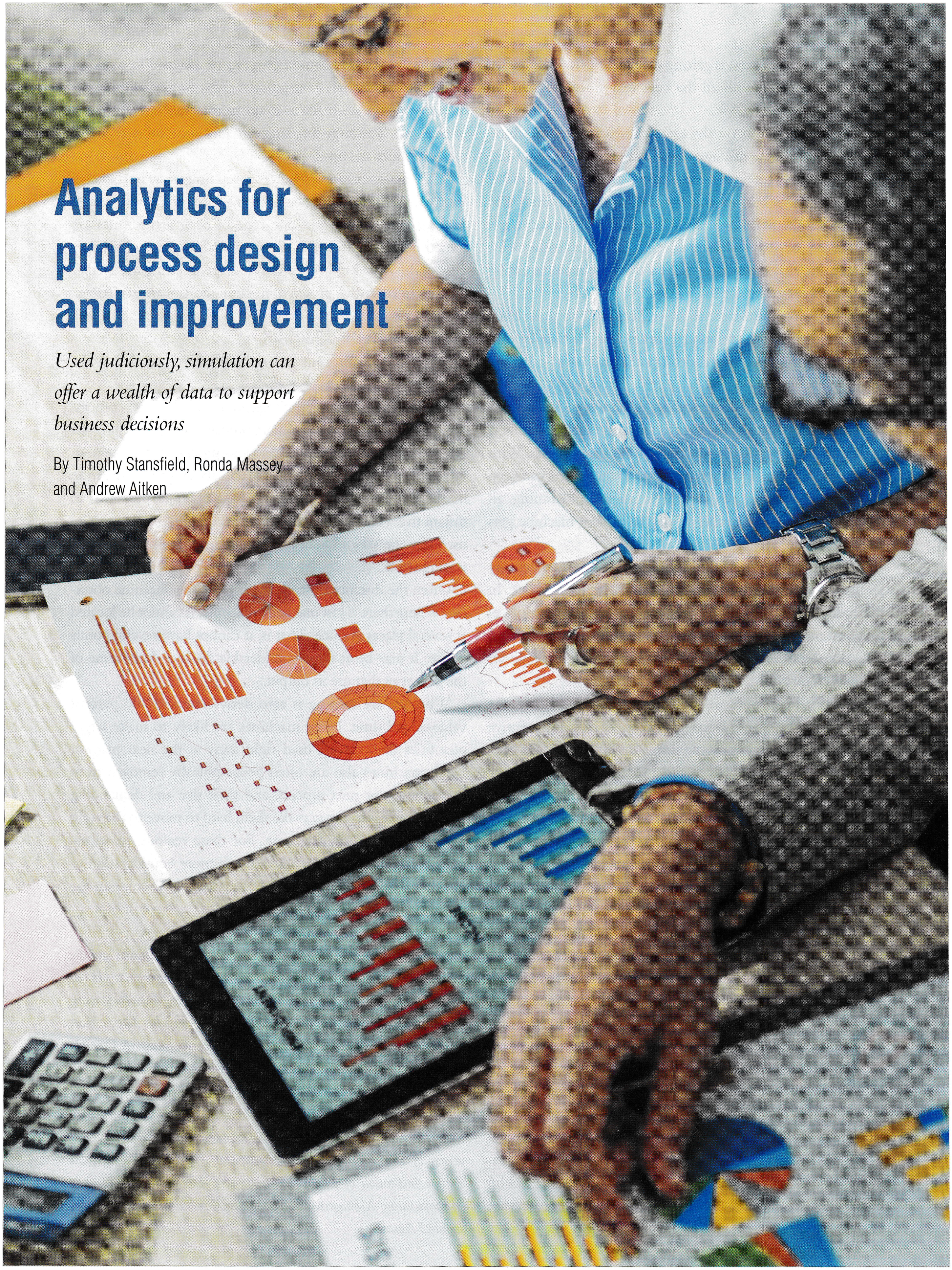


Analytics for process design and improvement

Used judiciously, simulation can offer a wealth of data to support business decisions

By Timothy Stansfield, Ronda Massey and Andrew Aitken

Industrial engineering is often at the forefront of the practical use of technology, simulation, analytics and operational intelligence to improve the systematic approach to process design and improvement. The contemporary industrial engineer now has the ability to use analytics within manufacturing's design and improvement processes to drive performance and business intelligence to new plateaus.

