Recent advances and trends in predictive manufacturing systems in big data environment

Jay Lee*, Edzel Lapira, Behrad Bagheri, Hung-an Kao

NSF Industry/University Cooperative Research Center on Intelligent Maintenance Systems (IMS), University of Cincinnati, United States

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Abstract

The globalization of the world’s economies is a major challenge to local industry and it is pushing the manufacturing sector to its next transformation – predictive manufacturing. In order to become more competitive, manufacturers need to embrace emerging technologies, such as advanced analytics and cyber-physical system-based approaches, to improve their efficiency and productivity. With an aggressive push towards “Internet of Things”, data has become more accessible and ubiquitous, contributing to the big data environment. This phenomenon necessitates the right approach and tools to convert data into useful, actionable information.

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1. Manufacturing definition and trends

Manufacturing can be described as a 5M system which consists of Materials (properties and functions), Machines (precision and capabilities), Methods (efficiency and productivity), Measurements (sensing and improvement), and Modeling (prediction, optimization, and prevention). Additive manufacturing is a new paradigm for creating products using an integrated 5M approach but is limited to certain applications with low-volume or customized (such as defense or medical) applications.

To make manufacturers more competitive, there is a need to integrate advanced computing and cyber-physical systems to adapt to, as well as take advantage of, the current big data environment. With the advent of small sensors such as RFID technologies, collecting data has become a simple exercise, but the question remains if these devices or data provide the right information for the right purpose at the right time. Data is not useful unless it is processed in a way that provides context and meaning that can be understood by the right personnel. Just connecting sensors to a machine or connecting a machine to another machine will not give users the insights needed to make better decisions. The basic definition of a manufacturing information system can be further enhanced with a 5C functions, which consist of Connection (sensor and networks), Cloud (data on demand and anytime), Content (correlation and meaning), Community (sharing and social), and Customization (personalization and value). Current manufacturing systems require deeper analysis of various data from machines and processes. For example, traditional overall equipment effectiveness (OEE) only provides the status of production efficiency [1]. It does not paint a clear view of the relationship between performance and the cost involved in sustaining a certain OEE level. Furthermore, machine condition data is not correlated with controller and inspection data to distinguish between process and machine degradation.

2. Productivity transformation: the visible and invisible opportunities

Generally, manufacturing issues can be mapped into two spaces (see Figure 1): visible and invisible. Some
examples of visible issues include machine failure, product defects, poor cycle times, time delays, drop in (OEE), etc. Invisible issues may occur, such as machine degradation, component wear, lack of lubrication, etc. In each of these spaces, issues are treated in both deterministic and uncertain levels. The traditional manufacturing space (lower left space) depicts problem solving for well-defined problems such as quality, productivity, and costs issues, etc., through continuous improvement, best practices, and standard work. Competitive manufacturers use new methods and technologies to work with their suppliers and partners to integrate design and manufacturing for problem avoidance (upper left space). For example, advanced modeling and simulation have been used to avoid poor porosity in super alloy casting process to eliminate cracks due to thermal flight during welding. Many companies have also developed new methods and techniques for the unknown problems and further provide value-added solution to their customers (lower right space). Examples include GE Aviation’s On-Wing Support Smart Engine Service for reducing maintenance costs, and John Deere’s Agri Service for providing farmers with crop yield management beyond farming equipment. Current efforts in cyber-physical system-based approach will produce many new value-creation opportunities for future manufacturing (upper right space) [2]. A NIST-sponsored workshop has defined cyber-physical systems as consisting of computational and physical components, seamlessly and closely integrated to perceive changes in the real system [3]. For example, (a) future machines will have a twin (an Avatar) integrated in both the physical and cyber spaces; (b) self-aware sensors can perceive changes in machine behavior with precision meaning; and (c) machines can form communities to enable peer-to-peer comparison [4].

Manufacturing companies employ continuous improvement through waste reduction (greener) and work reduction (leaner) for enhanced operations. Yet, there are still many invisible issues and uncertainties (worry) in manufacturing that can exist both internal and external to the factory. Examples of internal issues include degradation of machine and the manufacturing processes and the occurrence of failure events without any recognizable symptoms (component level); variation of cycle time due to inconsistent operation, unplanned breakdown of systems and the presence of scraps and rework that disrupt normal production planning and scheduling (system or production process level). Meanwhile, external uncertainties, typically stemming from product development all the way through the supply chain, can manifest as: (1) unreliable downstream capacity; (2) unpredictable variation of raw materials or parts in terms of delivery, quantity and quality, (3) market and customer demand fluctuation, and (4) incomplete product design due to the lack of accurate estimation of product state during production and usage, among others. These invisible worries and uncertainties have adverse effects in manufacturing if there are no predictive analytics and control strategies implemented. New, smarter technologies are needed for worry reduction to make manufacturing more transparent.

