New solutions for production dilemmas

Risk-based planning and scheduling is the wave of the future

BY DAVID STURROCK

If you ask a group of plant managers to list their top problems, many will mention meeting customer commitments, or, more specifically, creating a plan or schedule and performing to that schedule. Why? You might expect that the companies still scheduling with magnetic boards or spreadsheets would have problems as complexity and volume increase. But many have made significant investments in enterprise resource planning (ERP) systems and still have found them to fall short in detailed production scheduling tasks. Many of those same companies have gone on to implement advanced planning and scheduling (APS) solutions to integrate detailed production scheduling into their ERP, and they still have problems. What is missing? Why do they still not have enough forward visibility to support meeting customer delivery commitments?

For the most part, the ERP system and day-to-day production remain disconnected. APS solutions have some widely recognized shortcomings. A critical problem with the traditional APS approach is that it requires that all the data be fully known and deterministic – all processing times must be fixed. APS solutions typically integrate the data from the ERP system but rarely deal with current data from their factory floor. For example, equipment downtimes, work in progress details, and shift information often are ignored. And when an employee calls in sick, the APS solution typically is not updated to reflect the change in resource availability.

Hence, the resulting APS-generated schedule is by nature optimistic and different from what occurs in the real facility. It is common that what starts off as a feasible schedule turns infeasible over a short time as variation and unplanned events degrade performance. It is normal to have large discrepancies between predicted schedules and actual performance. Without a clear picture of the factory floor, it is difficult to generate an accurate production schedule. To protect against delays, the scheduler must buffer with some combination of extra time, inventory or capacity, all adding cost and inefficiency to the system. And to do this effectively while minimizing waste requires the scheduler to exercise significant judgment based on years of experience.

The human-based solution

Companies now cope with software limitations by relying on experienced people to make up for shortcomings of their planning tools. A person with years or perhaps decades of experience might know a good way to work around common problem situations and essentially say, "Ignore what the plan says. Do this instead." But that experience level varies from person to person, and this approach puts daily production efficiency in the hands of just one or two key individuals. Further, the schedules manually generated with this approach might not be as good as they could be because people cannot process all the information necessary to create a good production schedule.

Perhaps more importantly, this human-based solution might not be viable in the long run. Studies have shown that many industrialized nations are approaching a major staffing crisis triggered by a growing number of employees reaching retirement age and a shrinking number of qualified employees to replace them. Production schedules often are created by some of the more experienced workers. When these highly experienced people leave, their critical knowledge is lost, and it is challenging to find people with the experience and judgment needed to create good schedules.

Possible solutions to these problems include using some well-established technologies in new ways. But first, let's explore the problem in a bit more depth.

Why variability matters

Variability is the often unpredictable deviation of processing that occurs in every real system. This variability often is accounted for ineffectively, and sometimes ignored totally, in common planning/scheduling systems. Think about your drive to work. If someone asks how long it takes, you can probably give an answer based on a typical day, perhaps 30 minutes. But does it require exactly 30 minutes every day? In fact, if you travel in the late evening, it might only require 20 minutes. However, during a heavy rush hour it might require 40 minutes. And when there is an accident or construction it might require more than an hour.

Now let's think about the simplest production system possible – a single machine producing a single part type with a single arrival rate. And let's say this machine works 24 hours, seven days a week with no breaks or downtime. Anyone could predict its operation, right? If that machine had parts arriving at exactly 60 minutes apart and it took exactly 55 minutes to process each part, you could predict the average waiting time of each part to be zero minutes because each part is finished before the next part arrives. But if each part arrives an average of 60 minutes apart (using a random exponential distribution) and takes an average of 55 minutes to process (again using a random exponential distribution), can you still predict the results? Except for queuing theory experts, it is the rare person who can correctly predict the average waiting time of about 10 hours.

The impact of variability is hard to predict and often is not intuitive in even the simplest systems. Think how much harder it would be in any real system. Yet even though such variability can have a huge impact on production, it is virtually ignored by most common scheduling approaches.

