Chapter 7
Predictive Big Data Analytics and Cyber Physical Systems for TES Systems

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Abstract In today's competitive business environment, companies are facing challenges in dealing with big data issues for rapid decision making for improved productivity. Many manufacturing systems are not ready to manage big data due to the lack of smart analytics tools. U.S. has been driving the Cyber Physical Systems (CPS), Industrial Internet to advance future manufacturing. Germany is leading a transformation toward 4th Generation Industrial Revolution (Industry 4.0) based on Cyber-Physical Production System (CPPS). It is clear that as more predictive analytics software and embedded IoT are integrated in industrial products and systems, predictive technologies can further intertwine intelligent algorithms with electronics and tether-free intelligence to predict product performance degradation and autonomously manage and optimize product service needs. The book chapter will address the trends of predictive big data analytics and CPS for future industrial TES systems. First, industrial big data issues in TES will be addressed. Second, predictive analytics and Cyber-Physical System (CPS) enabled product manufacturing and services will be introduced. Third, advanced predictive analytics technologies for smart maintenance and TES with case studies will be presented. Finally, future trends of digital twin industrial systems will be presented.

7.1 Introduction

In today's competitive business environment, companies are facing challenges in dealing with big data issues for rapid decision making for improved productivity. Many manufacturing systems are not ready to manage big data due to the lack of smart analytics tools. U.S. has been driving the development Cyber-Physical Systems (CPS) and Industrial Internet to advance future manufacturing. For instance, GE has announced Predix™ as a cloud-based service platform to enable

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industrial-scale analytics for management of asset performance and optimization of operations [1]. Also, National Instruments introduced Big Analog Data™ three-tier architecture solution [2], as well as LabVIEW Watchdog Agent™ Toolkit to support smart analytics solutions throughout different big data applications [3, 4]. At the same time, Germany is leading a transformation toward 4th Generation Industrial Revolution (Industry 4.0) based on Cyber-Physical Production System (CPPS). It is clear that as more predictive analytics software and embedded Internet of Things (IoT) are integrated in industrial products and systems, predictive technologies can further intertwine intelligent algorithms with electronics and tether-free intelligence to predict product performance degradation and autonomously manage and optimize product service needs,

This book chapter will address the trends of predictive big data analytics and CPS for future industrial Through-life Engineering Services (TES) systems. First, industrial big data issues in TES will be addressed. Second, predictive analytics and CPS enabled product manufacturing and services will be introduced. Third, advanced predictive analytics technologies for smart maintenance and TES with case studies will be presented. Finally, future trends of digital twin industrial systems will be presented.

7.2 Industrial Big Data Issues in TES Systems

Through-life Engineering Services (TES) systems aim at addressing the support requirements for performance-based contracts, of which maintenance is the major engineering service [5]. This has been motivating the users to become increasingly interested in minimizing the whole lifecycle ownership of assets [6]. With the prevalence of smart sensors and IoT technologies such as RFID and MTConnect, data acquisition becomes more and more cost-effective and pervasive, but the question remains if these data will provide us the right information for the right purpose at the right time. Merely connecting sensors to machines or connecting machines to machines will not facilitate rapid decision making. Current manufacturing systems will necessitate a deeper analysis of various data from machines and processes.

The aforementioned issues in TES systems can be addressed by industrial big data. Industrial big data is a systematic methodology to convert different sources of data (sensors, controllers, history, human, fleet peer-to-peer system) into smart actionable information in order to reduce costs and generate business revenues. Industrial big data analytics draws actionable information from raw data collected from various sources to support rapid decision making, so that businesses will be able to increase operation efficiency, improve services, create novel business models, and ultimately, generate more revenues [7]. A research conducted by Accenture and General Electric forecasted that the values created by Industrial Internet of Things and industrial big data could be worth $500 billion by 2020 [7].

The concept of industrial big data in industry is related to big data in information technology, but there are certainly distinctive characteristics between them. Both industrial big data and big data refer to data generated in high volume, high variety, and high velocity ("3 V" problems) that require new technologies of processing to enable better decision making, knowledge discovery and process optimization [8]. Sometimes, the feature of veracity is also added to emphasize the quality and integrity of the data [9]. However, for industrial big data, there should be two additional "V's". One is "Visibility", which refers to the discovery of unexpected insights of the existing assets and/or processes and in this way transferring invisible knowledge to visible values. The other "V" is "Value", which put an emphasis on the objective of industrial big data analytics—creating values. This characteristic also implies that, due to the risks and impacts industry might face, the requirements for analytical accuracy in industrial big data is much higher than big data analytics in general, such as social media and customer behavior [10–13].

