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SIMULATION AND SCHEDULING (PANEL)

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ABSTRACT

Simulation has been used predominantly in the evaluation of systems during the design phase. It has not been as successful as an operation tool. Scheduling, on the other hand, is done traditionally via mathematical model. The interaction between these two fields of operations research has been complementary. Traditionally, a schedule is created as an initial guess and is evaluated with a simulation model. A schedule with "acceptable" features can then be adopted for operations.

In recent years, as the speed of computer accelerated, real time simulation for the purpose of operation and control is proposed. Simulation based software for operation and control of production system has also evolved into commercial products. As with any new technology, there are different point of views among the researchers, software developers, and users. This panel session will provide a forum for discussion of philosophical issues as well as illuminating merits of each approach.

This paper presents (in alphabetical order) brief position statements by the panelist to serve as a lead into the discussion.

WAYNE J. DAVIS

Before addressing the combined issues of simulation and scheduling, it is necessary to generalize upon the current association of the two terms. Scheduling is a class of decision-making for the allocation of essential resources toward the completion of a prespecified set of requirements. Historically, project scheduling is one form of scheduling where the utility of simulation has already been demonstrated. More recently, the coupling of scheduling with simulation has explored the scheduling of manufacturing systems. Yet, in general, scheduling is only one type of decision making that pertains to discrete-event systems, a class of systems which characterizes both the project management and the manufacturing system.

Recently, there has been an impetus toward the formalization of decision making as it pertains to discrete-event systems. Ho [1989] and Cao and Ho [1990] provide an excellent overview and a matrix for classifying the decision-making tools employed in the analysis of discrete-event systems. Methods such as finite state machines, Petri nets, Min-Max algebra, Markov chains, queueing networks, and simulation are cited. It should be noted, however, that most of the theoretical and experimental development of these techniques has focused on the steady-state analysis of discrete-event systems On the other hand, the recent literature that applies simulation to the scheduling of manufacturing systems (e.g. Davis and Jones [1988], Davis et al. [1989], Erikson et al. [1987], Grant et al. [1988], Harmonsky [1990], Sadowski [1985], Wu and Wysk [1989], and Yamamoto and Nof [1985]) provides two new fundamental trends. First is the trend toward the real-time analysis of the projected system response. In other words, the current state of the system is being considered as the initiation point for the analysis of the near-term system response, and decisions are made in real time. The second trend is that the simulation model is advocated as the controller to implement the schedule which was selected in real time.

The influence of the current state of the system upon decisions has received far too little attention in the literature. Nearly all of the previous statistical analysis methods pertaining to discrete-event simulation have taken specific precautions to remove the effects of the initial state from the projected steady state response of the system. Even the terminating simulation which typically considers the system trajectory between a prespecified initial and final state, is primarily designed to project the long-term expected response at a particular point within the operating cycle. The influence of an arbitrary initial state upon the projected response for the scheduled system is startling. Recently, Flanders [1991] attempted to optimize the schedule for a flexible manufacturing system (FMS) which addresses a nearly constant, daily parts demand. The original task was to define the schedule that minimized the makespan needed to produce this constant daily requirement in order to generate additional slack capacity. This slack capacity could then be reassigned toward the production of other parts. Using a genetic algorithm approach to search for the optimum schedule , several discoveries were made. First, given the complexity of the FMS, the optimal schedule was difficult to discover. That is, the convergence process was often erratic. Second, when an improved schedule was generated, its performance on a day-to-day basis was truly unpredictable. The required makespan to produce the constant daily production requirement could exceed its minimum value by nearly 50%. The experienced level of uncertainty was totally unexpected given the numerous deterministic assumptions that had been made. The only considered source of uncertainty was the remaining tool life for the cutting tools positioned at each machine at the beginning of the day.

