Today’s communication networks, air traffic control systems, national electrical grids, unmanned aircraft systems, and numerous other industries depend on complex systems—or systems of systems—that require a delicate balance of component functionalities to achieve a greater common objective. It makes sense that these highly engineered and intricate tools dictate a correspondingly sophisticated level of support. But that support can be pricey, with long-term sustainment expenses often exceeding acquisition costs. To keep a system operational and affordable, it’s important to understand the specific needs and timing of support and sustainment outlays.

Analyzing the combined behavior and support requirements of complex systems has long been impractical. There are too many variables, and professionals lack real insight into what each variable means to the broader reality of operations. However, recent advances in modeling and computational methods can help users overcome these challenges. In particular, tailored combinations of modern simulations and optimization methods can provide an efficient and proven means for analyzing system performance.

**ALIGNING PERSPECTIVES**

Historically, system design and operational performance fall within the realm of reliability engineering, while system maintenance and failure recovery require logistics expertise. Unfortunately, the fundamental principles of reliability engineering and logistics have not always aligned. For the logistician, increased system reliability (fewer things breaking down) implies a reduced need for spare parts and a smaller maintenance workload. For the reliability engineer, an increase in system reliability (perhaps through redundant subsystems) actually might amplify the demand for spare parts and add to the maintenance workload.

Today, it’s possible to achieve better cross-discipline alignment thanks to a more universal understanding of the physics of failure, sensor technologies, and data analytics. (See sidebar.) Advances in these areas provide both the theoretical and practical means to enable system prognostics as well as an opportunity to realize the efficiency of support systems without overburdening budgets.

**OPERATIONS AND SUPPORT IMPLICATIONS**

If left alone, a system will fail. Users therefore must determine whether restorative action will be performed preemptively or remedially. The top row of Figure 1 depicts a typical failure and the repair actions that are taken once that failure is detected. In contrast, the goal of modern operations and support is to detect component degradation and perform repairs before any actual failure occurs. The benefits of this include shortening the time a component is offline and improving overall system availability.

The duration of a failure is determined by a system’s ability to accommodate that failure. Successful operations and support functions carefully integrate the timing of each detection and repair decision with the requisite logistics and repair requirements. Fortunately, technology can warn us
when restorative actions are needed. This provides more time for planning and minimizes the hours it takes to return the system to full operation.

When considering the support required by a system of systems, it also is important to weigh the trade-offs among failure modes—specifically, a component failure versus a system failure. A component failure within a tightly coupled system of systems should not be measured in isolation because there will always be some kind of effect on the whole. For example, think about a subsystem undergoing maintenance to repair the failure of a particular component, such as replacing a blade in a gas turbine engine. It usually is faster and less disruptive to simultaneously perform restorative maintenance on related components—for example, replacing any other blades that are from the same stage in the engine. Similarly, if the system is undergoing scheduled maintenance, knowing the likelihood of an impending issue makes it possible to avoid failure by using a preemptive fix.

Accurate and useful modeling of operations and support also hinges on selecting an appropriate level of model granularity. If the performance of a system of systems is governed by a network of interrelated subsystems, then judging the performance of each subsystem in isolation is ineffectual. But the holistic approach demands more detail and data, which may become noise. Modeling this kind of granularity is difficult but not insurmountable if users employ a set of specialized and hierarchically integrated models. This technique can address even the most complex operations and support problems and help decision makers evaluate all resource allocation alternatives.

**INTEGRATING MODELS**

Hierarchical modeling techniques maximize the simulation capabilities of stochastic Petri nets—which are models that describe systems and quantify their operational timing and performance—together with the analytical capabilities of readiness-based sparing (investing in spare parts) for optimizing logistics support. Stochastic Petri nets enable decision makers to visualize the dynamic realities of an operational environment by modeling a system in terms of both its static and dynamic components. Further simplifying the process, an abridged Petri net approach retains the versatility of the original in terms of modeling power but streamlines the choice of building blocks. Using this method, visual complexity is significantly reduced, resulting in a simpler and more transparent model built using a graphical interface. Abridged Petri nets depict a component’s state by positioning a token (such as the small ground control station and aircraft icons in Figure 2) inside a particular place (the circles). Tokens are dynamic objects that move from place to place to visually represent changes in the simulation.

Figure 2 shows an abridged Petri net test case depicting an unmanned aircraft system’s deployment to survey a forest that is prone to wildfires. The goal of the endeavor was to determine the most effective way for
a group of systems to achieve uninterrupted coverage for mapping and surveilling woodland regions. The mission-critical coverage is augmented by balancing investments in spare parts, additional aircraft, and support infrastructure.