Compared to big data in general, industrial big data is usually more structured, more correlated, and more orderly in time and more ready for analytics [10]. This is because industrial big data is generated by automated equipment and processes, where the environment and operations are more controlled and human involvement is reduced to minimum. Nevertheless, the values in industrial big data will not reveal themselves after connectivity is realized by IoT. Even though machines are more networked, industrial big data usually possess the characteristics of "3B" [10], namely:

- Below-Surface

General big data analytics often focuses on the mining of relationships and capturing the phenomena. Yet industrial big data analytics is more interested in finding the physical root cause behind features extracted from the phenomena. This means effective industrial big data analytics will require more domain know-how than general big data analytics.

- Broken

Compared to big data analytics, industrial big data analytics favors the "completeness" of data over the "volume" of the data, which means that in order to construct an accurate data-driven analytical system, it is necessary to prepare data from different working conditions. Due to communication issues and multiple sources, data from the system might be discrete and un-synchronized. That is why pre-processing is an important procedure before actually analyzing the data to make sure that the data are complete, continuous and synchronized.

- Bad-Quality

The focus of big data analytics is mining and discovering, which means that the volume of the data might compensate the low-quality of the data. However, for industrial big data, since variables usually possess clear physical meanings, data integrity is of vital importance to the development of the analytical system.

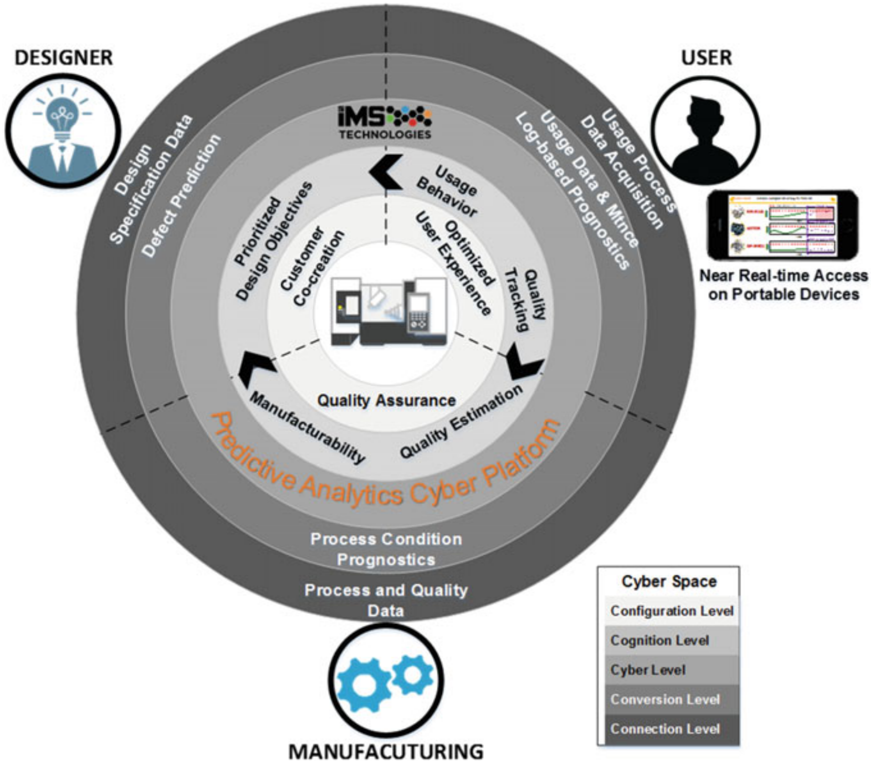

Fig. 7.1 Vision for predictive analytics and Cyber-Physical Systems-Enabled TES system

Low-quality data or incorrect recordings will alter the relationship between different variables and will have a catastrophic impact on the estimation accuracy.

