extensions of the underlying constraint-directed scheduling concept subsequently have been embodied in Isis-2 and Opis (opportunistic intelligent scheduler) [71].

The general scheduling knowledge-based system (Gensched) is a multidomain intelligent scheduling system that uses a mixture of optimization techniques, hierarchical planning, and heuristic search to provide planning and scheduling capabilities for a wide range of problems [69]. Efforts to date have concentrated on developing the conceptual model for applications in a manufacturing environment, building a petroleum routing scheduler, and producing a hierarchical planner and scheduler. Reduction of the Gensched conceptual model to actual practice, however, does not as yet appear to have been demonstrated.

AI concepts and techniques also were used in the prototype fault identification and expediting repair (Fixer) system [63]. Fixer was developed for aircraft repair-job scheduling. The scheduling of aircraft repair jobs can be characterized as stochastic, dynamic job-shop scheduling, with varying objectives and constraints. The current version of the Fixer prototype uses heuristics to avoid the combinatorial problem. The heuristics are the loading rules found in the operations research scheduling literature.

Plannet (planning and scheduling expert system) is a knowledge-based system for scheduling cargo operations for NASA's space shuttle program. A set of rules are applied to an initial schedule in order to improve upon it. Current rules of the system deal with allocating overtime and extra resources when there exists a possibility that a mission completion time will be missed. Manual or semi-manual scheduling are also possible, and the user has immediate feedback as to how the changes affect the schedule [69].

IV. Conclusion

No single modeling paradigm currently appears to offer the basis for unified theory of production scheduling, or to provide an appropriate calculus for generating schedules, or even to support a complete representation of the attributes of the complex production scheduling environment. Control theory, simulation, and AI knowledge-representation schemes appear to be capable of capturing a wide range of problem attributes but fail as yet to provide insights on workable solution strategies. Machine sequencing, resource-constrained project scheduling, and AI search techniques offer insight into possible solution approaches, but do not nearly address the richness of the complex scheduling environment. At least in the near term, we suspect that a synthesis of paradigms will be required [12], [13].

One such synthesis might rely on the control paradigm to define the nature and objectives of scheduling problems, serving as a problem framework. Within this framework, combined solution heuristics from machine scheduling, resource-constrained project scheduling, and AI search could be used to generate candidate schedules. The performance of candidate schedules could be verified using simulation models, where the simulations could be manipulated interactively by an expert scheduler. Such a synthesis would seemingly wed the rich modeling aspects of control and simulation and with the solution-oriented techniques of heuristic algorithms. This and other syntheses appear to merit further exploration [12].

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