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Service innovation and smart analytics for Industry 4.0 and big data environment

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Abstract

Today, in an Industry 4.0 factory, machines are connected as a collaborative community. Such evolution requires the utilization of advance-prediction tools, so that data can be systematically processed into information to explain uncertainties, and thereby make more “informed” decisions. Cyber-Physical System-based manufacturing and service innovations are two inevitable trends and challenges for manufacturing industries. This paper addresses the trends of manufacturing service transformation in big data environment, as well as the readiness of smart predictive informatics tools to manage big data, thereby achieving transparency and productivity.

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1. Introduction

In today’s competitive business environment, companies are facing challenges in dealing with big data issues of rapid decision-making for improved productivity. Many manufacturing systems are not ready to manage big data due to the lack of smart analytic tools. Germany is leading a transformation toward 4th Generation Industrial Revolution (Industry 4.0) based on Cyber-Physical System-enabled manufacturing and service innovation. As more software and embedded intelligence are integrated in industrial products and systems, predictive technologies can further intertwine intelligent algorithms with electronics and tether-free intelligence. These technologies will then be used to predict product performance degradation, and autonomously manage and optimize product service needs.

Nowadays, smart factories focus mostly on control-centric optimization and intelligence. Moreover, greater intelligence can be achieved by interacting with different surrounding systems that have a direct impact to machine performance. Achieving such seamless interaction with surrounding systems turns regular machines into self-aware and self-learning machines, and consequently improves overall performance and maintenance management. Although the autonomous computing methodology has been implemented successfully in computer science, self-learning machines are still far from implementation in current industries. Transformation from today’s status into more intelligent machines requires further advancement in the science by tackling several fundamental issues. These issues can be divided into five distinct categories as follows:

- Manager and Operator Interaction: Currently, operators control machines, managers design logistic schedules and machines are only performing the assigned tasks. Although these tasks are usually optimized by expert operators and managers, a significantly important factor is missing in these decisions: the health condition of the machine components.

- Machine Fleet: It is very common that similar or identical machines (machine fleet) are being exposed to completely different working conditions for different tasks. In contrast, most predictive and prognostic methods are designed to

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support a single or limited number of machines and working conditions. Currently, available prognostic and health management methods are not taking advantage of considering these identical machines as a fleet by gathering worthwhile knowledge from different instances.

- Product and Process Quality: As the final outcome of the manufacturing process, product quality can provide much insight on machine condition via backward reasoning algorithms. Product quality can provide feedback for system management, which can be used to improve production scheduling. Currently, such feedback loop does not exist and needs further research.

- Big Data and Cloud: Data management and distribution in Big Data environment is critical for achieving self-aware and self-learning machines. The importance of leveraging additional flexibility and capabilities offered by cloud computing is inevitable, but adapting prognostics and health management algorithms to efficiently implement current data management technologies requires further research and development.

- Sensor and Controller Network: Sensors are the machine's gateway to sense its surrounding physical environment. However, sensor failure and degradation may pass wrong and inaccurate readings to decision-making algorithms, which will result in an incorrect outcome.

With these issues in mind, the objective of the paper is to review how current manufacturing industries evolve for the upcoming industrial big data environment, and propose the key technology for sustainable innovative service. The paper is organized as follows: Section 2 focuses on trends of service innovation in manufacturing industries and unmet needs of an Industry 4.0 factory; Section 3 describes the proposed self-aware and self-maintenance machine systems based on industrial big data analysis; Section 4 presents two case studies that have been conducted to demonstrate the feasibility of the proposed framework; and Section 5 concludes the paper with some perspectives.

2. Trends and unmet needs for Industry 4.0 era

The discovery of new technologies has escorted industry development from the early adoption of mechanical systems, to support production processes, to today's highly automated assembly lines, in order to be responsive and adaptive to current dynamic market requirements and demands. Under the Industry 4.0 concept, astounding growth in the advancement and adoption of information technology and social media networks has increasingly influenced consumers' perception on product innovation, quality, variety and speed of delivery. This requires establishing the factory with capabilities of self-awareness, self--prediction, self--comparison, self-reconfiguration, and self--maintenance. Accompanied with this new technology, two types of innovative development are receiving more attention by academia and industries: service innovation and industrial big data. In this section, previous research on these two topics will be reviewed and discussed.