Therefore, simply transferring the techniques developed for general-purpose big data analytics might not work well for industrial big data analytics. Industrial big data requires deeper domain knowledge, clear definitions of analytical system functions, and the right timing of delivering extracted insights to the right personnel to support wiser decision making [10, 14]. Predictive analytics and Cyber-Physical Systems are two core technologies that will help generate the most values from industrial big data in TES systems, which will be introduced in later sections. As Fig. 7.1 shows, predictive big data analytics and Cyber-Physical Systems will not only benefit users from predictive maintenance, but will also nurture customer co-creation through feedbacks to design and proactive quality assurance during manufacturing, which will lead to a more comprehensive TES system.

7.3 Predictive Analytics and Cyber-Physical System-Enabled Manufacturing and Services

Predictive analytics and Cyber-Physical Systems (CPS) are the core technologies of industrial big data [10, 11]. CPS systems require seamless integration between computational models and physical components [15]. Each physical component and machine will have a Digital Twin model in the cyber space composed of data generated from sensor networks and manual inputs. As shown in Fig. 7.2, a CPS can be constructed by following the "5C" architecture, which serves as a guideline for the development of CPS for industrial applications [16]. Specifically, the "5C" architecture refers to the following levels of work flow:

1. Smart Connection Level: From the machine or component level, the first thing is how to acquire data in a secure, efficient and reliable way. It may include a local agent and a communication protocol for transmitting data from local machine systems to a remote central server. Previous research has investigated robust factory network schemes based on well-known tether-free communication methods, including ZigBee, Bluetooth, Wi-Fi, UWB, etc. [17–19].
2. Data-to-Information Conversion Level: In an industrial environment, data may come from different resources, including controllers, sensors, manufacturing systems (ERP, MES, SCM and CRM system), maintenance records. These data or signals represent the condition of the monitored machine systems. However, they must be converted into meaningful information for a real-world application, including health assessment and fault diagnostics.
3. Cyber Level: Once we can harvest information from machine systems, how to utilize it is the next challenge. The information extracted from the monitored system may represent system conditions at that time point. If it can be compared

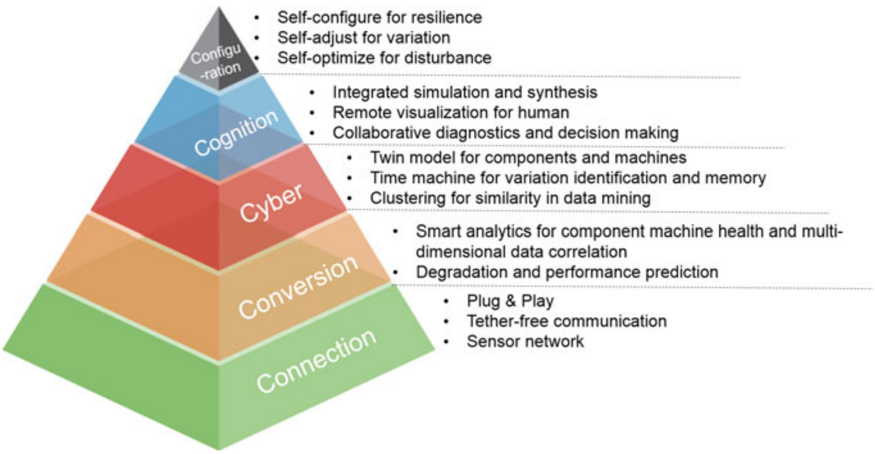

Fig. 7.2 "5C" architecture for Cyber-Physical Systems [16]

with other similar machines or with machines in different time histories, users can gain more insights on the system variation and life prediction. It is called cyber level because the information is utilized in creating cyber avatars for physical machines and building a great knowledge base for each machine system.

4. Cognition Level: By implementing previous levels of CPS, it can provide the solutions to convert the machine signals to health information and also compare with other instances. In cognition level, the machine itself should take advantage of this online monitoring system to diagnose its potential failure and alert its potential degradation in advance. Based on the adaptive learning from the historical health evaluation, the system then can utilize specific prediction algorithms to predict the potential failure and estimate the time to reach certain level of failures.
5. Configuration Level: Since the machine can online track its health condition, the CPS can provide early failure detection and send health monitoring information to operation level. This maintenance information can be fed back to factory systems so that the operators and factory managers can make the right decision based on the maintenance information. At the same time, the machine itself can adjust its working load or manufacturing schedule in order to reduce the loss caused by the machine malfunction and eventually achieve a resilient system.