Algorithmic versus simulation-based solutions

While many planning and scheduling approaches are available, they can be classified broadly as algorithmic or simulation-based. Algorithmic-based scheduling solutions are based on either generic or custom-coded algorithms. The custom-coded algorithms tend to produce better results but are more expensive to implement and maintain. Unfortunately, efficient generic algorithms are not available for many of the difficult problems in production scheduling. Algorithmic-based solutions are best suited for long-term supply chain planning applications where large computation times are less of an issue, the environment is less dynamic, and the constraints are less complex to represent.

Simulation-based scheduling solutions are based on a generic or custom-built facility model. While some software tools feature a simulation component based on a generic fixed facility model, the greatest accuracy and flexibility results from use of a custom facility model. Simulation-based scheduling solutions are best suited for highly dynamic factory scheduling applications where a fast response is required and a detailed, accurate representation of complex constraints on equipment and operators must be represented to generate a good schedule.

The full flexibility of simulation generally is not available in most scheduling packages as their facility models are based on a predetermined data structure. For example, they often are unable to represent material handling or unusual machine configurations accurately. Much greater flexibility is available using an off-the-shelf simulation package such as ExtendSim, Arena and Simio (among others). These packages often allow creation of the facility model more intuitively by graphically describing the workflow. The facility will be modeled by dropping objects onto a workspace and connecting objects to other objects. The objects will represent resources, and the links will represent the various routes that are needed to produce a product. The objects can be extended to model the exact behavior of the corresponding resources. Today's simulation packages typically offer 3-D animation, so you can see your schedule results in all four dimensions, including time.

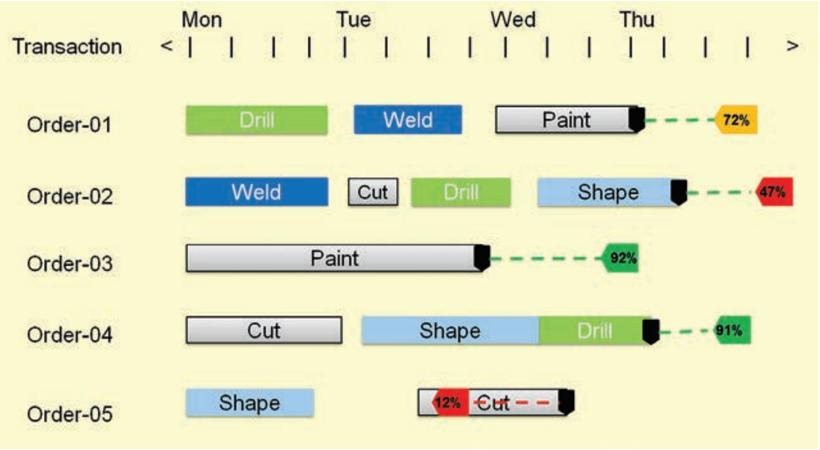
The data schema needed to run the schedule is also customizable. Simulation packages designed to work across numerous industries (e.g., healthcare, mining, packaging, complex assembly) generally require that the data elements needed to drive the simulations also be flexible. Data can be modeled within the simulation package to match the data needs to schedule the facility. The data needed can be maintained within the model or interfaced to an external system. Simulation packages have standard methods for importing and exporting data from text files, spreadsheets and databases. They also have solid application program interfaces – a set of routines, protocols and tools for building software – that enable integration to almost any external data source, including an existing SAP or APS system.

The ability to create and analyze experiments in simulation packages drastically exceeds the capabilities that exist in traditional APS solutions. Typical APS solutions might have the

ability to compare the performance of two schedules using a number of predetermined factors (due date, lead time, WIP). With simulation-based systems, the use of experiments is enhanced. The number of factors and number of schedules that can be compared is endless. In addition, add-ins can be used within the experiments to help determine optimum scenarios. Simulation-based scheduling can deliver much more detailed analysis to help determine the best production schedule to run given your constraints and key performance indicators.

EXAMINING VARIABLES

Figure 1. This Gantt chart has incorporated risk analysis by including the expected variability.



