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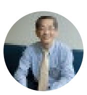

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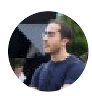

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Recent Advances and Trends of Cyber-Physical Systems and Big Data Analytics in Industrial Informatics

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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. Germany is leading a transformation toward 4th Generation Industrial Revolution (Industry 4.0) based on Cyber-Physical System based 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 to predict product performance degradation and autonomously manage and optimize product service needs. This article addresses the trends of industrial transformation in big data environment as well as the readiness of smart predictive informatics tools to manage big data to achieve transparency and productivity.**

Keywords—Industry 4.0; Cyber Physical Systems; Prognostics and Health Management; Big Data;

I. INTRODUCTION

In the past decade, emergence of promising tools such as Enterprise Systems provided companies with solutions to improve their productivity and service quality. But today's competitive nature of world industry enforces companies to implement more recent technologies to secure their position among competitors [1]. Recent technological advances in the field of communication and computer science have provided cost-effective solutions for companies to acquire and transfer gigantic amount of data from their fleet of assets. Consequently Handling these huge sets of data is not easily achievable, therefore supporting "Big Data" is one of the most recent topics in the world industry. Introduction of methods and terms such as internet of things and interconnected systems are among the efforts of researchers and industrial companies to address applicable solutions in the "Big Data" environment. Therefore, the requirement of systematic approaches to handle and analyze enterprise data in the Big Data environment is the purpose of several research studies including current paper. [2].

II. RECENT ADVANCES AND TERMINOLOGIES

In such competitive and creative environment, new terms and phrases have born to address the current requirement and demands of the industry. Recently, Germany has announced the Industry 4.0 methodology as the fourth industrial revolution. Three past revolutions are "First mechanical loom" in 1784, "First assembly line" in 1870, "First programmable logic controller (PLC)" in 1969 respectively. Based on the industry 4.0 terminology, intelligent data analysis and interconnected systems are combined together to generate a brand new aspect in factory transformation and production management. Table 1 represents the differences between a today's factory and an Industry 4.0 factory. In current industry environment, providing high-end quality service or product with the least cost is the key to success and industrial factories are trying to achieve as much performance as possible to increase their profit as well as their reputation. In this way, various data sources are available to provide worthwhile information about different aspects of the factory. In this stage, the utilization of data for understanding the current condition and detect faults and failures is an important topic to research. e. g. in production, there are various commercial tools available to provide OEE (Overall Equipment Effectiveness) information to factory management in order to highlight root cause of problems and possible faults in the system. In contrast, in an Industry 4.0 factory, in addition to condition monitoring and fault diagnosis, components and systems are able to gain self-awareness and self-predictiveness, which will provide management with more insight on the status of the factory. Furthermore, peer-to-peer comparison and fusion of health information from various components provides a precise health prediction in component and system levels and enforce factory management to trigger required maintenance at the best possible time to reach just-in time maintenance and gain near zero downtime. In addition to Industry 4.0, Cyber-physical system (CPS) is a phrase representing the integrated computational and physical capabilities such as sensing, communication and actuation to physical world[3], which is addressed by American government since 2007 as a new developments strategy[4],[5].

Table 1: Comparison of today's factory and an Industry 4.0 factory

		Today's Factory		Industry 4.0 Factory	
	Data source	Key attributes	Key technologies	Key attributes	Key technologies
Component	Sensor	Precision	Smart Sensors and Fault Detection	Self-Aware Self-Predict	Degradation Monitoring & Remaining Useful Life Prediction
Machine	Controller	Producibility & Performance (Quality and throughput)	Condition-based Monitoring & Diagnostics	Self-Aware Self-Predict Self-Compare	Up Time with Predictive Health Monitoring
Production System	Networked manufacturing system	Productivity & OEE	Lean Operations: Work and Waste Reduction	Self-Configure Self-Maintain Self-Organize	Worry-free Productivity

Applications of CPS include but not limited to manufacturing, Secure Control, medical devices, Environmental Control, aviation, advanced automotive systems, process control, energy control, traffic control and safety, smart structures and so on[6]. Having in mind that CPS is in its immature stage and it covers a broad range of scientific era, interactive collaborations between industry and academia, especially long-term collaborations such as the tasks that have been done in Advanced Research and Technology for Embedded Intelligence Systems (ARTEMIS) in Europe or Center for Intelligent Maintenance Systems (IMS) in United States will help in identification of challenges and significantly accelerate the progress of CPS[4], [7].

