Predictive Factories:

The Next Transformation

By Prof. Jay Lee & Dr. Edzel Lapira

New approaches to predictive maintenance offer manufacturers the promise of greater transparency into the performance and health of essential plant equipment, longer life for valuable production assets, minimum disruptions, and more competitive factories of the future.

THE GLOBALIZATION OF THE WORLD'S ECONOMIES IS DRASTICALLY changing the scale and landscape of today's markets, challenging established manufacturing strategies. Aggressive competition from emerging economies has already put a severe strain on local manufacturing sectors in developed nations, which are being forced to undergo significant changes in order to increase their competitiveness.

These prevailing market conditions, aided by advances in information, communication, and other emerging technologies, are now spurring the next evolution in manufacturing. We believe that the concepts behind predictive manufacturing have an important role to play in this next wave of industrial transformation.

From Mass Production to Predictive Manufacturing

Historically, the evolution of manufacturing (Figure 1) has been fueled by advances in automation, information technology, instrumentation, and sensing, as well as the formalization of well-documented and structured methodologies and techniques by successful corporations such as Ford and Toyota.

When demand for manufactured goods and products soared after World War I, mass production platforms were developed to produce large amounts of standardized units using assembly lines, as pioneered and popularized by Henry Ford. By utilizing interchangeable parts, manufacturers could minimize production costs, because one part could readily replace another. This is an efficient manufacturing strategy, especially in high-volume production of limited models of a product.

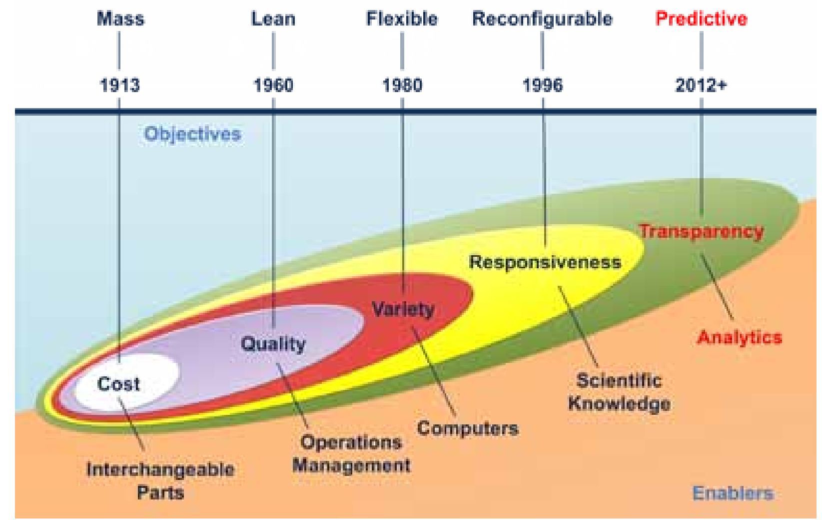
By the late 1960s, the Toyota Production System (TPS) was emerging as a response to the productivity lag between Japanese and Western manufacturing sectors. The prime directive of TPS is to reduce costs by focusing on quality and eliminating sources of waste that were prevalent in mass production, such as overproduction, waiting, transport, processing, inventory, motion, and defects. This entailed an intensive operations management effort in which processes are reviewed and measured to identify and eliminate sources of waste, while maintaining high product-quality standards. In contrast to mass production, the objective of TPS is to produce few models in low volumes, with production triggered by customer-pull so that the manufacturer creates only what has been ordered. This is also known as just-in-time manufacturing. Similar concepts were introduced in other developed countries with the development of Lean principles and Six Sigma techniques.[2]

Previous spread, Veer.com/ Baloncici

"A significant amount of **industrial equipment is now outfitted with sophisticated sensor arrays** capable of capturing highly granular data readings on asset performance."

Figure 1

Evolution of Manufacturing Paradigms



(Revised from NSF ERC Reconfigurable Manufacturing Systems Report #1)[1]

With the advent of computers and equipment controllers for early industrial robots and machine tools in the 1980s, manufacturers could provide increased variety and individual customization at prices that were comparable to standard goods and services. This approach was known as mass customization, or flexible manufacturing, and resulted in improved market share for those companies that successfully adopted a flexible production model.