An even more astounding fact is that the actual mode of optimization for a given performance index can change as a function of the initial state. It is widely recognized that scheduling represents a multi-criteria optimization which includes the consideration of performance indices such as the total makespan, the combined process utilization, the average job tardiness, among others. To illustrate the manner in which the mode of optimization can be modified, let us consider the process utilization criterion which is typically maximized. For a given initial condition, one scheduling alternative might provide a similar production throughput with less utilization of the processes than another scheduling alternative. In this situation, process utilization should be minimized rather than maximized. That is, the optimization for the process utilization criterion has been completely reversed from its traditional maximization. Repeated experiments of real-time, discrete-event simulations for manufacturing systems, have resulted in similar situations. In short, changing the mode of optimization for a given performance criterion is not an exceptional situation.

In employing the simulation model as the foundation of the controller for the manufacturing itself, there are several additional concerns. The first set of concerns arise from the current capabilities of the simulation languages themselves. That is, most available simulation languages are woefully inadequate in the modeling of the controlling elements of automated manufacturing systems. The focus of nearly all existing simulation languages is toward the modeling of job flow and the allocation of the primary manufacturing processes. The restrictions in modeling the management of supporting resources are obvious. The inclusion of material handling is a major advancement, yet often many of the inherent assumptions made by the simulation languages render these features unusable. For example, some languages assume that the distance from station A to station B is the same as that for station B to station A. For unidirectional cart paths, this is seldom the case. The cart paths themselves are resources that must be managed when multiple transporters are to be modeled and a contention for paths exists when the movement of one transporter interferes with another. The inclusion of supporting resources such as tooling and fixturing represents another major concern which cannot be easily addressed with most simulation languages.

Moreover, existing simulation languages do not readily permit the incorporation of essential control logic for existing controllers into the model. This control logic is another supporting resource whose detailed modeling is absolutely essential. As an example, Hedlund et al. [1990] and more recently Dullum [1991] investigated the expected production capabilities of a proposed FMS to be operated by the U.S. Army Rock Island Arsenal. The vendor for the proposed system provided a simulation study demonstrating an expected average utilization in excess of 70% for each of the seven included milling machines. Their study, however, neglected the detailed operation of the tool management system and the associated controllers for both the cell and the four material handling systems. When these details were included in the simulation, it was demonstrated that the 70% utilization could not be achieved while all seven machines were operating. The true average utilization was about 45%. An average utilization of 70% could only be achieved when four of the seven machines were idled. It took over two man-years to develop the detailed simulation model. The major portion of this effort was devoted to the inclusion of the control elements to manage the supporting resources and the material handlers. Since the inclusion of the control elements was not straightforward, the resulting simulation code is nearly impossible to modify or document.

The consequences of each of initial condition and control concerns is further confounded when they are integrated. It is the control actions that influence the changes in the state of the system. As shown above, the scheduling problem is dependent upon this state. The current scheduling problem in turn influences the selection of an optimal control strategy whose implementation will again modify the state of the system. What emerges is a collection of functions that must be addressed concurrently in real-time to define and implement a production schedule. Recently, Davis, Jones and Saleh [1991b] defined a generic controller for real-time decision-making as it applies to the real-time control of discrete-event systems. In their definition, they outlined four fundamental functions to be addressed concurrently. First is the assessment function, which is responsible for the continuous updating of the decision to be addressed by the controller--in this case, the real-time production scheduling problem. Second is the optimization function, which is responsible for the selection of the current optimal control law whose implementation generates the optimal schedule. Third is the execution function, which is responsible for the implementation of the current optimal control law as well as maintaining a feasible system response to react to disruptions between planned and realized system response. The final function, the monitoring function, is responsible for coordinating the other functions within the controller. Whenever infeasibilities are recognized with respect to the system constraints for the scheduled subsystems, the monitoring function attempts to reconcile these infeasibilities by first reoptimizing the current control law, and if this step fails, by redefining the current decision so that a feasible solution can exist.

It must also be recognized that the real-time decision making associated with a large-scale, discrete-event system is beyond the scope of a single generic controller. That is, the overall decision must be decomposed among several decision-making entities. The manner in which this decomposition is defined, as well as the associated interactions which must occur in real-time among the various decision-making entities, has yet to be explored. It is clear that the principles of decomposition theory in mathematical programming and decentralized control theory must be integrated and embellished to address the stochastic properties and the multi-criteria performance considerations of the proposed optimization and control of a discrete-event system. Additionally, one must not forget that the decision and control problems being addressed are continually being modified as the state of the system changes.