For the first level, communication protocols play a significant role to enable tether-free communication between machines and data acquisition systems. In this way, recently developed communication protocols such as MTConnect [17] can help users acquire controller signals. Authors of the research in [18] demonstrated that using new communication protocols, in this case MTConnect, paves the way of acquiring data from band saw machines and other manufacturing equipment. Although these methods are helping to make data acquisition more efficient, the challenge of dealing with different sources of data is still in place [19].

The second level of the architecture, data to information conversion, has also received considerable attention specifically for prognostics and health management (PHM). Lee et al. [20] provides a relatively comprehensive review on current PHM approaches for rotary machinery. Trendafilova et al. [21] presented a non-linear data analysis method using accelerometer measurements to identify the backlash severity for industrial robot joints. Liao et al. [22] developed a method to use multiple baselines for identifying faults in band saw machines axis. They used vibration, temperature and torque measurements to train various baselines in self-organizing maps models. As it is obvious with these cases, using induced faults and laboratory situation can cover some key failure signatures of the target system but it is not possible to identify all the possible failure modes which happen in real-life situation.

The third level of the proposed “5C” architecture, the cyber level, intends to provide more intelligent and time-based methods. Using equipment history and algorithms that improve and adapt themselves provides more reliable and robust methods for equipment health monitoring and life estimation. Such algorithms are able to learn the equipment behavior over time and improve initial failure signatures. Even if the original target equipment is unavailable or failed, these models will still be available and can be applied to any other similar equipment. These cyber-models use historical data to improve themselves and data from similar machines to gain more knowledge. Wang et al. [23], developed a trajectory similarity based prognostics method which uses historical data to identify the remaining useful life of assets. Yang et al. [24] developed an adaptive prognostics and health management method for adaptively identifying new working regimes in the data and build new models base on them. Lapira [25] developed a method to use different clustering algorithms to perform machine to machine comparison and generate the health status of wind turbines and industrial robots. This fleet based similarity approach provided more accurate estimation of machines' status by peer comparison and identifying a more reliable baseline.

The cognition level intends to apply decision making and reasoning methods to recommend actionable operations to maintain optimal production while extend the lifetime of assets. There are few researches that focus on using real machine status for decision making such as the work by Haddad et al. [26] where authors used the asset remaining useful life (RUL) as input to option theory to identify the appropriate time for maintenance actions. This study only focused on deciding the maintenance time and did not consider changing working regime and reducing load of the machine as possible options.

The configuration level provides machine with self-adjusting and self-configuration capability. Most of the current research is focused on keeping humans in the decision making loop. Therefore, there are significant research opportunities on developing the concept of self-configuration and self-adjustment concept.

The "5C" architecture has indicated that Cyber-Physical Systems is focused on transferring raw data to actionable information, understanding process insights, and eventually improve the process by evidence-based decision making. Improved processes will further increase productivity and reduce costs. This aligns with the mission of TES systems, which supports usage performance requirements throughout product lifecycle and create values for customers.

7.4 Advanced Analytics for Smart Maintenance and TES with Case Studies

In industrial applications, the "5C" architecture can be applied hierarchically to different levels including components, machines, and fleets. At each level, specific analytics are required to generate useful information from raw data and consequently discover useful knowledge about the system.

1. Component level: At this level, digital twins from critical components of each machine are modeled in the cyber space. They work in parallel with the physical component while possessing huge differences: they are not bounded by time or location. These digital twins capture significant changes in the health status of each component and once the physical component is degraded, they will give prediction of the remaining useful life. Additionally, as these digital twins are on the cloud, they can interact with other components even though they are geographically distributed. Such models are very inclusive as they log lifespan of components undergoing various stress level and working regimes. Consequently, the system will gain self-awareness.
2. Machine Level: This level incorporates knowledge generated in the component level in addition to machine operation history, system settings and other attributes to create a digital twin for each machine. Adequate analytical methods have to be applied at data-to-information Conversion Level and Cyber Level to generate machine level performance and health metrics. At this stage, digital twins of similar machines are comparable to each other to identify low performance machines regardless of working regime.
3. Fleet Level: As mentioned before, cyber models are not bounded by time or location. This advantage provides opportunity to design and incorporate methods for reactively modifying the production flow. For example, leveraging the historical machine performance data and component status (from component and machine levels), it is possible to optimize the working regime among the fleet in order to maximize the life span of all components and at the same time maintain optimal productivity. This level brings self-maintainability and self-configurability to the system.