3. Predictive manufacturing systems in big data environment: needs and technologies

Transparency is the ability of an organization to unravel and quantify uncertainties to determine an objective estimation of its manufacturing capability and readiness [5]. Most manufacturing strategies assume continuous equipment availability and constant optimal performance, however, this is never the case in a real factory. In order to achieve transparency, the manufacturing industry has to transform itself into predictive manufacturing. Such evolution requires the utilization of advanced prediction tools so that data can be systematically processed into information that can explain the uncertainties and thereby enable personnel to make more informed decisions. The aggressive adoption of the “Internet of Things” ideology has helped in laying the foundation for predictive manufacturing by setting the essential structures of smart sensor networks and smart machines [6]. The goal of a predictive manufacturing system is to enable machines and systems with “self-aware” capabilities. The core technology is the smart computational agent that contains smart software to conduct predictive modeling functionalities [2].

Prognostics and health management (PHM) is a critical research domain that leverages on advanced predictive tools. Insights into future equipment performance and estimation of the time to failure will reduce the impacts of these uncertainties, and give users the opportunity to proactively implement solutions to prevent performance loss of the manufacturing system.

The conceptual framework of a predictive manufacturing system (see Figure 2) starts with data acquisition from the monitored assets. Using appropriate sensor installations, various signals such as vibration, pressure, etc. can be extracted. In addition, historical data can be harvested
Figure 2. Predicting manufacturing system framework using Watchdog Agent® predictive analytics.

for further data mining. Communication protocols, such as MTCredit® and OPC, can help users to record controller signals. When all the data are aggregated, this amalgamation is called “Big Data”. The transforming agent consists of several components: an integrated platform, predictive analytics and visualization tools. The deployment platform is chosen based on: speed of computation, investment cost, ease of deployment and update, etc. The actual processing of big data into useful information is performed by predictive analytics such as the Watchdog Agent® that has been developed by the Center for Intelligent Maintenance Systems (IMS) since 2001 [8,9]. The algorithms found in the Watchdog Agent® can be categorized into four sections: signal processing and feature extraction,
health assessment, performance prediction, and fault diagnosis. By utilizing visualization tools, health information (such as current condition, remaining useful life, failure mode, etc.) can be effectively conveyed in a radar chart, fault map, risk chart, or by health degradation curves. The calculated health information can be made accessible to existing company management systems (ERP, MES, SCM and CRM system), to achieve enterprise control and optimization. With manufacturing transparency, management then has the right information to determine facility-wide OEE. With the prediction capability, equipment can be managed cost effectively with just-in-time maintenance. Finally, historical health information can be fed back to the equipment designer for closed loop lifecycle redesign.

4. Cyber-physical models for future manufacturing

Current PHM implementations mostly utilize data during actual usage while analytical algorithms can perform more accurately when more information throughout the machine’s lifecycle, such as system configuration, physical knowledge and working principles, are included. There is a need to systematically integrate, manage and analyze machinery or process data during different stages of machine life cycle to handle data/information more efficiently and further achieve better transparency of a machine’s health condition for the manufacturing industry.

With such motivation, a cyber-physical (coupled) model scheme has been developed and is illustrated in Figure 3. The coupled model is a digital twin of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data driven analytical algorithms as well as other available physical knowledge. It can also be described as a SS systematic approach consisting of Sensing, Storage, Synchronization, Synthesis and Service. The coupled model first constructs a digital image from the early design stage. System information and physical knowledge are logged during product design, based on which a simulation model is built as a reference for future analysis. Initial parameters may be statistically generalized and can be tuned using data from testing or the manufacturing process using parameter estimation. The simulation model can then be considered a mirror image of the real machine, which is able to continuously record and track machine condition during the later utilization stage. Finally, with ubiquitous connectivity offered by cloud computing technology, the coupled model also provides better accessibility of machine condition for factory managers for cases in which physical access to actual equipment or machine data is limited.

References