2.1. Manufacturing servitization and innovation

Many advanced countries whose economic base is the manufacturing industry have made efforts to transform their economy and reinvigorate the industry. They suffer threats from emerging markets and the global manufacturing supply chain. Therefore, manufacturing firms not only seek manufacturing technique innovation, but are also beginning to focus on induction and impetus of service. This way, the fuzzy boundary of the manufacturing industry and service industry drive will stimulate the development of manufacturing servitization.

Servitization was proposed by Vandermerve and Rada in 1988 [1]. They emphasized the concept of customer focus; combining products, services, support, and knowledge are the most important elements. Furthermore, the authors also asserted that not only service industries, but also manufacturing industries should focus on innovative value-added service development in order to quickly enhance their core competencies. Baines defined manufacturing servitization as innovation of organizational capabilities and processes, from product sales to integrated product services [2].

Servitization is defined as the strategic innovation of an organization's capabilities and processes to shift from selling products, to selling an integrated product and service offering that delivers value in use, i.e. a Product-Service System [3]. The concept of a Product Service-System (PSS) is a special case of servitization. Mont defines PSS as a system of products, services, supporting networks, and infrastructure that is designed to be competitive, satisfy customers' needs, and have a lower environmental impact than traditional business models [4]. In the PSS business model, industries develop products with value-added services, instead of a single product itself, and provide their customers with services that are needed. In this relationship, the market goal of manufacturers is not one-time product selling, but continuous profit from customers by total service solution, which can satisfy unmet customers' needs.

2.2. Industrial big data environment

Recently, big data becomes a buzzword on everyone's tongue. It has been in data mining since human-generated content has been a boost to the social network. It has also been called the web 2.0 era since late 2004 [5]. Lots of research organizations and companies have devoted themselves to this new research topic, and most of them focus on social or commercial mining. This includes sales prediction, user relationship mining and clustering, recommendation systems, opinion mining, etc. [6-10]. However, this research focuses on 'human-generated or human-related data' instead of 'machine-generated data or industrial data', which may include machine controllers, sensors, manufacturing systems, etc.

Under the above-mentioned Industry 4.0 era, intelligent analytics and cyber-physical systems are teaming together to realize a new thinking of production management and factory transformation. Using appropriate sensor installations, various signals such as vibration, pressure, etc. can be extracted. In addition, historical data can be harvested for further data mining. Communication protocols, such as MTConnect [11] and OPC, can help users record controller signals. When all of the data is 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. [12]. The actual processing of big data into useful information is then the key of sustainable innovation within an Industry 4.0 factory.

3. Self-aware and self-maintenance machines for industrial big data environment

The recent developments of an Internet of Things (IOT) framework and the emergence of sensing technology have created a unified information grid that tightly connects systems and humans together, which further populates a big data environment in the industry. With more advanced analytics, the advent of cloud computing and a Cyber-Physical Systems (CPS) framework, future industry will be able to achieve a fleet-wide information system that helps machines to be self-aware and actively prevents potential performance issues. A self-aware and self-maintained machine system is defined as a system that can self-assess its own health and degradation, and further use similar information from other peers for smart maintenance decisions to avoid potential issues. Smart analytics for achieving such intelligence will be used at the individual machine and fleet levels.

For a mechanical system, self-awareness means being able to assess the current or past condition of a machine, and react to the assessment output. Such health assessment can be performed by using a data-driven algorithm to analyze data/information collected from the given machine and its ambient environment. The condition of the real-time machine can be fed back to the machine controller for adaptive control and machine managers for in-time maintenance. However, for most industrial applications, especially for a fleet of machines, self-awareness of machines is still far from being realized. Current diagnosis or prognosis algorithms are usually for a specific machine or application, and are not adaptive or flexible enough to handle more complicated information. The reasons for why a self-aware machine has not been fully realized are summarized as follows:

Lack of a closely coupled human-machine interaction: a major influential factor for machine condition and performance is human operation and management. Productivity and production quality can be greatly affected by task design and scheduling. Current machines can only passively listen to the operators' commands and react, even when the assigned task is not optimal for its current condition. A smarter machine system, on the other hand, should be able to actively suggest task arrangements and adjust operational parameters to maximize productivity and product quality.