The late 20th century and early 21st century saw the proliferation of new information technology systems and the birth of social media networks. These greatly affected the evolution of customer requirements, causing significant manufacturing impacts on innovation, quality, product variety, and speed of delivery. The commoditization of consumer goods and shorter product lifecycles from design to production forced companies to reevaluate their manufacturing strategies in order to quickly fulfill market demand. This led to the emergence of reconfigurable manufacturing systems that are designed to rapidly change a plant's structure, including its hardware and software, so that production capacity and functionality can be quickly adjusted.

But while all these historical production paradigms can still provide substantial benefits to manufacturers in certain market sectors, even the strictest compliance to any of these approaches does not guarantee that maximum benefits can be achieved. The key limitation across these paradigms is a lack of manufacturing transparency.

Today, transparency is becoming increasingly important, as it allows companies to quantify real manufacturing capability and readiness, minimizing the role of uncertainty in production decisions.

The fundamental problem is that these traditional strategies tend to assume ideal conditions in the factory—such as continuous asset availability and sustained optimal performance—each time an asset is used. This, however, is never the case in a factory environment. To overcome the problem, manufacturers must focus on bringing far greater transparency to their assets. This next phase in the evolution of production is becoming known as predictive manufacturing.

"Labor is a major factor behind the migration of manufacturing back to North America, particularly in cases where a product's labor content can be reduced through automation."

Predictive Manufacturing: The Next Phase

There already exists a plethora of advanced predictive analytic algorithms that companies can harness to achieve greater transparency across the production floor. One area that leverages these predictive algorithms is prognostics and health management, or PHM. This technique is an evolved form of the traditional manufacturing maintenance strategy. It estimates the current health of plant equipment, detects incipient failures, and predicts the next fault event.

Predictive manufacturing therefore provides far greater visibility into the actual health condition of a production asset—or, inversely, its state of degradation. It also provides a valuable trajectory of machine performance, and key insights into when and how a piece of equipment or a component is likely to fail.

This increase in transparency can lead to a number of benefits for manufacturers, including:

› **Cost reduction:** Since there is clear information about the actual condition of the equipment, maintenance can be planned only when it is needed (just-in-time maintenance), which maximizes the life and use of a machine's consumables and components.

› **Operational efficiency:** Knowing when an asset or its component is going to fail will allow for better scheduling of maintenance and production. This maximizes asset availability and uptime. Since component use is prolonged, mean time between failures (MTBF) is increased. With an accurate fault diagnosis module, troubleshooting time and mean time to repair (MTTR) are reduced, resulting in shorter unplanned downtimes.

› **Product quality improvement:** Equipment variability and drift can then be accounted for in production process control, so that product quality deviations can be minimized, which avoids unnecessary reworking, scrap, and excursions.

"By making the manufacturing capability transparent, plant and corporate managers have the right information to assess facility-wide overall equipment effectiveness (OEE).

Big Data and Predictive Manufacturing

A significant amount of industrial equipment is now outfitted with sophisticated sensor arrays capable of capturing highly granular data on asset performance. In addition, the increasingly popular concept of the "Internet of things," whereby assets are connected using cost-effective networking systems and advanced communication protocols and adapters, has enabled engineering assets to be easily tethered to manufacturing execution systems (MES) and enterprise resource planning (ERP) systems.