7.4.1 Advanced Predictive Analytics and Algorithms

The effectiveness of the proposed CPS architecture relies on the performance of the data analysis and management functions deployed in the cyber level. Served as a bridge connecting the lower level data acquisition and upper level cognition functions, the cyber level is required to autonomously summarize, learn and accumulate system knowledge based on data collected from a group of machines. The system knowledge includes possible working regimes, machine conditions, failure modes and degradation patterns, which is further used by cognition and reconfiguration functions for optimization and failure avoidance. On the other hand, because of complications in machine configuration and usage patterns, autonomous data processing and machine learning is of high priority since the traditional ad hoc algorithm model can hardly be applied to complex or even unexpected situations. New methods have to be developed to perform these tasks and generate appropriate results. In this section, we introduce the “Time Machine” as the framework for performing analytics on the cyber level. This framework consists of three major parts [27]:

1. Snapshot Collection: Information is continuously being pushed to the cyber space from machines. The role of snapshot collection is to manage the incoming data and store the information in an efficient fashion. Basically, to reduce required disk space and process power, snapshots of machine performance, utilization history and maintenance have to be recorded instead of the whole time-series. These snapshots are only taken once a significant change has been made to the status of the monitored machine. The change can be defined as dramatic variation in machine health value, a maintenance action or a change in the working regime. During the life cycle of a machine, these snapshots will be accumulated and used to construct the time-machine history of the particular asset. This active time-machine record will be used for peer-to-peer comparison between assets. Once the asset is failed or replaced, its relative time-machine record will change status from active to historical and will be used as similarity identification and synthesis reference.
2. Similarity Identification: In cyber level, due to availability of information from several machines, the likelihood of capturing certain failure modes in a shorter time frame is higher. Therefore, the similarity identification section has to look back in historical time machine records to calculate the similarity of current machine behavior with former assets utilization and health. At this stage, different algorithms can be utilized to perform pattern matching such as match matrix [28], fleet-based fault detection [25], and trajectory similarity-based methods [23]. Once the patterns are matched, future behavior of the monitored system can be predicted more accurately.
3. Synthesis Optimized Future Steps: Predicting remaining useful life of assets helps to maintain just-in-time maintenance strategy in manufacturing plants. In addition, life prediction along with historical time machine records can be used to improve the asset utilization efficiency based on its current health status. Historical utilization patterns of similar asset at various health stages provide required information to simulate possible future utilization scenarios and their outcome for the target asset. Among those scenarios, the most efficient and yet productive utilization pattern can be implemented for the target asset.

New algorithms have to be designed to comply with the proposed Time Machine framework. In this section, two representative machine learning and knowledge extraction methodologies are introduced for performing health assessment and prognostics within the CPS structure.

7.4.1.1 Similarity-Based Fleet-Sourced Health Monitoring

Considering a machine fleet, similarity always exists among machines—machines that are performing similar tasks or at similar service time may have similar performance and health condition. Based on such similarity, machine clusters can be built, as a knowledge base representing different machine performance and working conditions.

As for algorithms, unsupervised learning algorithms such as Self-Organizing Map (SOM) and Gaussian Mixture Model (GMM) can be used for autonomously creating clusters for different working regime and machine conditions. The adaptive clustering methodology [24] utilizes an on-line update mechanism: the algorithm compares the latest input (Time Machine) to the existing cluster and tries to identify one cluster that is most similar to the input sample using multidimensional distance measurement. Search of 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 labeled as having the health condition defined by the identified cluster. Meanwhile, depending on deviation between 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 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-growing cluster will be used as the knowledge base for health assessment in the proposed cyber space. With such mechanism, different machine performance behaviors can be accumulated in the knowledge base and utilized for future health assessment.

7.4.1.2 Prognostics of Machine Health Under Complex Working Conditions

After the health condition and the working regimes are identified for each machine, the next step is to predict the remaining useful life (RUL). First, using utilization history and measurement data, the relationship between machine degradation and the utilization (stress) history is built. Many existing prediction algorithms fail to perform well for in-field machines because they cannot handle dynamic or complex-working regimes that may alter the actual degradation path from previously learned ones. The proposed utilization matrix based prediction is grounded on the understanding that the fundamental reason for machine degradation is not only time, but also other stress factors. As a consequence, a general-purpose prediction algorithm has to be based on the stress versus life relationship.