When selecting a simulation product for design use, you should consider how appropriate it is for what you want to model, as well as its ease of learning, ease of use, and the time required to create a solution. When looking for a simulation product for use with scheduling, you should consider the features it has that specifically make scheduling easier. The more basic products allow sufficient data import and export to support scheduling activities, but these would require more custom work and possibly programming to prepare them for effective use by a scheduler. Some products have features like the ability to generate Gantt charts automatically, which helps support scheduling activities. The top tier products (from a scheduling perspective) have scheduling extensions that allow you to build a fully customized scheduling environment within a single product with no programming required. They provide a fast and flexible route to a custom solution.

How simulation works

When you have a critical scheduling problem, speed of implementation is important. One advantage of using the fixed model available in traditional scheduling systems is that by giving up flexibility and accuracy, you often implement a solution much faster. You can get similar rapid implementation in a simulation-based approach by starting with a somewhat simplified facility model, while retaining the advantage of later enhancing the model to solve your unique problems.

There is an old saying that often is applied to scheduling: "When you are up to your waist in alligators, it is hard to remember that your objective is to drain the swamp." A simulation solution based on a custom facility model can be implemented at any desired level of detail, allowing the tool to start generating useful schedules quickly. You can deal with the biggest alligators while simultaneously starting to drain the swamp. The model can be enhanced as needed to improve the results by incorporating the best practices of the experienced schedulers. For example, after you have a working schedule, you can pick an area with the greatest potential payback and improve that next, thus continuing to drain the swamp. You can keep repeating this step as necessary until your solution is as good as you need. As your system changes, often you can update the model to match the new system behavior, usually with much less expertise required than with custom algorithms.

The base simulation technology used is similar to what you may be using for evaluating design and process changes. Depending on the simulation tool you select, you may have a design model that could be used as a starting point. If you don't, you might want to take advantage of the opportunity to model your facility with the objective of identifying bottlenecks and other problem areas to improve efficiency. Then take advantage of your simulation product features to extend that facility model for scheduling purposes.

While custom simulation models can be as complex as needed and consume and produce a great deal of data, it is not necessary (or even wise) to start with such a complicated model. Simulation is a perfect example of the Pareto Principle, as about 80 percent of the benefits typically come from about 20 percent of the effort. The key is to implement the most important 20 percent first. For example, if process planning by part family provides good enough results, then there may be no need to provide any more detail than that in

ANALYZING THE METRICS

Figure 2. RPS records statistics based on any targets by which your system can be measured. This chart shows an analysis of target budgets and ship dates.