Since the decision-making and control of the discrete-event system is dependent upon the ability of the controller to predict the future response of the system, real-time, discrete-event simulation is an essential technology which must be developed to implement the proposed generic controller. Furthermore, the applicability of this technology is not limited to a single function within the generic controller but is critical to the implementation of all functions. Like the generic controller, the technology of real-time simulation requires considerable additional theoretical and conceptual development. Davis, Wang and Hsieh [1991a] have provided an overview of the essential requirements for implementing a real-time, discrete-event simulation, and have highlighted several fundamental issues that remain to be resolved. Among these requirements is the generation of sufficient simulation trials to allow a prediction of future system responses. The simulation trials must be initiated to the current state of the controlled subsystem, and this state is constantly evolving with time. How does one generate a sufficient number of simulation trials under these circumstances? What potential does the new computing platforms, especially the concurrent computers, provide in addressing this issue? Even if sufficient data can be generated, how does one address the statistical analysis of the projected response in real-time? These are some of the questions yet to be addressed. Furthermore, given that the statistical analysis can be performed, how does one further assess the statistical tradeoffs that currently exist when multiple performance criteria are to be considered in the comparison of a preselected set of decision (scheduling) alternatives? Simply stated, the operative real-time, discrete event simulation will produce data at a rate that will exceed the ability of any decision maker's comprehension. The statistical analysis and compromise analysis for the real-time, discrete-event simulation must be automated. Yet there must be an interface through which the decision maker can participate in assessing key considerations. Further, within each generic controller, several real-time simulations will likely be operating concurrently while for a real-world, discrete-event system there are likely to be several generic controllers interacting to address the overall decision making and control problem.

Is this complexity really essential? We can simplify, only if we are willing to accept the inherent costs. These costs arise in a loss of predictability and flexibility. Simplifying assumptions limit the ability of the model to accurately predict the true performance of the system. That is, the projected responses from the simplified model may not be realistic, or even feasible. If a disruption occurs, we must be able to assess whether immediate attention is required, or if the perturbation will correct itself. To allocate the future usage of a given resource, we desire to predict the probability that a given resource will be available at any given point in time. We also desire the capacity to assess true statistical tradeoffs among the performance criteria given the current state of the system. We might consider only a single performance criterion, but then we can never be certain that the considered criteria is the most fundamental given the current state of the system. Furthermore, we may not even be certain whether the given criterion should be maximized or minimized at the given moment. With respect to flexibility, simplifying assumptions typically limit the actions that we can take to control the system. For example, we can state that all processing durations will be constant to simplify the models. However, if we actually implement these assumptions, we forego any potential benefits that might accrue from accelerating tasks that are known to be critical to the overall production flow.

Ho [1989] has argued that the understanding and control of physical systems has advanced considerably with centuries of theoretical and experimental development. The behavior of these systems can typically be captured using differential equations. Man-made systems, on the other hand, are discrete-event in nature and defy this form of representation. Ho's assertion can be taken one step further. Most constraints pertaining to discrete-event systems simply defy a priori specification as a set of functional equalities and/or inequalities. To date, discrete-event simulation is perhaps the most powerful tool which exists in the analysis of these systems. Nevertheless, discrete-event simulation is neither a mechanism for decision making nor control, but rather a predictive device to assist in the implementation of these processes. Real-time decision-making and the on-line control of discrete-event systems are in their infancy. Yet, the need for these tools is growing at an alarming rate. Certainly, the effective management of our factories is crucial to the profitability of industry. There are also other urgent problems requiring our attention. Real-time, vehicular traffic control for metropolitan areas is essential. Real-time management of air traffic is crucial both at the airports and in the flight lanes. The effective distribution of relief supplies to famine stricken areas of the world is crucial. The response to natural tragedies including earthquakes, volcanoes and hurricanes is a constant concern. The need for further research is obvious.