In the implementation of advanced terms such as Industry 4.0 and Cyber Physical Systems, sole presence of connectivity between machines and using sensors is not useful. To leverage these advanced technologies, correct information has to be present at the right time for the right purpose. In this situation, a 6C system that is consist of Connection (sensor and networks), Cloud (data on demand), Cyber (model & memory), Content (meaning and correlation), Community (sharing & collaboration), and Customization (personalization and value) [7] can enhance the information system. In this scenario and in order to provide useful insight to the factory management and gain correct content, data has to be processed with advanced tools to generate relative information. Considering the presence of visible and invisible issues in an industrial factory, the information generation algorithm has to capable of detecting and addressing invisible issues such as machine degradation, component wear, etc in the factory floor.

III. Prognostics and Health Management

Prognostics and health management (PHM) is an enrich research area that mostly deals with component wear and degradation. Factory wide transparency is one of the most important targets of PHM because in contrast with visible issues, invisible issues might happen due machine degradation, component wear and etc. while operators and factory managers are not aware of them. Indentifying those issues can lead to serious downtimes in the factory floor and PHM as an ever-growing pioneer research domain provides useful approaches to detect those invisible problems and avoid unplanned downtimes to overwhelm uncertainties in the systems. Remaining useful life prediction, fault diagnosis and fault detection are among the useful tools provided by PHM algorithms for bringing transparency in every aspect of future industry by analyzing sensory and system level data. In Past few years, different aspects of industry as well as different machines or components have been targeted by researchers for developing reliable PHM solutions. Aircraft engines [8], industrial robots [9], machine tools [10], electrical motors[11], wind turbine[12], batteries [13], gearboxes [14], bearings [15], pumps [16] and etc are only few examples of a broad range of assets.

IV. Integrated Systems

In previous sections, we introduced Industry 4.0 and Cyber-Physical Systems as two leading infrastructures for managing data and leaning toward more efficient production in current industry. In addition, we presented prognostics and health management methods as powerful and applicable approaches for detecting invisible faults and failures among factories fleet. In current section, advantages of implementing PHM algorithms in Industry 4.0 and CPS application will be presented and the next section introduces a methodology for implementing cyber-physical systems in industry 4.0 applications.

Today, most PHM methods have only access to target asset data. Asset data might contain hundreds of sensory and system data readings and provide good insight and prognostics results for the current asset. But, there are much more sources of information that are not considered in today's implementation of PHM methods. Peer-to-peer evaluation through fleet of assets, life-cycle historical data from identical assets and system configuration are few examples of the huge portion of data that is ignored by now.. For example, in PHM, various failure signatures are required for accurate fault diagnosis of assets and improve the reliability of maintenance scheme.