Predictive analytics can help manufacturers correlate processing parameters to lost overall equipment effectiveness, predict specific preventive maintenance requirements, develop processing expectation patterns to performance and offer a wide range of data-driven business decision support.

The key to success is applying the right tools, a systematic approach to the operational intelligence design process and a sustainable model of analysis and adjustments, all while containing the efforts in terms of costs and benefits.

It is also important to recognize that simulation modeling and predictive analytics are best-suited for organizations facing either high capital investment decisions or that frequently make operational resourcing decisions when faced with volatile demand. Collecting the data and then modeling and analyzing it are significant investments. Therefore, you should use modeling and analytics selectively as a risk-avoidance or cost improvement effort.

A systematic approach to operational intelligence

Our goal is to provide a specific approach to analytic intelligence that is realistic, results-oriented and cost-effective. A fundamental requirement of success is a proven systematic approach, a developed template that any organization can implement to meet its competitive challenges. The measures of success include the outcomes of the long-term intelligence improvements as well as the cost and timing of the long-term processes to get there.

1. Pick the members and champion of your performance/operational intelligence team. The selection of a champion and team members, not to mention leadership and technical support for this type of assignment, often is driven by individual business cultural processes. Three specific recommendations could help ensure the long-term success of this endeavor. The first is to select a team leader who believes in statistical modeling and has a practical understanding of complex statistical modeling's implications.

Second, select a technical member or partner who has a proven record of analytics success in production processes. Often, this is not a current employee. Since this person's role might be project-specific, it's less important to have a full-time worker on board.

Third, establish a pilot team and plan to roll the outcomes into the current management's standard operating procedures. The organization can establish new pilot teams as programs roll to the other assets targeted for improvement.

2. Identify the project objectives and expected outcomes of the modeling effort. The selected team must determine specific and challenging outcomes for the assignment. The intent is to ensure that the modeling outcomes are realistic, relevant, cost-effective and understandable. This is often the perfect time for the team to decide whether the modeling efforts will cost too much, if this is the appropriate time or if the needed analytical data is generally available. Depending on the project's objectives, a simplified design assessment may be an appropriate route.

3. Map the intended analytical simulation process in detail. A process mapping exercise can help the team establish a clearly defined set of goals, along with creating a unified understanding of the system. This document must include routine and nonroutine process steps, queueing requirements and options, cycle times and variances, statistical models of interference times and occurrences, labor requirements and limitations, and appropriate production inputs such as volumes, mix and variations. The process of mapping the intended situation will challenge the seemingly obvious inputs and parameters, as well as establish a priority for what analytics are needed to make sure the modeling solutions have the desired effects.

4. Prioritize the analytics selected for the simulation models. Using historical analytics can remove the opinions and assumptions of the team, helping move the discussion to a strictly data-driven model. The sources of data analytics can be similar processes with production monitoring, historical PLC data of capital performance, inventory status and quantities from ERP systems, historical staffing records, etc. These analytics can be collected across minute time frames and clearly define the statistical performance implications of labor, capital, inventory, model mix, etc.

5. Select the appropriate simulation technology and partners. The unique aspects of this type of process design assessment often require teaming partners with investment in technology. The simulation modeling and analytics consulting options are often driven by the marketing programs of these technology organizations. Selecting the appropriate partners is critical to cost-effective designs, timely and relevant decisions and long-term success. Enterprises should base these selections on the partners' cultural fit with the organization, situational production and process experience, and their proven technical capability.

6. Develop the operational intelligence simulation and assess specific costs and benefits. The model development process will require individual team member expertise, and effectively communicating the programming, analytics, output reporting and statistical transparency can help develop trust. The modeling statistician should provide the team with a timely summary of the analytic sources, statistical summaries and explanations and required inferences. There's always the risk that the team could see simulation modeling as nothing more than complex programming and code, so modeling experts should constantly refer to and revise the process mapping to ensure a cohesive team effort.