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RICKI G. INGALLS

In the last several years, the simulation community has moved from its traditional role of evaluating the performance of systems to using simulation in a variety of other areas including production scheduling. Although I applaud the effort of moving the application of simulation modeling into other areas, I believe that the move into production scheduling is often misguided and will prove to be unfruitful.

At this point, I would like to differentiate between two simulation application efforts that are at times intermingled. One is the real-time prediction of system performance using simulation and the other is production scheduling.

The real-time evaluation of future performance of the system has the following characteristics.

1. The objective of the simulation system is to warn the people who own the production system that there are dangerous situations looming ahead if corrective action is not taken.
2. The time horizon for the analysis is relatively short, normally less than one shift and very often less than four hours.
3. The model is run often, if not continuously.
4. The answer is statistical in nature, meaning that the warning is probabilistic.
5. The answer is used locally, meaning that the production system is the only corporate system that is directly effected by the simulation system.

This area fits well with the capabilities of discrete event modeling. If the simulation system runs several replications and does proper analysis of the results, the simulation system can predict the probabilistic behavior of the production system. This application is very valuable because it helps to prevent situations that can adversely effect production.

Production scheduling, on the other hand, has a very different set of characteristics.

1. The objective is to develop a schedule that satisfies the constraints of demand, inventory, materials, and resource availability.

2. The time horizon under consideration can range from days to months. The time horizon is often set by the user so that he is comfortable that the time horizon encompasses all of the significant information needed to develop the schedule.
3. The schedule is regenerated only when it is necessary to regenerate it. It is rare that a production schedule is regenerated every shift. Most often it is regenerated once a day or once a week.
4. The answer is deterministic in nature.
5. The answer is used an input to other systems in the corporation, including the MRP system, accounting and financial systems, and as demand for supplier facilities.

This is where a discrete event model is not the right tool. Perhaps a discrete event model could be manipulated to work, but it's like trying to kill a fly with a hand grenade. The end result would be that the fly is dead, but there are better tools available to get the same result.

The problems associated with using discrete event modeling for scheduling production facilities are numerous. Below are listed just a few of them.

1. Discrete event modeling does not implicitly take into account non-resource constraints, especially demand and inventory. This is due to the fact that discrete event modeling has no mechanism to look at the entire time horizon at once.
2. In production systems other than job shops, dispatching rules are seldom used to move product through a facility.
3. The primary strength of discrete event modeling, the modeling of stochastic behavior, should not be used when determining a schedule. If it is used, the schedule is perhaps more bogus than if it were not used.
4. Unless the discrete event model uses search techniques, it has no concept of what it would take to make an infeasible schedule a feasible one.
5. It is often desirable to vary a schedule as little as possible from the previous schedule. Discrete event modeling does not have a mechanism to directly implement that preference.

KENNETH J. MUSSELMAN

Manufacturing's challenge is to continuously improve in the face of change. A manufacturer's survival can depend on it. This where computer-assisted modeling and analysis techniques play an important role. They provide timely decision support to help master change...again and again.

One of the most successful modeling and analysis techniques in use today is simulation. Its power and versatility have helped it gain widespread acceptance in the manufacturing community. Simulation's initial thrust was in the area of system design, where it was and is still being actively used to determine the number and types of resources required to meet a given production level. Successes in this area have paved the way for its use in other areas of manufacturing as well. These areas and the decisions supported within these areas include:

Area	Decisions Supported
Capacity Scheduling	How much capacity(e.g., overtime) is needed? When ? Where ?
Logistics Scheduling	When are materials, tools, etc. needed ? When is the best time to conduct preventative maintenance ?
Production Scheduling	What resources should be assigned to what work orders ? What sequence should we run ?
Schedule Adjustment	How should we run, given this machine just failed ?