Lack of adaptive learning and full utilization of available information: PHM systems cannot be widely implemented in the industry because of their low level of adaptability, which eventually leads to a lack of robustness in the health monitoring algorithms. The problem behind such an issue is that for a PHM system, development and implementation are usually separated. The PHM algorithm is developed by data collected from experiments, and does not change during implementation unless being re-trained by experts. In most cases, the algorithm only handles condition monitoring data from real machines using a pre-defined procedure without attempting to learn from it. Such a situation is far from optimal, because real-time data collected from machines in the field is usually from more machine units and of a much longer time duration, which means it contains much more information than the lab-generated data. Algorithms that are capable of learning from such data will be able to achieve optimal flexibility and robustness for handling different situations.

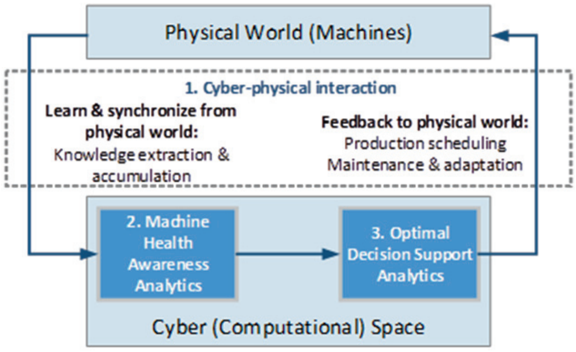

Figure 1: Cyber-physical system framework for self-aware and self-maintenance machines

In order to solve the aforementioned research gaps, a unified Cyber-Physical System framework for self-aware and self-maintenance machines has been developed that can extract meaningful information from big data more efficiently, and further perform more intelligent decision-making. The proposed system framework is shown in Figure 1.

Within the scope of this research, physical space is considered:

- A fleet of machines, including
  - Condition Monitoring (CM) data previously and presently collected
  - Controller parameters
  - Digitized machine performance (e.g. product quality measurement)
  - Machine and component configuration, model information
  - Utilization history, tasks being performed
- Human actions, including
  - Maintenance activities
  - Human controlled operating parameters and usage pattern

While in the cyber (computational) space, firstly, the data and information format needs to be properly defined so that information collected from the physical space can be recorded and managed. Secondly, the cyber space is designed to be able to summarize and accumulate knowledge on machine degradation, so that such knowledge can be used for health assessment of new machines. Lastly, health assessment results should be fed back in time to the physical space so that proper action can be taken.

3.1. Machine health awareness analytics with self-learning knowledge base

Unlike most of the existing CPS which are control- or simulation-oriented, the proposed CPS uses a knowledge base and related algorithms to represent machine degradation and performance behavior in the physical world. Machine health awareness analytics are designed to fulfill such a task. Using adaptive learning and data mining algorithms, a knowledge base representing machine performance and degradation mechanisms can be automatically populated. The knowledge base will be able to grow with new data to eventually enhance its fidelity and capability of representing complex working conditions that happen to real-world machines. With data samples and associated information collected from machines, both horizontal (machine to machine) and vertical (time to time) comparison will be performed using specifically designed algorithms for knowledge extraction. Whenever health information of a particular machine is required, the knowledge base will provide necessary information for health assessment and prediction algorithms. Because of the comprehensiveness of the knowledge base, PHM algorithms can be more flexible on handling unprecedented events, and more accurate on PHM result generation.

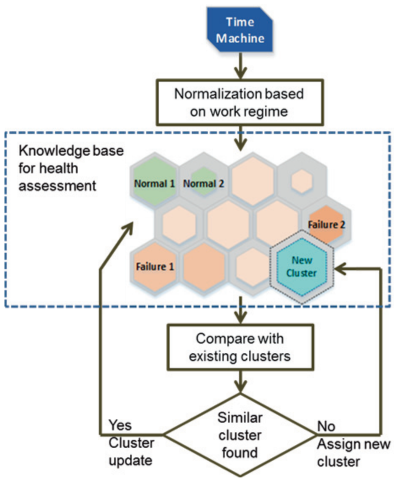

Figure 2: Adaptive learning for machine clustering

The adaptive learning and knowledge extraction is further explained in Figure 2. Considering a machine fleet, similarity always exists among machines. Machines that are performing similar tasks or that are at similar service times may have similar performance and health conditions. Based on such similarities, machine clusters can be built as a knowledge base representing different machine performances and working conditions.