7. Redefine and revise the operational intelligence simulation models to ensure long-term relevance and success. The design efforts of this team are based on the best data and collective knowledge members can collect. Plan and expect timely gates of significant team decisions. However, details and revisions should be refined and revised throughout the assignment. The ongoing predicted operational costs can begin with an optimal solution that can be improved as additional analytics and models are recycled and adapted by new analytics.

8. Develop and document the long-term roles, responsibilities and measures of analytics success. Organizations should use analytics and simulation modeling in a selective manner. This tool can be improved for future use in terms of proper assignment selection, individual capabilities and passions, consistent statistical and simulation models and processes, standard operating procedures and defined team expectations. Carefully measuring lessons learned and refining this process will ensure the organization's modeling success. In addition, an organization's experience with these design assessment tools will determine appropriate timing and milestone expectations during future assignments.

Actionable operational intelligence modeling success

Recent successes in the appropriate use of analytics and operational intelligence included stories about an automotive component manufacturer, a maker of electric motors and pumps, and a car company.

Success story 1: The first automotive component manufacturer used current asset performance analytics to model, predict and prevent nonplanned lost time in production. The company was servicing all of the major U.S. automotive companies with customer-specific versions and options of its products. The asset investment was the major production cost, and the production philosophy to maximize return demanded a 24/7 production operation and schedule. The production requirements did not require JIT (just-in-time) delivery but certainly were limited by reasonable working capital quantities, containers and space. Therefore, frequent changeovers, typically one per shift, on each of the production lines provided an opportunity for process variation. In addition, processing parameters were often product-specific, conditional to the current environment and dependent upon technical decisions made by varied personnel.

Process control charts were in place based on timely operator interactions and internal MES (manufacturing execution system) designs. The overall OEE performance was 60 percent to 70 percent for each line over a typical month. A major issue is that the process controls were based on the best historical knowledge of the asset and program designers. These people are extremely knowledgeable and could be considered industry experts. However, there were nearly 100 processing parameters realistically associated with any instant of production for just one line. Monitoring these parameters across the product and conditional mixes required assumptions of expected tolerances and allowed technical personnel on site the autonomy to make decisions. The contemporary ability to collect extremely granular, high performance time-series data gives management the statistical ability to drive significant improvement.