Target Summary | Target Detail | Risk Plots | Detailed Results | Reports

	Target Ship Date - Plan		Target Ship Date - Risk Analysis		Target Cost - Plan		Target Cost - Risk Analysis	
Order ID	Value	Status	Expected	OnTime Probability	Value (USD)	Status	Expected (USD)	OnBudget Probability
Order01	10/10/2011 3:50:59 PM	OnTime	10/11/2011 6:26:57 AM	96.43%	118,788.0374	OnBudget	120,878.7556	96.43%
Order02	10/17/2011 10:24:27 AM	Late	10/16/2011 9:14:19 PM	24.00%	148,506.2568	Overrun	146,067.8080	3.57%
Order03	10/11/2011 1:12:35 PM	OnTime	10/11/2011 2:01:43 PM	96.43%	112,452.3968	OnBudget	113,782.0536	96.43%
Order04	10/12/2011 3:22:11 PM	OnTime	10/12/2011 11:34:42 PM	96.43%	118,444.3561	OnBudget	119,710.2639	96.43%
Order05	10/20/2011 10:16:37 AM	Late	10/20/2011 11:03:39 AM	18.43%	153,280.1730	Overrun	153,369.6228	3.57%
Order06	10/7/2011 3:00:04 PM	OnTime	10/8/2011 12:01:58 PM	96.43%	83,344.2703	OnBudget	87,545.6239	96.43%
Order07	10/18/2011 1:34:03 PM	OnTime	10/18/2011 6:44:59 PM	96.43%	132,911.5901	Overrun	136,360.9910	5.42%
Order08	10/12/2011 9:00:35 AM	OnTime	10/12/2011 8:00:11 AM	96.43%	96,545.9561	OnBudget	96,338.5255	96.43%
Order09	10/17/2011 4:46:03 PM	OnTime	10/18/2011 1:17:16 AM	96.43%	121,683.9901	OnBudget	121,686.2457	96.43%
OrderWIP1	10/6/2011 3:50:54 PM	OnTime	10/7/2011 10:39:30 PM	96.43%	116,695.3923	OnBudget	122,893.3740	74.14%
OrderWIP2	10/5/2011 3:30:06 PM	OnTime	10/5/2011 10:41:03 PM	35.14%	117,758.4330	OnBudget	119,326.6223	96.43%
OrderWIP3	10/6/2011 10:15:13 AM	OnTime	10/6/2011 3:23:24 PM	96.43%	122,260.0723	OnBudget	123,280.1906	96.43%
OrderWIP4	10/5/2011 9:12:04 AM	OnTime	10/5/2011 8:27:19 AM	96.43%	126,210.6703	OnBudget	125,687.7450	96.43%
OrderWIP5	10/4/2011 11:50:28 AM	OnTime	10/4/2011 11:11:36 PM	96.43%	114,712.2703	OnBudget	116,983.1193	96.43%
OrderWIP6	10/3/2011 12:00:00 AM	OnTime	10/3/2011 12:00:00 AM	96.43%	123,000.0000	OnBudget	123,000.0000	96.43%
OrderWIP7	10/3/2011 1:48:01 PM	OnTime	10/3/2011 2:33:40 PM	90.86%	118,952.0806	OnBudget	119,096.6163	96.43%

your process plans. On the other hand, if late supplier orders are a major source of disruption, then you might want to build in extra detail around supplier delivery performance variability into your model. And by all means, you never want to re-enter data. You should be able to tie your simulation model to take its input directly or indirectly from your existing data systems, such as a link to output from SAP.

Accounting for risk

Process variability introduces risk into schedule execution. Manufacturers have made strides to capture the variability of their systems using history and overall equipment effectiveness calculations. This data provides a historical view of how their systems perform that demonstrates the inconsistency and variability in their manufacturing process. Unfortunately, as discussed above, most APS systems cannot handle that data and so cannot generate schedules using this valuable information. Simulation technology provides the opportunity to account for the variability in an adequate manner. A risk-based planning tool now becomes the intersection between what the business needs and what the system is capable of achieving given the constraints and variation of the factory.

While your base plan must be created deterministically, technology can add stochastic analysis for more advanced scheduling. Risk-based planning and scheduling (RPS) is one name for this technology. RPS extends traditional APS to account fully for the variation present in nearly any production system and provides the necessary information to the scheduler to allow the upfront mitigation of risk and uncertainty. You can leverage your existing investment in planning systems, such as SAP's APO, to close the gap between master planning and detailed production scheduling, thereby driving more revenues and greater customer satisfaction at reduced cost.

RPS begins with a deterministic schedule generated by executing the simulation model with all randomness turned off. Note that this is roughly equivalent to the APS solution, albeit with the potential for much greater facility detail and real-time facility data. However, RPS then uses the same simulation model to replicate the schedule generation multiple times, all while including variability such as downtimes and late material problems. In Figure 1, you see a typical Gantt chart generated without variability, but it has incorporated risk analysis that results from the subsequent inclusion of the expected variability. RPS records statistics on the schedule performance across replications, including targets like the likelihood of meeting a due date, production budget, expected milestone completion date, or any other targets by which your system can be measured (Figure 2).