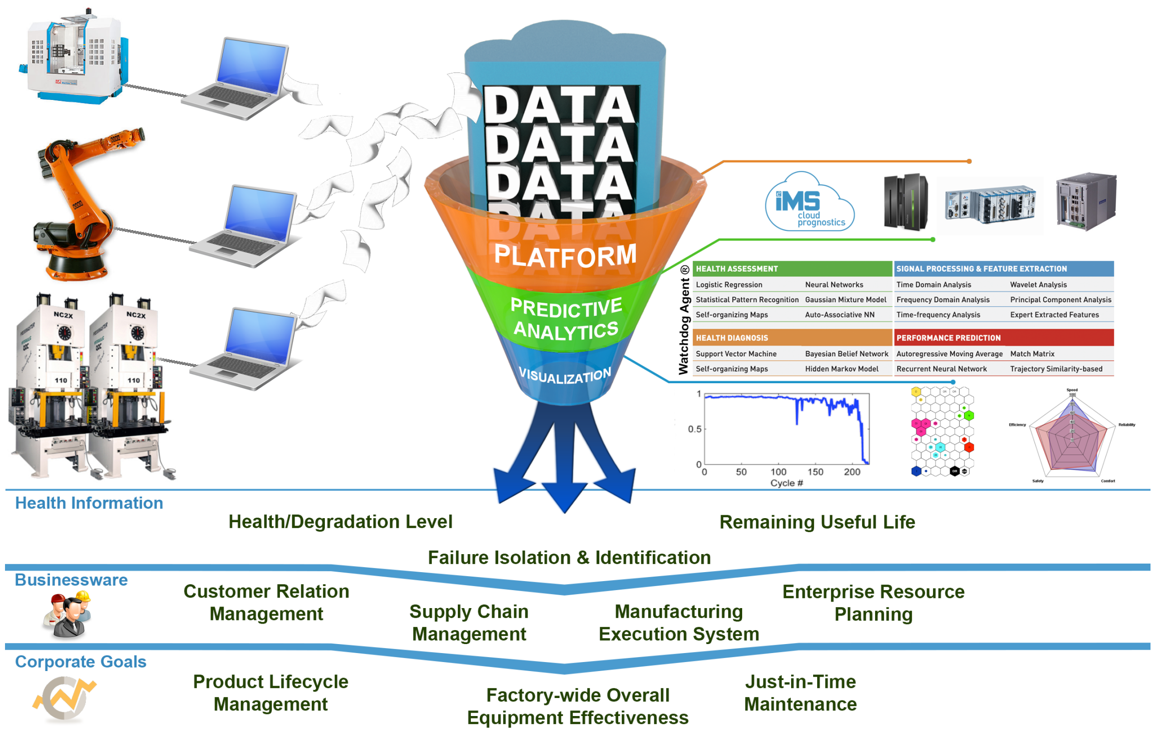

Fig. 1. The general framework of the application of PHM algorithms in detecting invisible issues in industry using Watchdog Agent® tool

Acquiring every possible failure signature from one instance of assets is not likely to happen but in an interconnected system which manages hundreds of similar assets among the fleet, the occurrence likelihood of various failures much higher. Therefore, the PHM analytical engine can capture those failure signatures from various assets to refine its failure detection and estimation capabilities. This huge improvement is possible by utilizing the concept of cyber-physical systems for PHM applications in which a cyber twin model (avatar) of real machine is created and operated in cloud platform parallel to actual asset. Leveraging the Integrated knowledge available in cyber physical model, health condition of assets can be accurately simulated and appropriately presented to dedicated users upon their demand without geographical limitations. Furthermore, the interconnectivity of fleet of identical assets to their cyber-physical model not only provides the opportunity of peer-to-peer evaluation and prognostic library accumulation but also enables PHM algorithms to have access to various life stages of different assets as well as test stage data.

V. METHODOLOGY FOR DESIGNING CPS BASED INDUSTRY 4.0 SYSTEMS

Knowing the capabilities of cyber-physical systems, a promising methodology for designing Industry 4.0 applications based on Cyber-Physical Systems can be developed. As it was discussed in previous section, interconnectivity provides access to vast amount of data. But, sole availability of data does not create a significant advantage. Therefore, an adaptive yet powerful methodology is required to manage, categorize and process data for further analysis by PHM algorithms. This method has to be broad enough to truly leverage all the advantages of cyber-physical systems.

In this article, we propose “Time Machine Methodology for Cyber-Physical Systems” which is in charge of perfectly organize available data in Big Data environment to be prepared for usage in PHM algorithms. Every single component of the fleet will have a representative Time Machine record in the cyber space. This cyber delegate extracts worthwhile information from the pool of available data and normalizes it for further analysis. Extracted information include but not limited to implementation history, stress and load, operation parameters, system configurations and maintenance records. Once the actual component is failed, it will be removed from the parent machine and will no longer exist to participate in analytics. But its cyber twin (Time machine record) will remain without any time constraints. Unlimited existence of cyber twins results in continuous accumulation of Time Machine records and consequently gathering various operation parameters from broad range of identical components. Normalization of parameters, in which further research efforts have to be conducted, ensures the comparability of time machine records with each other for identical components. Additionally, time machine records obey the hierarchical relation of actual components as well and every cyber twin has access to records of its predecessor and ancestor components. Such information rich environment brings significant robustness to PHM algorithms for continuous and accurate predicting and monitoring of the factory. Ultimately, this methodology brings ultimate implementation of cyber physical system into action for designing an Industry 4.0 factory.