For systems such as CNC machines, more dimensions (e.g. material hardness, machining parameters, volume of removed material, etc.) need to be added to the stress matrix to cover all major factors that cause degradation. After the definition of stress matrix, machine learning algorithms such as Bayesian Belief Network (BBN) and Hidden Markov Model (HMM) can be used to relate the different degradation rates observed in machine fleet to corresponding stress history.

Eventually degradation rate can be generated for prediction under different usage patterns that may occur in real world applications.

7.4.2 *Case Studies*

7.4.2.1 Self-aware Band Saw Machine

The core components of band saw machines are band saws used for cutting. As cutting volume grows, the band saws will gradually wear down, which results in a decline in processing efficiency and quality. For this reason, the plant must arrange a large number of workers to keep an eye on the machine operations and the wear of band saws, and determine the replacement timing based on experience. As quality requirements vary with different cutting tasks, and factors influencing quality cannot be root caused easily, the healthy band saws would be replaced well before they break. Thus, it is necessary to gather processing data from band saw machine controllers and add-on sensors, and develop a predictive CPS platform for band saw degradation analysis and prognostics, thereby making the band saw machine more intelligent by providing customers with visualized productivity management services.

In the course of processing, an intelligent band saw machine can analyze data in near real time: It first identifies condition parameters of the current work piece, and then extracts diagnostic characteristics from vibration signals and other critical parameters. After normalizing diagnostic characteristics in light of working conditions, it maps the current diagnostic characteristics to areas on the health map representing the current health stage. Such information is divided into three categories: working condition information, diagnostic information, and health status information. With voluminous lifecycle information files on band saws, users can conduct data mining through big data analysis.

While making band saw machines self-aware and intelligent, the manufacturer developed an intelligent cloud service platform to provide users with customized band saw machine health and productivity management services. As shown in Fig. 7.3, after status information gathered by band saw machines is transmitted to the cloud for analysis, users can get the health condition of key components, degradation of band saws, operation parameter matching and risk assessment through the user interface on portable devices or web interface. This makes every band saw machine operating condition quantitative and visual. With the platform, users can also manage their production plans, and manage band saw machines and band saws as required by the production tasks. When a band saw is worn to a point that it cannot meet machining quality requirements, the system will automatically remind the user to replace it, and automatically generate an order for the band saw in the material management ERP system. While dramatically boosting the efficiency of human resources, it avoids uncertainties brought about by management based on

Fig. 7.3 Intelligent management of band saw machine

experience. Meanwhile, the service life of band saws is prolonged, and quality management is conducted in a quantitative and transparent manner.

After demonstration at the International Manufacturing Technology Show (IMTS) 2014 in Chicago, the manufacturer's intelligent band saw machines and intelligent cloud services drew great attention. Seen as outstanding demonstration of intelligent equipment, such products and services have won great popularity among customers.

7.4.2.2 From Lean to Smart—Production Line Smart Maintenance

Automobile Manufacturer B has introduced a prediction analysis model in the health management of industrial robots. As such industrial robots were widely applied under different working conditions for different manufacturing purposes, installing external sensors for them was not feasible, and their health status should be analyzed based on parameters obtained in the controller. One type of the industrial robots deployed by Automobile Manufacturer B is the six-axis robotic arm, which would completely shut down when a fault occurs on any axis. To address this problem, Automobile Manufacturer B first identified the robotic arm working conditions based on the revolving speed signals of its servo axes and then established a health evaluation model for the status parameters (such as torque and

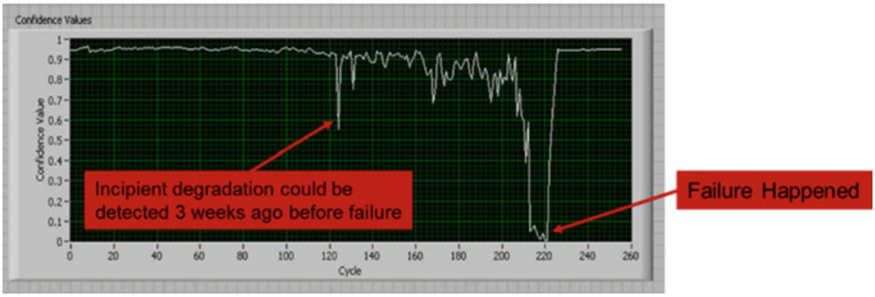

Fig. 7.4 Predictive analysis results for industrial robotic arms

temperature) under each working condition, so as to predict a fault three weeks in advance.

