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A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems

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Abstract

Recent advances in manufacturing industry has paved way for a systematical deployment of Cyber-Physical Systems (CPS), within which information from all related perspectives is closely monitored and synchronized between the physical factory floor and the cyber computational space. Moreover, by utilizing advanced information analytics, networked machines will be able to perform more efficiently, collaboratively and resiliently. Such trend is transforming manufacturing industry to the next generation, namely Industry 4.0. At this early development phase, there is an urgent need for a clear definition of CPS. In this paper, a unified 5-level architecture is proposed as a guideline for implementation of CPS.

Keywords: Cyber-Physical System; Industry 4.0; Health management and prognostics; Time machine

1. Introduction

Cyber-Physical Systems (CPS) is defined as transformative technologies for managing interconnected systems between its physical assets and computational capabilities [1]. With recent developments that have resulted in higher availability and affordability of sensors, data acquisition systems and computer networks, the competitive nature of today's industry forces more factories to move toward implementing high-tech methodologies. Consequently, the ever growing use of sensors and networked machines has resulted in the continuous generation of high volume data which is known as Big Data [2,3]. In such an environment, CPS can be further developed for managing Big Data and leveraging the interconnectivity of machines to reach the goal of intelligent, resilient and self-adaptable machines [4,5]. Furthermore by integrating CPS with production, logistics and services in the current industrial practices, it would transform today's factories into an Industry 4.0 factory with significant economic potential [6,7]. For instance, a joint report by the Fraunhofer Institute and the industry association Bitkom said that German gross value can be boosted by a cumulative 267 billion euros by 2025 after introducing Industry 4.0 [8]. A brief comparison between current and Industry 4.0 factories is presented in Table 1 [9].

Since CPS is in the initial stage of development, it is essential to clearly define the structure and methodology of CPS as guidelines for its implementation in industry. To meet such a demand, a unified system framework has been designed for general applications. Furthermore, corresponding algorithms and technologies at each system layer are also proposed to collaborate with the unified structure and realize the desired functionalities of the overall system for enhanced equipment efficiency, reliability and product quality.

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2. CPS 5C level architecture

The proposed 5-level CPS structure, namely the 5C architecture, provides a step-by-step guideline for developing and deploying a CPS for manufacturing application. In general, a CPS consists of two main functional components: (1) the advanced connectivity that ensures real-time data acquisition from the physical world and information feedback from the cyber space; and (2) intelligent data management, analytics and computational capability that constructs the cyber space. However, such requirement is very abstract and not specific enough for implementation purpose in general. In contrast, the 5C architecture presented here clearly defines, through a sequential workflow manner, how to construct a CPS from the initial data acquisition, to analytics, to the final value creation. As illustrated in Fig. 1, the detailed 5C architecture is outlined as follows:

2.1. Smart connection

Acquiring accurate and reliable data from machines and their components is the first step in developing a Cyber-Physical System application. The data might be directly measured by sensors or obtained from controller or enterprise manufacturing systems such as ERP, MES, SCM and CMM. Two important factors at this level have to be considered. First, considering various types of data, a seamless and tether-free method to manage data acquisition procedure and transferring data to the central server is required where specific protocols such as MTConnect [10] and etc. are effectively useful. On the other hand, selecting proper sensors (type and specification) is the second important consideration for the first level.

2.2. Data-to-information conversion

Meaningful information has to be inferred from the data. Currently, there are several tools and methodologies available for the data to information conversion level. In recent years, extensive focus has been applied to develop these algorithms specifically for prognostics and health management applications. By calculating health value, estimated remaining useful life and etc., the second level of CPS architecture brings self-awareness to machines (Fig. 2).

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

	Data source	Today's factory		Industry 4.0	
		Attributes	Technologies	Attributes	Technologies
Component	Sensor	Precision	Smart sensors and fault detection	Self-aware Self-predict	Degradation monitoring & remaining useful life prediction
Machine	Controller	Producibility & performance	Condition-based monitoring & diagnostics	Self-aware Self-predict Self-compare	Up time with predictive health monitoring
Production system	Networked system	Productivity & OEE	Lean operations: work and waste reduction	Self-configure Self-maintain Self-organize	Worry-free productivity

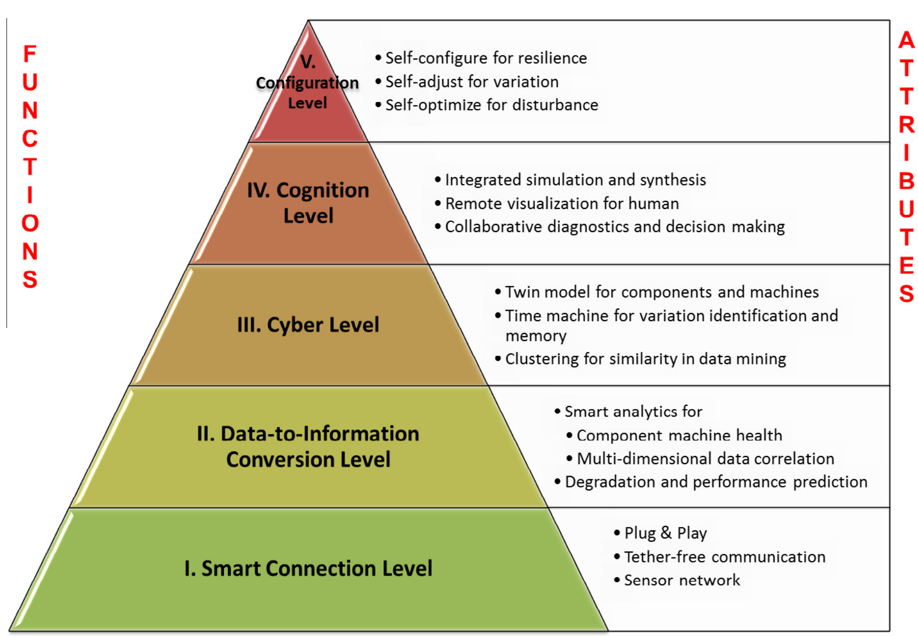

Fig. 1. 5C architecture for implementation of Cyber-Physical System.