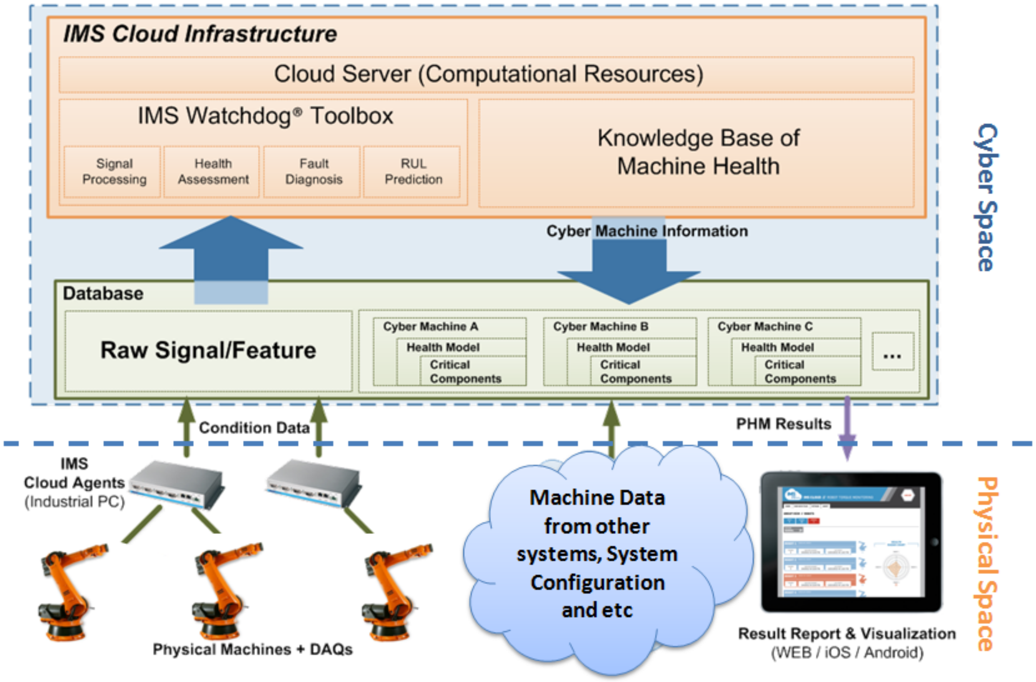

Fig. 2. Cyber-Physical Model for Industrial Robot Monitoring

VI. CASE STUDIES

A. Industrial Robot

In this section we consider the development of a cyber physical system for health monitoring of industrial robots. Fig. 2. shows the schematic view of the cyber-physical model for current case study on industrial robots. This study was focused on preparing a predictive health monitoring solution for a fleet of 30 industrial robots in production line. Due to variety of line speeds, a more complicated multi-regime approach had to be undertaken for establishing a robust prognostics and health management algorithm as the core analytics of cyber physical system by using torque and speed data. Due to its non-invasive nature torque monitoring is a popular fault detection method for monitoring health condition of industrial robots and therefore, most of the research efforts in this area have been focused on this parameter. In addition, nonlinear relation between operating speed and torque cast a challenge on PHM algorithms to correctly determine the health state of the robot. In addition to condition data (torque and speed) the cyber physical model obtains various configuration parameters such as gear ratio, load ratio, pressure calibration, type of tooling for robot servo guns and assigned products to specific robots from production line.