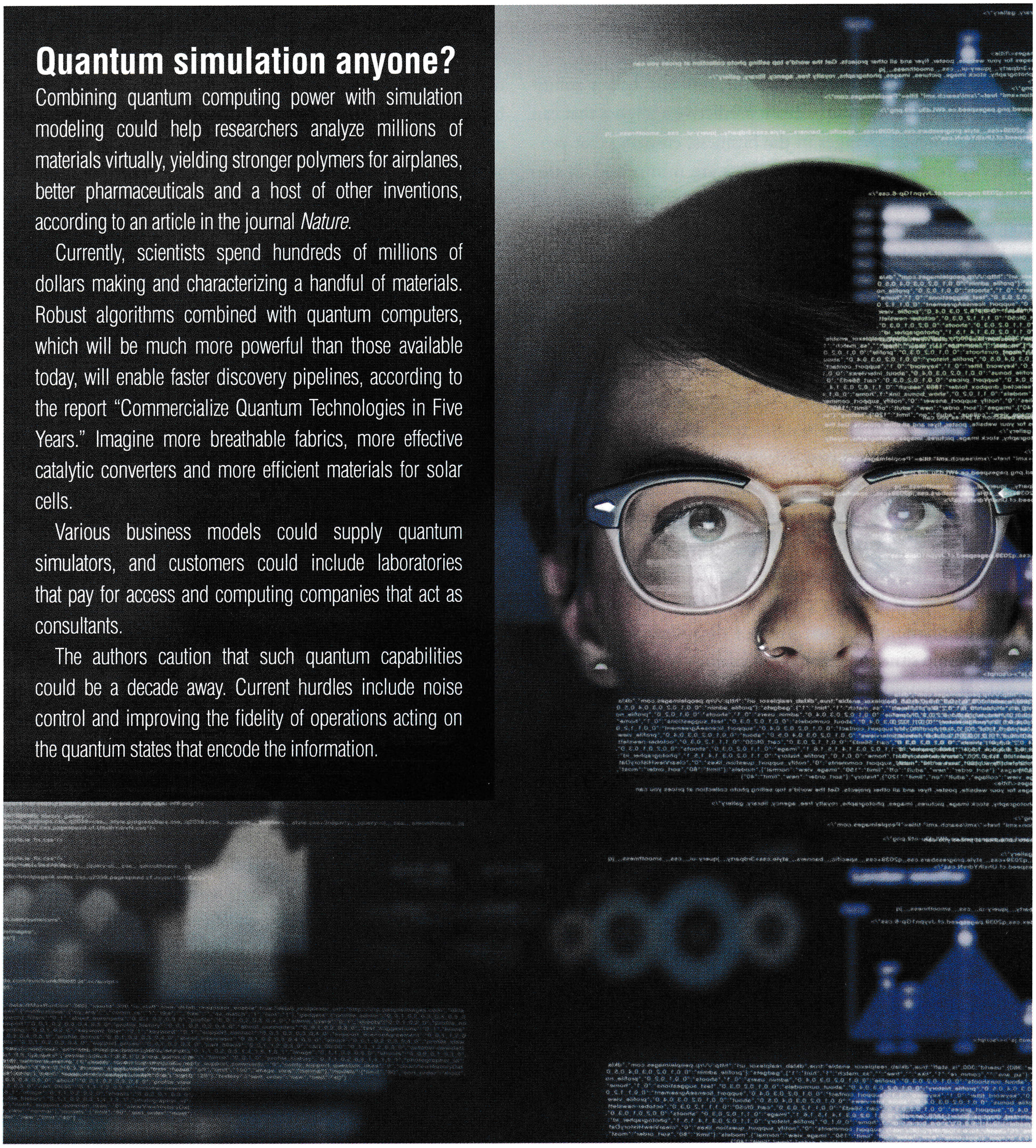
A pilot team was established. Team members followed a systematic approach, using a wide range of predictive analytics to identify what process parameters correlated to OEE losses. The immediate outcomes were driven by team-directed statistical simulation models of process variations, unexpected correlations, tolerance adjustments and other analytical tools that provided significant knowledge to the technical and managerial leadership. Specific process controls that limited operator interactions, new and adjusted MES controls of processing parameters and streaming feedback of processing performance has driven the OEE performance on this line to nearly 85 percent.

This represented nearly a 40 percent improvement over the past year. In addition, process performance moving forward will offer a sustainable improvement opportunity as process and product parameters change. This program has been established across all of the parallel lines within this facility with similar improvement results.

Success story 2: The second success story involves strategic planning for a new factory design. One of the world's leading suppliers of mission-critical electric motors and pumps for the oil, gas, nuclear, industrial and chemical markets relied on predictive simulation and analytics to plan an ambitious growth strategy and successfully communicate this vision of change to employees, customers and investors. To capitalize on opportunities across a number of its growing markets, the company recognized that it needed to undertake a business transformation project that focused on maximizing efficiency, aligning capacity to demand and boosting profitability.

Having already achieved substantial growth (from $22 million in 2011 to $32 million by 2015), the next stage was developing a plan that would double its main manufacturing facility in size to increase the number of units it could produce.

In the past, the organization used Excel to perform operational analysis and macro-level strategic planning. Given the importance and scale of the change required to meet accelerating demand, the executive management team decided that



Quantum simulation anyone?

Combining quantum computing power with simulation modeling could help researchers analyze millions of materials virtually, yielding stronger polymers for airplanes, better pharmaceuticals and a host of other inventions, according to an article in the journal *Nature*.

Currently, scientists spend hundreds of millions of dollars making and characterizing a handful of materials. Robust algorithms combined with quantum computers, which will be much more powerful than those available today, will enable faster discovery pipelines, according to the report "Commercialize Quantum Technologies in Five Years." Imagine more breathable fabrics, more effective catalytic converters and more efficient materials for solar cells.