The flow in Figure 2 illustrates a basic four-aircraft mission cycle, creating a framework for adding system-of-systems complexities to the model. For example, a local ground control system would launch and recover each unmanned aircraft system. Once in route, a remote ground control system takes over. If either control system is inoperative, the mission may be compromised or curtailed, thus diminishing the time orbital coverage can be maintained. This model facilitates the collection of operationally relevant statistics. In this particular scenario, the measure of interest is orbital coverage; for a public utility, it might be uninterrupted power service; for a metropolitan area’s subway system, it could be on-time trains; and so on.

SPARE PARTS MANAGEMENT
For a system to achieve its operational objectives, adequate logistical support for spare parts and maintenance is crucial. Users must know how to develop and compute spare parts requirements, so a system-oriented approach is essential. This enables decision makers to answer a fundamental inventory management question: What mix of spare parts would be required to keep the system at the desired level of operational availability for each

THE GOAL OF MODERN OPERATIONS AND SUPPORT IS TO DETECT COMPONENT DEGRADATION AND PERFORM REPAIR BEFORE ANY ACTUAL FAILURE OCCURS.

ENABLING PREDICTIVE ANALYTICS
Advances in our understanding of the physics of failure, sensor and data transmission technologies, data collection and storage capacity, and data processing provide the technological means to enable predictive analytics—an increasingly accurate prediction of a physical component’s residual life based on usage and condition monitoring. The potential of these integrative efforts is significant, but some challenges do exist, not the least of which is how to manage the disparate but tightly coupled technologies.

It is important to place predictive analytics within the context of big data, the industrial internet, and the internet of things. When the focus is on establishing statistical relationships between measurable inputs and outputs of interest based on large volumes of data, the result is a “black box” that maps those inputs and outputs without any causal insights. This emphasis on correlation—at the expense of causation—is deliberate and motivated by the fact that identifying true causality often is unattainable because of the complexity of the underlying natural phenomena (such as human preferences).

In contrast, the systems (process) models discussed in this article rely on a certain causal structure. Although seemingly at cross purposes, predictive analytics and systems modeling are complementary. On one hand, predictive analytics enable the identification of the statistical properties of physical components that operate within and are supported by systems. On the other, the established structure and dynamics of engineered systems enables the establishment of causal models of the future in areas where correlation is currently the only realistic goal.

Therefore, it is necessary to understand causation in order to understand a system’s likely response to changes before those changes are made. This is the intersection of predictive analytics and systems modeling—and where tomorrow’s challenges will reside for supply chain managers.
specific scenario? Readiness-based sparing combines probability theory and mathematical modeling to produce the optimal sparing solution. When an inventory performance target is entered (in terms of cost or system availability), the model calculates the optimal spare parts mix needed to meet that target. The corresponding fill rate and logistics delay then are estimated based on the spare parts mix.

Unfortunately, this sparing model is decoupled from the operational details. The demand for parts is an input; it does not predict the specific impact of logistics delays, which is an output. Similarly, the availability of individual systems is used as a proxy for operational effectiveness. And just as with previous examples, the relationship between availability and operational effectiveness becomes far more complicated when several systems must be considered simultaneously.

Hierarchical integration of models enables users of complex systems to balance the resources at their disposal with desired performance outcomes. In the aforementioned wildfire mapping scenario, deployment costs vary by equipage. Two unmanned aircraft systems with significant spare parts support can generate nearly the same amount of cumulative orbital coverage as four systems with a smaller spare parts investment but a greater deployment footprint. Dispatching three unmanned aircraft systems realizes some of the potential efficiencies of the smaller deployment yet offers protection from unforeseen events.

As another example, a test case of this hierarchically integrated modeling methodology was based on the Deep-Ocean Assessment and Reporting of Tsunamis (DART), a tsunami-warning system operated by the National Oceanic and Atmospheric Administration (NOAA). The integrated models demonstrated how the timeliness of critical-event warnings from a geographically dispersed sensor net could be directly related to the sparing and maintenance decisions required to sustain continuous operation at each buoy station.

**SYSTEM SUSTAINABILITY**
Assessing the effectiveness of operations and support activities from a system-of-systems perspective enables professionals to make better-informed decisions about how to allocate limited resources to ensure safe and reliable operations. The combination of modern
analytical tools and discrete-event simulations provides valuable insights into the likely effects of resourcing decisions. Moreover, cross-discipline alignments—such as system prognostics, preemptive maintenance, and robust sparing solutions—have the potential to lead to more efficient operation and support of complex engineering systems, but only if the user thoroughly understands the processes involved in operating and sustaining the entire system of systems.

Transparent and auditable analytical and simulation models that are carefully integrated can offer meaningful insight into the operation of a system of systems. Such models also play a critical role when quantifying the risks and rewards associated with new system-management initiatives. Only with this level of detailed knowledge can a system manager fully evaluate the true cost of maintaining and operating a complex system and capture the value of pursuing a new technology or initiative.

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