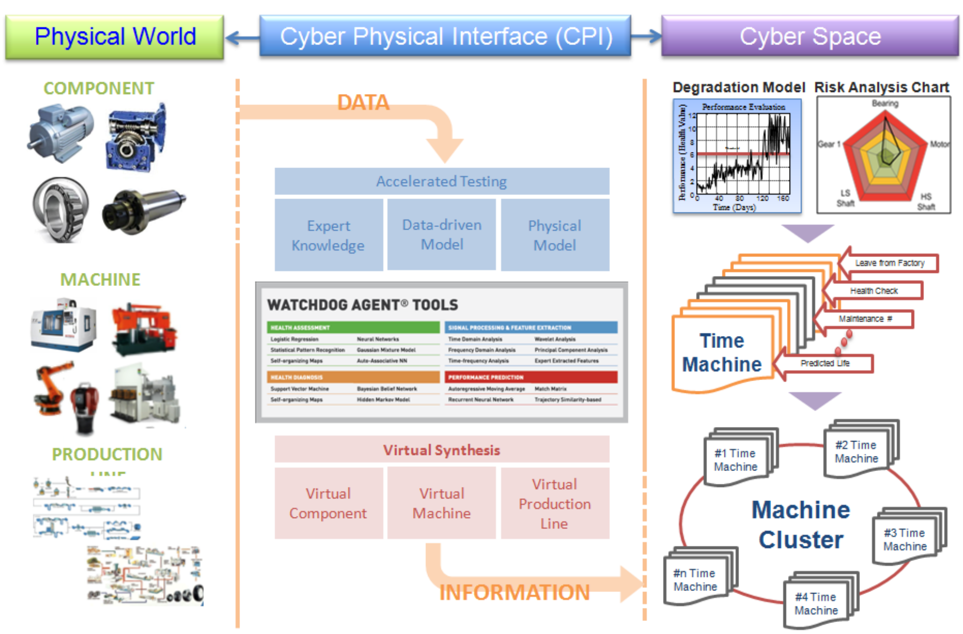

Fig. 3. Methodology for Designing CPS based Industry 4.0 Systems

These configuration parameters help the core of the model to standardize and adaptively cluster the operation data for more accurate processing. Ultimately, the entire analytical engine of this study was set and established on the cloud where the whole dataset (condition and configuration data) were stored on the cloud storage and health monitoring algorithm used the data stored on the cloud (from entire fleet) to calculate the health condition of each individual instance. The outcome of PHM algorithms were presented to users as enriched infographics through a web-based user interface

B. *Virtual Battery*

The battery pack is one of the most significant components of an Electric or Hybrid Vehicle. The uncertainty in the driving range, the batteries reliability and service life, and battery safety concerns, are all challenges that must be overcome in order to achieve more widespread adoption of electric vehicles. In order to meet the challenges and rising demand in hybrid and electric vehicles in recent years, the importance of batteries has become more and more important[17]. Therefore, fully understanding of the dynamic performance of batteries under various conditions is of significant importance. However, batteries operation condition includes several stress factors such as environment temperature, humidity, driving style, charging level, discharge rate and road conditions. To achieve this battery understanding a battery model is needed which should provide capabilities for health evaluation and failure prediction, through simulation of cell performance under different conditions. Additionally, using such a battery model, the functionality of a manufactured battery can be fed back to design and manufacturing suppliers to recognize the potential impact of design and enhancement of manufacturing process on battery performance[18].

An overview of the electric vehicle and battery health management and prognostic platform is illustrated in fig. 4, which includes algorithms for state of charge and state of health estimation and driving behavior classification.

Presently, most of the battery models focus on individual battery cells, or on battery package not including the detailed dynamics within the battery. However, all components in a battery are associated with each other. The interactions among all the cells, conductors, BMS, and environment temperature will play a significant role in battery performance, and deserve an integrated study. Moreover, manufacturing practice strongly impact on battery application conditions & user behavior.

Therefore a simulated framework is needed which is capable of execution the functions discussed above by integrating various models to emulate the multi-regime changes in battery parameters and inputs and investigate their impacts on battery functionality .