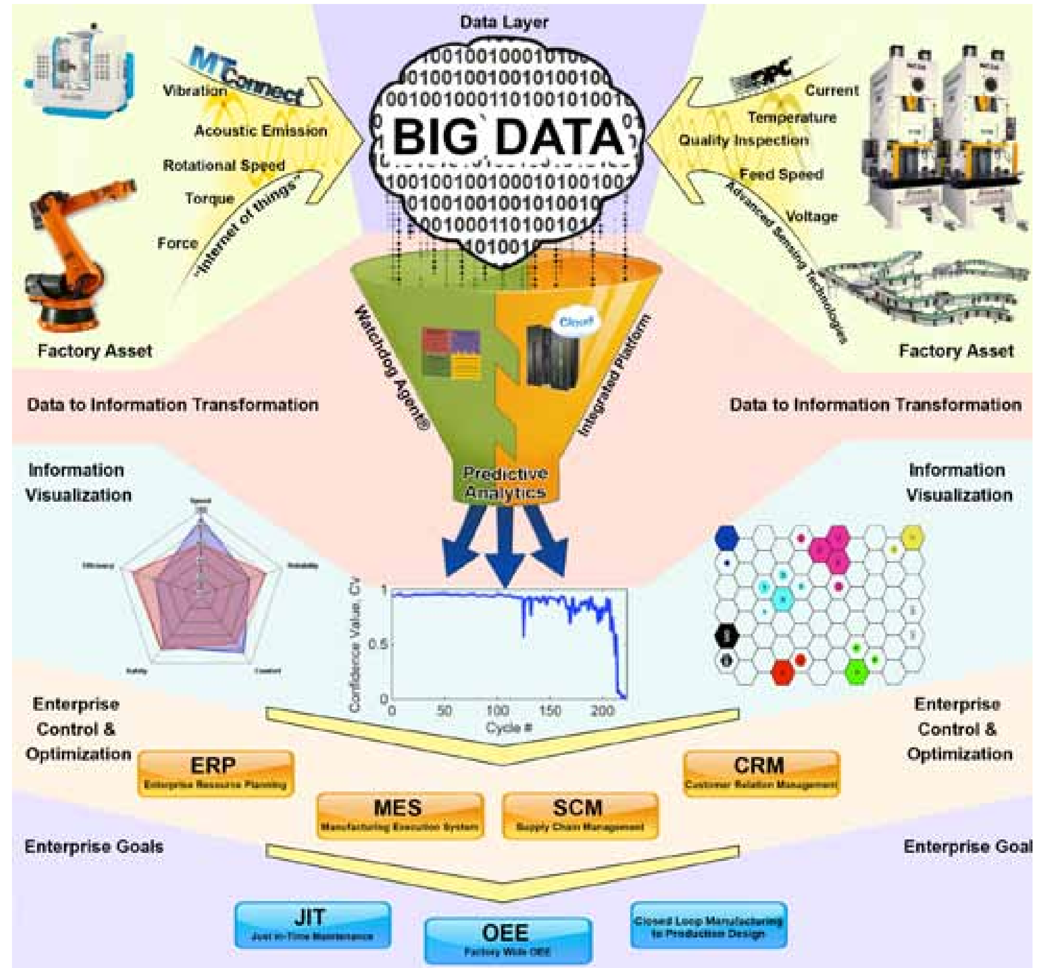
These huge technological strides in sensing and connectivity have allowed for seamless data aggregation from various measurement points within the production facility. However, capturing huge amounts of data in the form of product genealogy, equipment sensor readings, and traceability has resulted in an unprecedented flood of information. This creates an enormous challenge for companies trying to effectively manage the "Big Data" explosion and extract information quickly so that more-informed decisions can be made within an ever-shrinking time horizon.[3]

Big Data demands the development of mechanisms for converting this engineering data into useful information. Predictive manufacturing deals with this challenge through a series of transformation processes, including digitization, digestion, delivery, and clear decision recommendations for users. Prognostics and health management tools offer one such solution.

Figure 2

Data Transparency

Using PHM tools as part of an integrated platform to create transparency through predictive manufacturing.



PHM: An Evolved Approach

Prognostics and health management (PHM) approaches are designed to provide companies with a more objective assessment of the true condition of their engineering assets.

The traditional approach of reactive maintenance—essentially repairing a machine when it fails—may seem like the simplest option, but this approach is clearly inadequate in a modern factory. As throughput times have become increasingly fast due to improvements in plant automation, unexpected breakdowns have become prohibitively expensive and even catastrophic.

While more recent preventive maintenance (PM) strategies may offer higher

[1] Koren, Y. and Ulsoy, A.G. "Reconfigurable Manufacturing Systems." Engineering Research Center for Reconfigurable Machining Systems (ERC/RMS) Report # 1, The University of Michigan, Ann Arbor, 1997

[2] Nambiar, A.N. "Modern Manufacturing Paradigms –A Comparison." In Proceedings of the International MultiConference of Engineers and Computer Scientists, Vol. 3, IMECS 2010, Mar. 17-19, 2010, Hong Kong, 2010

[3] Berkley, J. "Big Data for Operations Intelligence." Manufacturing Transformation Blog. http://www.apriso.com/blog/2012/10/big-data-for-operations

availability through time-based conditioning/repair/replacement activities that preclude unexpected downtime, this approach also has two major disadvantages. First, PM is an expensive program to maintain, especially if PM intervals are kept very tight. Second, although PM activities ensure that components do not fail or exhibit significant behavioral changes, there is no insight learned about the equipment's actual degradation cycle that can be used to improve its design.