Algorithm-wise, unsupervised learning algorithms such as Self-Organizing Map (SOM) and Gaussian Mixture Model (GMM) can be used for autonomously creating clusters for different working regimes and machine conditions. The adaptive clustering methodology in Figure 2 utilizes an on-line update mechanism whereby the algorithm compares the latest input to the existing cluster, and tries to identify one cluster that is most similar to the input sample using multidimensional distance measurement. A search of a similar cluster can end with two results: 1) Similar cluster found. If it is this case, then the machine from which the sample has been collected will be labelled as having the health condition defined by the identified cluster. Meanwhile, depending on deviation between the existing cluster and the latest sample, the algorithm will update the existing cluster using new information from the latest sample. 2) No similar cluster found. In this case, the algorithm will hold its operation with the current sample until it sees enough count of out-of-cluster samples. When the number of out-of-cluster samples exceeds a certain amount, it means that there exists a new behavior of the machine that has not been modeled, so that the algorithm will automatically create a new cluster to represent such new behavior. In such case, the clustering algorithm can be very adaptive to new conditions. Moreover, the self-grow cluster will be used as the knowledge base for health assessment in the proposed cyber space. With such mechanism, different machine performance behavior can be accumulated in the knowledge base and utilized for future health assessment.

3.2. Decision support analytics for self-maintenance

The main objective of design, control and decision-making of machine operations is to meet the production goal with effective and efficient production planning and maintenance scheduling. The actual system performance often deviates from the designed productivity target because of low operational efficiency, mainly due to significant downtime and frequent machine failures. In order to improve the system performance, two key factors need to be considered: (1) the mitigation of production uncertainties to reduce unscheduled downtime and increase operational efficiency, and (2) the efficient utilization of the finite resources on the critical sections of the system by detecting its bottleneck components. With the advent of PHM development in a CPS framework, rich PHM knowledge is utilized to assist and enhance the capability of decision-making in production control and maintenance scheduling to achieve high reliability and availability.

3.3. Advantages of the CPS framework

The key innovation of such CPS framework is that it realizes a self-aware and self-maintenance system by integrating both sensor data as well as fleet-wide information, so that the data volume can be reduced and a similar pattern can be identified. Such strategy further ensures that information hidden under the industry Big Data can be properly utilized. The key advantages of the designed framework can be summarized into the following perspectives:

1. Unified Cyber-Physical System frameworks for machine-to-machine health modeling: the proposed CPS is not a CPS for one machine, but for a fleet of machines and human operators. The system enables machines to gather information from its peers, human operators and other surrounding environments so that machines can achieve self-awareness of their health condition via comparing with and learning from the past history of other peers.

2. Enable self-aware and self-maintenance intelligence using self-learning PHM algorithms: rigidness and inability of handling unprecedented events are major hurdles that prevent current PHM algorithms from being widely implemented in the industry. This paper proposes a solution of developing adaptive capability for anomaly detection, health assessment, and degradation prediction. Adaptive algorithms also enable the system to learn from in-field data and accumulate in-field knowledge that can hardly be gained in a test lab environment.

3. Smart decision support system for proactive maintenance scheduling: with connected machines and awareness of machine condition across the fleet, tasks and maintenance plans will be scheduled and optimized from the fleet level. By balancing and compensating the work load and stress for each machine according to their individual health condition, production and machine performance can be maximized.

4. Case study: smart remote machinery maintenance systems with Komatsu

This particular application was for a heavy-duty equipment vehicle used in mining and construction (Figure 3). The remote prognostics and monitoring system focused on assessing and predicting the health of the diesel engine component. For this remote monitoring application, the previously developed architecture for data acquisition and data storage consisted of sending a daily data set of parameters from the diesel engine to the remote location. The parameters included pressures, fuel flow rate, temperature, and the rotational speed of the engine. These parameters were taken at key operating points for the engine, such as at idle engine speed or at maximum exhaust gas temperature. The previously developed architecture was missing the necessary algorithms to process the data and assess the current health of the engine, determine the root cause of the anomalous behavior, and predict the remaining life of the diesel engine. The heavy-duty equipment manufacturer in collaboration with the Center for Intelligent Maintenance Systems (IMS) developed a systematic approach, utilizing several algorithms from the suite in the Watchdog Agent® toolbox to convert the diesel engine data into health information.