A "Virtual Battery" is a cyber-physical model resulting from merging the new battery technology with intelligent enabling tools to provide following solutions:

1. Enabling prognostics tools to transform data to health information regarding the health, reliability and operational readiness of the battery system.
2. Adequate visualization system to deliver the right information to the right people. Some information that requires the immediate intervention of the driver may be displayed for the actual user (driver) on the dashboard, while other forms of information (including more detailed diagnostic information) would be necessary for a maintenance personnel or logistics center and used to schedule maintenance or replacements.
3. Enabling tether-free communication to capture this information in real-time from the vehicle and deliver it to a central logistics center that will advise the driver about his battery condition and could use GPS trip information to direct the driver to the nearest service center or rapid charging center on his trip.
4. Simulating and predicting battery behavior such as SoC (State of Charge) and SoH (State of Health) in other operation conditions based on external parameters(environment , driving style, etc) and internal parameters (battery type, and battery age) without take a long time to test a battery in that condition.
5. Help the designers to find the flaws or design issues for a better hybrid cycle management in parallel with a better estimation of the selected pack's lifetime expectancy in the specific application.
6. Help the battery manufacturers to locate the faulty packs and study them to refine their design, manufacturing process or raw material selection.
7. Integration of the wireless solutions into the prognostic tool could also open an opportunity for better monitoring of the vehicle during standard or extended warranty period. The faulty system could be recalled for repair long before the usual inspection periods. This in turn can reduce the costs of warranty that could rise from such occasions. There is also a possibility to integrate this system into engine management sensors. This will enable the designers to study the battery aging process in different climatic conditions that the vehicle operates in. This over-time data acquisition could be an easy and cheap way to collect field data. These data could be used to design the next generation systems in a better way.

VII. CONCLUSION

In this article we introduced recent advances in industrial informatics with respect to Big Data environment, Cyber-Physical Systems and Industry 4.0. In addition, the importance of intelligent prognostics and health management in industry for retaining production and service excellence has been discussed. Furthermore, the fusion of cyber-physical systems and PHM algorithms in big data environment and the advantage of using interconnected systems has been presented along with two industrial application of cyber-physical systems.

Current industrial evolution is guiding industry toward maximum leverage from benefits of interconnected systems in big data environment where companies with more futuristic vision that establish new methodologies in their culture will have the opportunity of being significantly successful and profitable in recent future.