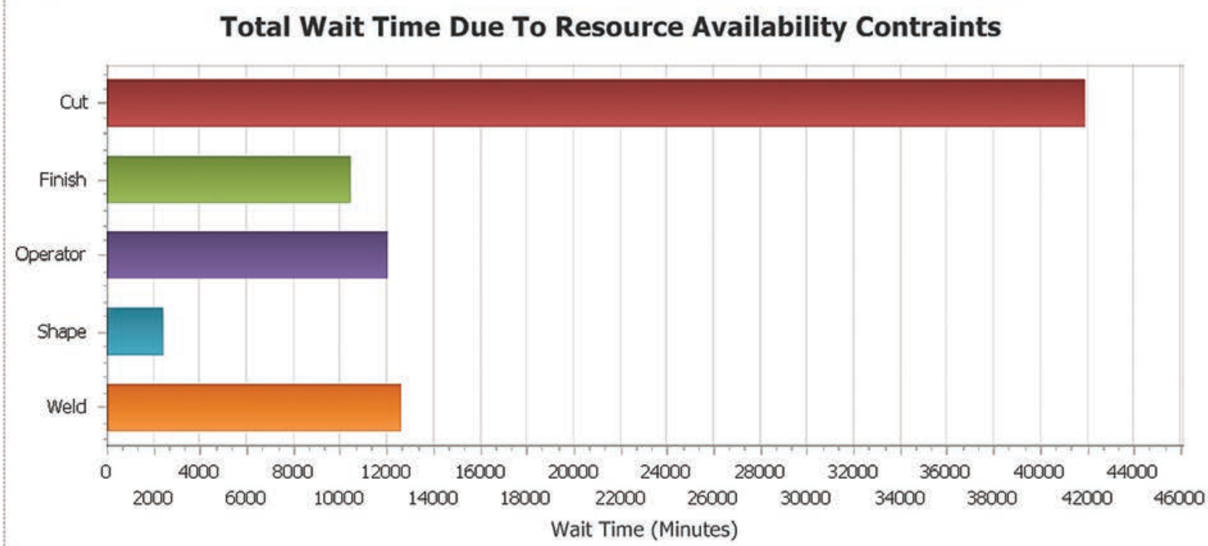
RPS allows for flexible scheduling strategies to support your key production objectives and lets you quickly reschedule in response to unplanned events. You can model your complex production processes to capture all critical constraints so that the resulting schedules reflect the reality of your systems. You can display schedules in a

CUT THIS

Figure 3. This root cause analysis details how the "cut" resource is a major contributor to non-value-added waiting time.

Resource Availability

Constraint Item	Occurences	Average Wait (Minutes)	Total Wait (Minutes)
Cut	12	3490.7728	41889.2730
Finish	10	1037.3421	10373.4211
Operator	10	1197.0285	11970.2847
Shape	2	1200.0407	2400.0813
Weld	11	1140.2064	12542.2707



wide range of outputs, including interactive Gantt charts that display individual waiting times at critical resources, as well as the root causes for non-value-added time in the system. Figure 3 illustrates an analysis that identifies the "cut" resource as a major source of non-value-added waiting time. Since RPS is an extension of your simulation model, you might be able to integrate a 3-D animation of your planned schedule to provide a unique and insightful preview of your facility operations. Figure 4 illustrates how you could view the anticipated shop floor situation at any future time specified.

A ROOM WITH A VIEW

Figure 4. Three-dimensional animation can let you view how the shop floor would look at any future time you specify.

Real solutions now

While the concept of simulation-based scheduling has been around for decades, to date it has been used mainly with inflexible standard facility models or custom-built solutions. Today's technology takes you well beyond those early solutions as well as providing a tool to help reduce your dependence on manual human judgment and reduce the impact of knowledge lost from employee turnover. The flexible models extend use to many industries and application areas. Risk-based planning and scheduling is a new technology that permits broader understanding of performance risks and their causes and provides a valuable management tool for evaluating strategic business decisions.

David Sturrock is vice president of operations for Simio LLC. He graduated from The Pennsylvania State University with a bachelor's degree in industrial engineering. He has more than 30 years of experience in simulation and has applied simulation techniques in the areas of production scheduling, transportation systems, plant layout, call centers, capacity analysis, process design, healthcare, packaging systems and real-time control. He has co-authored two simulation textbooks and teaches simulation at the University of Pittsburgh.