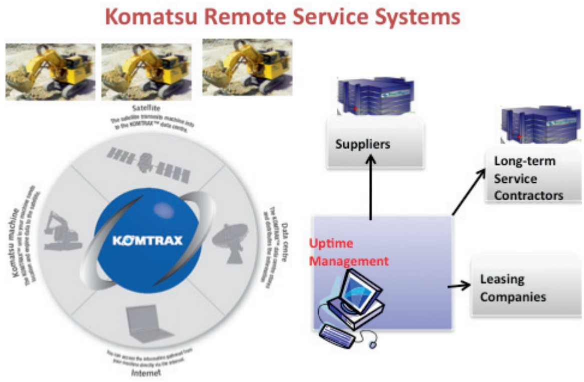

Figure 3: Komatsu smart bulldozer remote maintenance systems

The data preprocessing step consisted of using the Huber method for outlier removal, as well as the use of an auto-regressing moving average approach to predict a time series value a few steps ahead to replace missing values. The missing values could be due to an error in the transmission of the data to the remote location, or from an outlier removal preprocessing step. After preprocessing the data, the next step was to develop a methodology to classify the different engine patterns in the data to particular engine-related problems. The use of a Bayesian Belief Network (BBN) classification technique used the manufacturer's experience on engine-related problems, along with the pattern history of the data to build the model. This classification model was able to interpret the anomalous engine behavior in the data, and identify the root cause of the problem at the early stage of degradation.

The last remaining step is the remaining life prediction, and this used a fuzzy logic-based algorithm. The fuzzy membership functions were based on engineering experience as well as features extracted from the data patterns; this hybrid approach accounts for the uncertainty in the data and combines data-driven and expert knowledge for a more robust approach. An overall visualization of the final output is shown in Figure 4, highlighting the decision aid that can be provided to the maintenance technician.

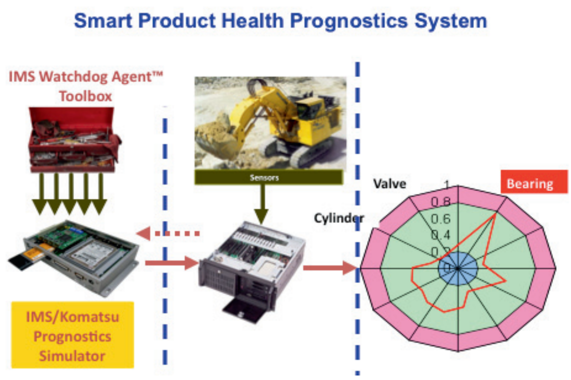

Figure 4: Machine health visualization using Watchdog Agent® technologies

5. Conclusion

Industry 4.0 proposes the predictive manufacturing in the future industry. The machines are connected as a collaborative community. Such evolution requires the utilization of advance prediction tools, so that data can be systematically processed into information that can explain the uncertainties and thereby make more "informed" decisions.

IT trends and unmet needs accompanying the upcoming Industry 4.0 era have been presented herein. This includes manufacturing servitization, which changes manufacturers' value proposition, and industrial big data, which makes manufacturing analytics more important than in the past decades. To sustain under these trends, a systematic framework is proposed for self-aware and self-maintained machines. The framework includes the concepts of cyber-physical system and decision support system. Lastly, a case study is presented in order to demonstrate the feasibility of the proposed work.

To summarize, the prognostics-monitoring system is a trend of the smart manufacturing and industrial big data environment. There are many areas that are foreseen to have an impact with the advent of the fourth industrial revolution, which four key impact areas emerge:

- Machine health prediction reduces the machine downtime, and the prognostics information will support the ERP system to optimize manufacturing management, maintenance scheduling, and guarantee machine safety.
- The information flow among the production line, business management level, and supply chain management make the industrial management more transparent and organized.
- The new trend of industry will reduce labor costs and provide a better working environment.
- Eventually, it will reduce the cost by energy-saving, optimized maintenance scheduling and supply chain management.

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