After that, Automobile Manufacturer B started to roll out the prediction analysis model on the six-axis servo robotic arms, conducted cluster analysis based on their types and working conditions, and formed “cyber fleets” for the various types of robotic arms. For each “cyber fleet,” Automobile Manufacturer B adopted cluster modeling to analyze data about the covered robotic arms, judged the abnormality of each robotic arm by comparing it with the whole community, and sorted all robotic arms in the community based on their health status (Fig. 7.4).

After conducting quantitative analysis on the health status of the robotic arms, Automobile Manufacturer B adopted an Internet-based model to manage the analysis results, and established an online monitoring system for the “cyber factory”. In the “cyber factory”, administrators can manage equipment status in a vertical and all-around manner at the levels of production system, production line, work station, single equipment and even key components, and carry out the maintenance and production plans based on the current equipment status. This system can generate a health report every day, which analyzes all equipment in the production line, sorts them based on their health status, and indicates the health risks and problematic parts of all equipment for equipment management personnel. In this way, potential risks will be identified in routine spot inspections and unnecessary inspections and maintenance can be effectively avoided. As a result, Automobile Manufacturer B successfully achieved the transition from preventative to predictive maintenance.

7.5 Future Trends of Digital Twin Industrial Systems

Through the discussion in precious sections, as shown in Fig. 7.5, it is evident that future industrial systems will shift from machine-based to evidence-based decision making, from solving visible problems to avoiding invisible problems [29], and from product-centric quality control to user-centric value creation.

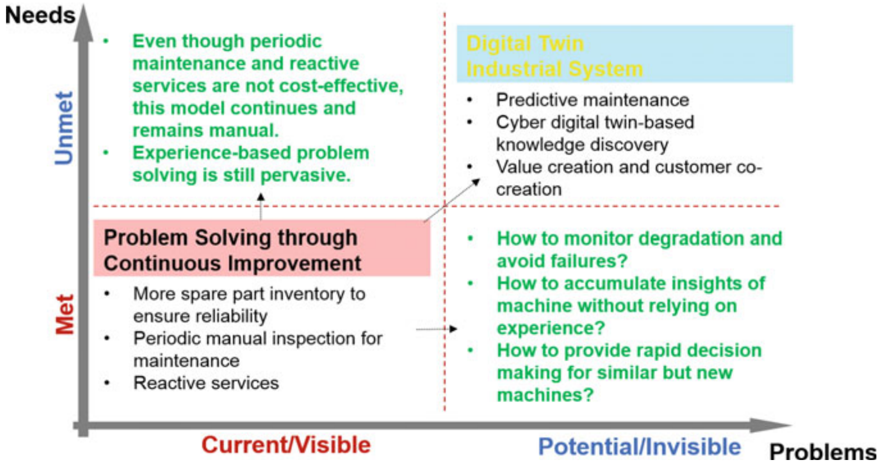

Fig. 7.5 Opportunity space of TES Digital Twin Industrial System

First, transformation from machine-based to evidence-based decision making will rapidly take place. Traditionally, manufacturing system management heavily depends on experienced personnel. In an aging society, knowledge loses with retired workforce. Therefore, a smart analytical system is needed to transform experience-based know-how into evidence-based decision making for sustainable operation.

Then, transformation from solving visible problems to avoiding invisible issues will become a new focus of the industry to change the mindset of smart maintenance. Manufacturing issues can generally be divided into visible and invisible categories [13]. Through smart analytics of interconnected multidimensional systems, correlations and causal functions can be modeled so that meaningful and actionable information can be extracted.

Eventually, transformation from product-centric quality control to user-centric value creation will naturally become the objective of the aforementioned efforts. Product quality is important, but that shall not be the end of TES systems. The final objective of manufacturing products and providing services is to optimize user experience and in return to improve design to further advance product features. Users will drive the needs of both product features and service models, and predictive analytics and CPS technologies will be the foundation of revealing and fulfilling such needs.

In future digital twin industrial systems, data will remain the most important medium to provide customized products and services for users. Through data, customers will be connected with the manufacturing systems closely and be involved in the design, manufacturing, and maintenance phases. Digital Twin Industrial System will not merely become a transformation of manufacturing systems, but a more profound and revolutionary change in business models, service models, supply chains and value chains. Its fundamental motivation comes from innovative technological changes in the business model and intelligent service system.

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