Condition-based maintenance (CBM), meanwhile, uses more-advanced sensor signals to help detect the occurrence of a fault or anomaly, isolate the faulty component, and identify the failure mode.

PHM is a natural extension of the CBM approach. By trending degradation patterns, it can predict, with some level of confidence, when equipment is going to reach failure conditions. With the use of advanced predictive tools and algorithms, manufacturing asset behavior is modeled and tracked using a set of metrics known as "health value" or "confidence value." Finally, prediction tools are utilized to infer when the machine is likely to fail. With such information, a much higher level of manufacturing transparency is achieved. Maintenance and production personnel can then collaboratively and proactively plan when to schedule repair/conditioning activities to avoid equipment failure so it does not interfere with planned production goals (see Figure 2).

PHM Tools in Action

The PHM process starts with the data acquisition from the factory assets that the manufacturer wants to monitor. Using sensor technologies, various measurements such as temperature, pressure, force, and electrical signals can be recorded. In addition, communication protocols such as MTConnect or OPC (OLE-DB Process Control) enable users to capture signals from the controller and provide valuable contextual information.

At this point, the collected measurements might be considered Big Data. The data must undergo some form of transformation before the manufacturer can extract useful information and achieve asset transparency. The transforming agent is an integrated approach that consists of an underlying deployment platform, PHM analytics, and a series of visualization tools. The deployment platform can be one implementation, or a combination of stand-alone, embedded, remote, or even cloud-based implementations. The choice of deployment platform depends on the application, environment, and other user-defined attributes (speed, cost, ease of deployment, etc.).

"Prognostics and health management, or PHM, estimates the current health of plant equipment, detects incipient failures, and predicts the next fault event."

The actual data-to-information transformation is performed by the PHM analytics tools, such as the Watchdog Agent developed at the Center for Intelligent Maintenance Systems (IMS). The data undergoes signal processing for filtering, outlier detection, conditioning, and, when applicable, a domain transformation/translation. Health indicators, used to identify faults or degradation, are then extracted from the processed data.

Typically, the array of health indicators this generates is too large to be efficiently manipulated by the deployment platform, or might not have sufficient quality for a specific monitoring task—such as fault detection, failure diagnosis, or performance prediction. So, a dimension reduction, or feature selection step, may need to be performed to retain only the relevant health indicators.

Then a manufacturer can quantify the performance of the equipment by statistically comparing current health indicators with known baseline (good) health metrics. If the current behavior is similar to the baseline condition, the confidence value (CV) will be high. Alternatively, the CV will be low when there is low correlation with the baseline metrics, or the current health indicators show deviation from normal behavior.

When repeatable degradation patterns are observed, prediction algorithms can be used to infer equipment performance during future usage. With the use of visualization tools (radar chart, fault map, risk chart, and health degradation curve), the proper health information can be clearly and easily conveyed to the right person. By allowing the extracted information to be accessible in existing ERP, MES, supply chain management (SCM), and customer relationship management (CRM) systems, a company can achieve greater enterprise control and optimization.

By making the manufacturing capability transparent, plant and corporate managers have the right information to assess facility-wide overall equipment effectiveness (OEE). Also, with the use of such advanced prediction tools, companies can plan more cost-effective, just-in-time maintenance to ensure equipment health over a longer period.

Finally, when sufficient historical health information has been retrieved, this can be provided to the manufacturing equipment designer for closed-loop lifecycle redesign, and to help them improve the next generation of models.

A More Predictive Future

From the early mechanization of production processes during the Industrial Revolution, to today's highly integrated and automated assembly lines, manufacturing has always been a vibrant industry with a dynamic ecosystem of innovation. Over time, it has undergone numerous transformations and innovations that have helped it adapt to continuously changing market demands.

As the manufacturing industry now approaches an increasingly connected, digitized, and information-rich future, companies must equip tomorrow's factories with the latest and most advanced diagnostics systems available in order to ensure maximum efficiency and operational performance from their assets, as they vie in ever-more competitive global markets.

The more predictive manufacturers can be about the health of the assets they use, the more effective their operations will be, and the more competitive their factories of the future will become. M

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