Various business models could supply quantum simulators, and customers could include laboratories that pay for access and computing companies that act as consultants.

The authors caution that such quantum capabilities could be a decade away. Current hurdles include noise control and improving the fidelity of operations acting on the quantum states that encode the information.

static Excel analysis could not help the organization deliver and communicate an accurate, trusted growth plan. The enterprise needed to model the complex dynamics of its operational processes more fully to understand how the business would look in five to 10 years, what future opportunities there might be and how operations would evolve over that period.

Most importantly, the enterprise needed to understand the timing of key asset investments. Complex resources and process variables all needed to be factored in, including new equipment specifications and capabilities, quantities and skills of labor, subassembly processes, cranes, forklifts and back-office policies and workflows.

Having concluded that Excel would not be a suitable tool, the design team looked at how predictive simulation and analytics could be used to create a virtual dynamic factory. The team created a "virtual factory" model that presented a picture of its manufacturing operations as they would evolve over the next five to 10 years.

The model highlighted exactly what would be required to meet demand and maximize profitability. The analysis factored in multiple influencers of plant capacity and performance, including factory layout, equipment requirements, shift patterns and peaks and valleys of demand. The model encompassed key milestones and product mixes and identified exactly what processes and resources would be needed at each milestone to keep pace with predicted demand.

This deep insight means that the business had a robust framework for producing relevant predictive analytics that can pre-empt forecast changes in the business, ensuring that productivity remains high and that costs are minimized. It also means that it has a highly credible plan to present to internal and external stakeholders. Predictive simulation and analytics has quickly become an invaluable tool in communicating with the organization's management team and company stakeholders. It can demonstrate the robustness of strategic plans to investors, providing transparency and instilling confidence to support more than $10 million of new capital investment. It has been invaluable in securing wider stakeholder engagement and buy-in, including the manufacturing workforce, subcontractors, customers and new sales prospects. It was a key differentiator in winning a recent multimillion-dollar contract.

Success story 3: A worldwide automotive company used current asset performance analytics to understand the operational and OEE implications of specific human interactions and decisions. This major production company has access to tremendous amounts of performance data across a wide range of production situations. To take advantage of this data and the statistical technology available, the organization assigned a design team the challenge of modeling and simulating the implications of past performance on future state production designs.

This predictive simulation and analysis project specifically aimed to develop control logic for two production lines to optimize the decal processes applied to more than 2,000 parts across numerous models and vehicle options. This control logic needed to find a distribution logic that would optimize direct and indirect staffing levels for the two production lines. The team collected historical performance data across a wide range of production situations at extremely short performance intervals. Historical direct and indirect labor staffing was correlated to this data, and statistical predictive models were developed to identify periods of high labor performance. The analytics were used to explain all performance variations and then provide the specific data requirements for future state simulations.

The team used these models to challenge the accepted staffing models. The new staffing models offered solutions with specific yet flexible labor and staffing assignments based on hourly volume, mix, changing labor content and seemingly unpredictable interferences. This integration into the organization's traditional production monitoring systems ensured manageable solutions to a complicated staffing assignment.

The intent of analytics is not to replace the current production monitoring system. Rather, analytics will ensure the system remains relevant as factors that influence performance change. The technical aspects of each of these remarkable improvement programs have required a commitment from management. The timing for these modeling improvement results has varied based on complexity, team commitment, information access and a variety of other project considerations. It has been shown that in general, significant team knowledge was gained in weeks, significant improvement gained in months and significant cost improvements were and will be sustained over the asset's remaining life.

Simulation can outline your future

Predictive simulation modeling has proven capable of delivering a wide range of operational benefits, including improving and supporting significant production design and improvement initiatives. The effectiveness and tangible business impacts from advanced predictive analytics methods such as simulation are enhanced by today's availability of better, relevant operational data and computing power. This means that such techniques are progressively becoming required tools to secure an organization's competitive advantage.

This article highlighted several important considerations that should be addressed and suggested a systematic approach that will create a continuous pattern of improvement. Carefully adhering to the presented outline can provide a sustainable framework for an organization to develop analytical methods and business intelligence for production design and operational improvement. ❖

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