Here, the emphasis is on controlling actual production subject to production, resource, and logic constraints. Data used to support this function typically includes:

* Current shop floor status
* Routings
* Machine and operator status per time period
* Order release schedule

Simulation is well suited to take full advantage of this data and effectively integrate it into its processing. The result is a realistic baseline that identifies what work orders to run and when. Moreover, the collective impact of all operational decisions can be taken into account to produce a better coordinated schedule.

Scheduling offers a new role for simulation in manufacturing. In the more traditional design role, simulation is used to predict how well a system will perform under various conditions. Now, in scheduling, it is used to dictate how the system should be run, thus establishing the future more than predicting it.

A manufacturer's ability to meet demand has been proven to be effectively supported and improved through the use of simulation. Simulation takes full advantage of available system data to drive to an accurate and comprehensive scheduling solution. The result is more efficient and productive operations, better evaluated risks, and reduced costs.

C. DENNIS PEGDEN

The traditional application of simulation in manufacturing is the design and analysis of the manufacturing facility. For these applications, simulations are used to determine the number and type of machines, compare alternate material handling systems, determine buffer sizes, and so forth. In these applications, the model is used during the design and analysis and then basically is put on the shelf once the design is implemented and the manufacturing system is fully operating.

A new and evolving manufacturing application area for simulation is the operational control of the manufacturing facility. Simulation can be used on an operational basis to support decisions regarding job scheduling, capacity planning, preventive maintenance, etc. In addition, simulation can be used to evaluate alternate responses to unplanned events on the shop floor such as machine breakdowns, material shortages, and so forth. Thus the model continues its usefulness throughout the operating lifetime of the facility.

The basic advantage that simulation has over other techniques in manufacturing control applications is that it can provide an accurate representation of the capacity of the facility. Unlike other approaches such as MRP or MRP II, simulation can model the details of the manufacturing facility, including the material handling component, and provide an accurate representation of the time required to process a job through the system.

One of the primary functions of simulation in control applications is the generation of a short-term finite schedule for the facility. This finite schedule is generated by initializing the simulation model to the current state of the facility and then simulating the flow of actual jobs through the system based on the planned release schedule of jobs to the floor. By changing the job selection rules at each workstation (first-in, first-out; critical ratio; shortest processing time; etc.), and other control policies (job splitting, overlapping, etc.) different alternate short-term schedules can be generated for the facility. These alternate schedules can then be compared based on job tardiness and other factors and the best schedule can then be selected for implementation.

The simulation model can also be used to evaluate the impact of planned maintenance schedules or capacity changes (e.g. adding a second shift at certain bottleneck stations) on job release dates. The simulation model provides the decision maker with a general-purpose "what-if" tool for day-to-day manufacturing decisions.

Future systems could also incorporate intelligence to generate automatically candidate solutions to a problem, simulate each candidate solution, and implement the best solution. Such a system could be used to automatically control a facility without human input.

Although the basic manufacturing modeling requirements are the same in both design and control applications, there are some basic differences in the requirements on the simulation tools needed in these applications. For example, in design applications, job arrivals and processing times are typically generated as samples from random variables, whereas in control applications, this information is typically read in from data files. Likewise, for design applications, we typically are only interested in summary performance measures for comparing systems. In contrast, in control applications we are not only interested in summary reports, but also reports detailing the behavior of individual jobs.

Perhaps the most significant difference between these areas of application is the type of user running the simulation. In the case of design models, the user is typically a manufacturing engineer and is often the person who developed the model. The person is trained in the use of the simulation tool. On the other hand, for control applications, the user of the model is typically the shop scheduler and is normally not the person who has developed the simulation model of the facility. Therefore, a much simpler and more specialized interface is required to allow the user to interact with and interpret the results from the model.

The current applications of simulation in manufacturing control are done either with a general-purpose simulation language, or a special-purpose shop floor modeling package. The advantage of the first approach is that the same tool can be used in both design and control applications. A model built for evaluation of the facility design can then be carried over and used to help control the facility. The disadvantage of this approach is that the general-purpose languages do not currently provide as standard features the wide range of input options and standardized reports that are useful for control applications.