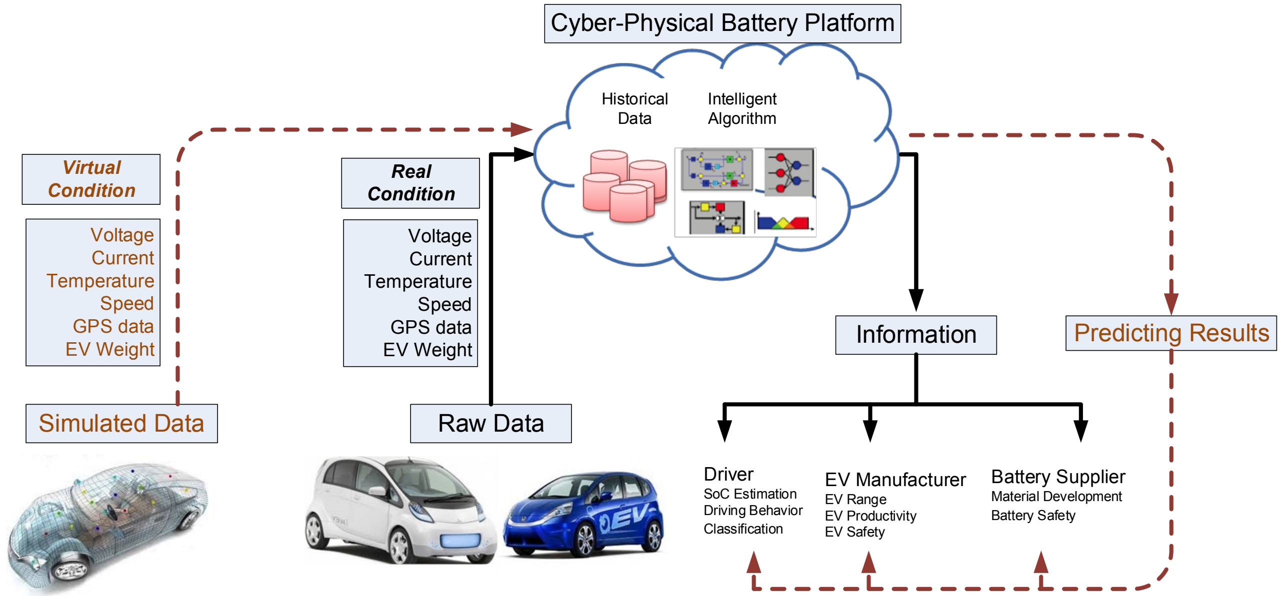

Fig. 4. Cyber Physical Battery Platform

References

[1] L. Da Xu, "Enterprise systems: state-of-the-art and future trends," Industrial Informatics, 2011.

[2] E. Dumbill, "Big Data is Rocket Fuel," Big Data, 2013.

[3] "Adaptive calibration for fusion-based cyber-physical systems," vol. 11, no. 4, pp. 1–25, Dec. 2012.

[4] "Cyber-physical systems," IEEE Control Systems Society, 2011.

[5] J. Shi, J. Wan, H. Yan, and H. Suo, "A survey of Cyber-Physical Systems," Signal Processing (WCSP 2011), pp. 1–6, 2011.

[6] "Cyber Physical Systems: the need for new models and design paradigms," Carnegie Mellon University.

[7] J. Lee, E. Lapira, B. Bagheri, and H. Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," Manufacturing Letters, 2013.

[8] T. Wang, J. Yu, D. Siegel, and J. Lee, "A similarity-based prognostics approach for Remaining Useful Life estimation of engineered systems," 2008 International Conference on Prognostics and Health Management (PHM), pp. 1–6, 2008.

[9] E. R. Lapira, "Fault detection in a network of similar machines using clustering approach," 2012.

[10] L. Liao and J. Lee, "Design of a reconfigurable prognostics platform for machine tools," Expert systems with applications, vol. 37, no. 1, pp. 240–252, 2010.

[11] B. Bagheri, H. Ahmadi, and R. Labbafi, "Application of data mining and feature extraction on intelligent fault diagnosis by Artificial Neural Network and k-nearest neighbor," 2010 XIX International Conference on Electrical Machines (ICEM), pp. 1–7, 2010.

[12] E. Lapira, D. Brisset, H. D. Ardakani, and D. Siegel, "Wind turbine performance assessment using multi-regime modeling approach," Renewable Energy, 2012.

[13] M. AbuAli, E. R. Lapira, W. Zhao, D. Siegel, M. Rezvani, and J. Lee, "Systematic Design of Prognostics and Health Management Solutions for Energy Applications," in Engineering Asset Management 2011, no. 22, J. Lee, J. Ni, J. Sarangapani, and J. Mathew, Eds. London: Springer London, 2013, pp. 243–250.

[14] B. Bagheri, H. Ahmadi, and R. Labbafi, "Implementing discrete wavelet transform and artificial neural networks for acoustic condition monitoring of gearbox," Elixir Mech Engg, 2011.

[15] O. D. Snell and I. Nairne, "Acoustic bearing monitoring—the future RCM 2008," Railway Condition Monitoring, 2008.

[16] A. Soylemezoglu and S. Jagannathan, "Mahalanobis-Taguchi System as a Multi-Sensor Based Decision Making Prognostics Tool for Centrifugal Pump Failures," Reliability, IEEE Transactions on, vol.60, no.4, pp.864,878, Dec. 2011.

[17] F. Ju, J. Wang, J. Li, and G. Xiao, "Virtual battery: A battery simulation framework for electric vehicles," Automation Science and Engineering, IEEE Transactions on , vol.10, no.1, pp.5,15, Jan. 2013.

[18] Y. He, W. Liu, and B. J. Koch, "Battery algorithm verification and development using hardware-in-the-loop testing," Journal of Power Sources, 2010.