Because both the design and control applications share the same basic manufacturing modeling requirements, the concept of a separate special-purpose package for shop-floor applications is unattractive. It is inefficient to build a model of a facility during the design phase with one simulation tool, and then discard that model and rebuild a new model of the same system using a different simulation tool for use in the control of the facility. The challenge for developers of simulation tools is to incorporate shop-floor control features such as improved data input, specialized reports (Gantt charts, tardiness reports, etc.), and customizable interfaces into existing simulation tools.

One important issue that is often over looked in the discussion of simulation-based shop floor scheduling is the proper handling of random events such as machine breakdowns. A typical suggestion is to ignore these random events when generating a schedule, and then reschedule the jobs whenever a significant event occurs that corrupts the current schedule. The problem is that any performance values (average tardiness, number of late jobs, etc.) generated by the simulation run using this approach are optimistic because they are based on an unrealistic facility capacity corresponding to no breakdowns. This approach to scheduling creates a situation where the actual performance is consistently worse than the performance predicted by the simulation. Therefore it is important to include these random events within the model for the purpose of predicting performance or comparing alternate scheduling strategies. Once a specific scheduling strategy has been selected and the predicted performance established, the short term schedule can then be generated with the random events eliminated from the model.

W. J. TRYBULA

The present approach of firms involved in marketing scheduling packages is focused on the largest corporations in the United States. The existing products require a considerable knowledge of computers, mathematics, and/or simulation. This approach leaves the majority of companies "out in the cold". We need a new focus which will bring these capabilities to the smaller manufacturers.

The existing method of scheduling in the average U. S. manufacturing has very little science and a large amount of experience. Typically, the schedules are generated by some one who has been in the job for years and relies on previous situations which had similar mixes of product. Consequently, the scheduling of the facility is a function that requires on-the-job training. Application of any type computer tool will be resisted because there is a reluctance to work with "computers".

In addition, the manufacturing firm is not very large. Consequently, the availability of personnel who understand the requirements for a mathematical scheduling package are a very scarce resource. This raises the question of what type of scheduling should be done.

In order to answer that question, it must be determined just what the scheduling process is trying to do. For this discussion, consider that the schedule has one or more feasible solutions. The goal of the scheduling process is to develop an acceptable solution -- one that works. It does not have to be the optimum schedule or have any other characteristics than it meets the criteria -- it works. Therefore, the process can stop once an acceptable answer is obtained. The inputs are the resources available, both people and equipment, along with the required production output. The amount of each resource required for any products must be available to the system. Having this information and either an unlimited number of computers or unlimited time, the solution can be obtained. The problem is how to solve these schedule challenges without involving sophisticated computer programs.

One final point in developing a method to schedule is that the entire problem does not have to be completely reevaluated. Work done in the area of scheduling has shown that if the "seed" or starting point for the calculations, the results can be made to converge rapidly. Most manufacturing schedules do not have major changes but only minor ones. Once an initial solution is obtained, any changes should be able to be solved quickly.

Small firms are very adaptable. PC programs, like TIMELINE, are being used to schedule facilities. There is a very large market which needs tools for running their businesses. The availability of sophisticated, expensive programs leaves them cold. We can either address their needs or they will go elsewhere.

AUTHOR BIOGRAPHIES

WAYNE J. DAVIS received the B.S., M.S., and Ph.D. degrees in engineering sciences from Purdue University, W. Lafayette, IN, in 1970, 1971, and 1975,respectively.

In 1975, he joined the faculty at the University of Illinois, Urbana, where he is currently a Professor of General Engineering. He has published in mathematical programming (particularly concerning the decomposition of large-scale programs), simulation, and manufacturing systems. During the past four years, he has been actively engaged in collaborative research with the Automated Manufacturing Research Facility at the National Institute of Standards and Technology in Gaithersburg, MD. Currently his primary research is directed toward real-time decision making and decision/control hierarchies for computer-integrated manufacturing.

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For the past nine years he has actively participated in the Winter Simulation Conference. In 1989 he served as General Chair.

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