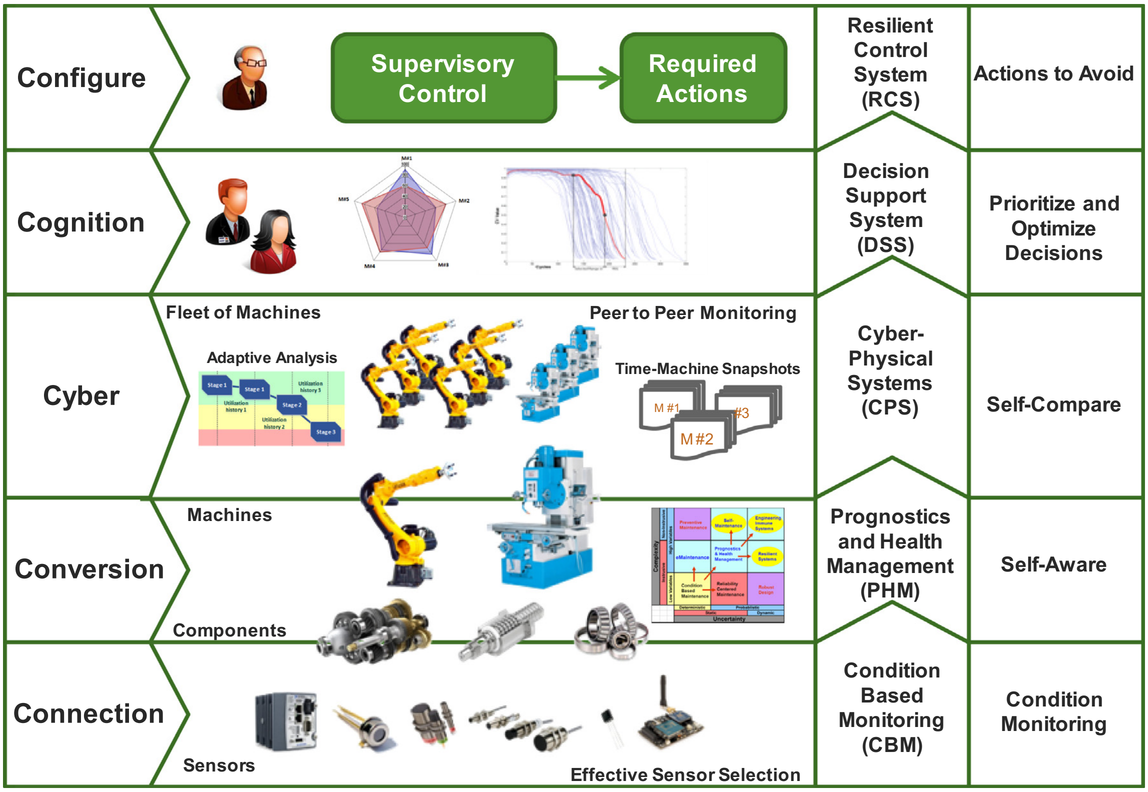

Fig. 2. Applications and techniques associated with each level of the 5C architecture.

2.3. Cyber

The cyber level acts as central information hub in this architecture. Information is being pushed to it from every connected machine to form the machines network. Having massive information gathered, specific analytics have to be used to extract additional information that provide better insight over the status of individual machines among the fleet. These analytics provide machines with self-comparison ability, where the performance of a single machine can be compared with and rated among the fleet. On the other hand, similarities between machine performance and previous assets (historical information) can be measured to predict the future behavior of the machinery. In this paper, we briefly introduce an efficient yet effective methodology for managing and analyzing information at cyber level (Section 3).

2.4. Cognition

Implementing CPS upon this level generates a thorough knowledge of the monitored system. Proper presentation of the acquired knowledge to expert users supports the correct decision to be taken. Since comparative information as well as individual machine status is available, decision on priority of tasks to optimize the maintaining process can be made. For this level, proper info-graphics are necessary to completely transfer acquired knowledge to the users.

2.5. Configuration

The configuration level is the feedback from cyber space to physical space and acts as supervisory control to make machines self-configure and self-adaptive. This stage acts as resilience control system (RCS) to apply the corrective and preventive decisions, which has been made in cognition level, to the monitored system.

3. Design of PHM based CPS systems

The extreme advantage of cyber level PHM is the interconnection between machine health analytics through a machine–cyber interface (CPI) at the cyber level, which is conceptually similar to social networks. Once the cyber-level infrastructure is in place, machines can register into the network and exchange information through cyber-interfaces. At this point, an algorithm has to be established to track the changes of a machine status, infer additional knowledge from historical information, apply peer-to-peer comparison and pass the outputs to the next level. New methods have to be developed to perform these actions and generate appropriate results. In this paper, we introduce the “time machine” that performs analytics at the cyber level and consists of three parallel sections as follows.

I. *Snapshot collection:* As illustrated in Fig. 3, information is continuously being pushed to the cyber space from machines. The role of snapshot collection is to

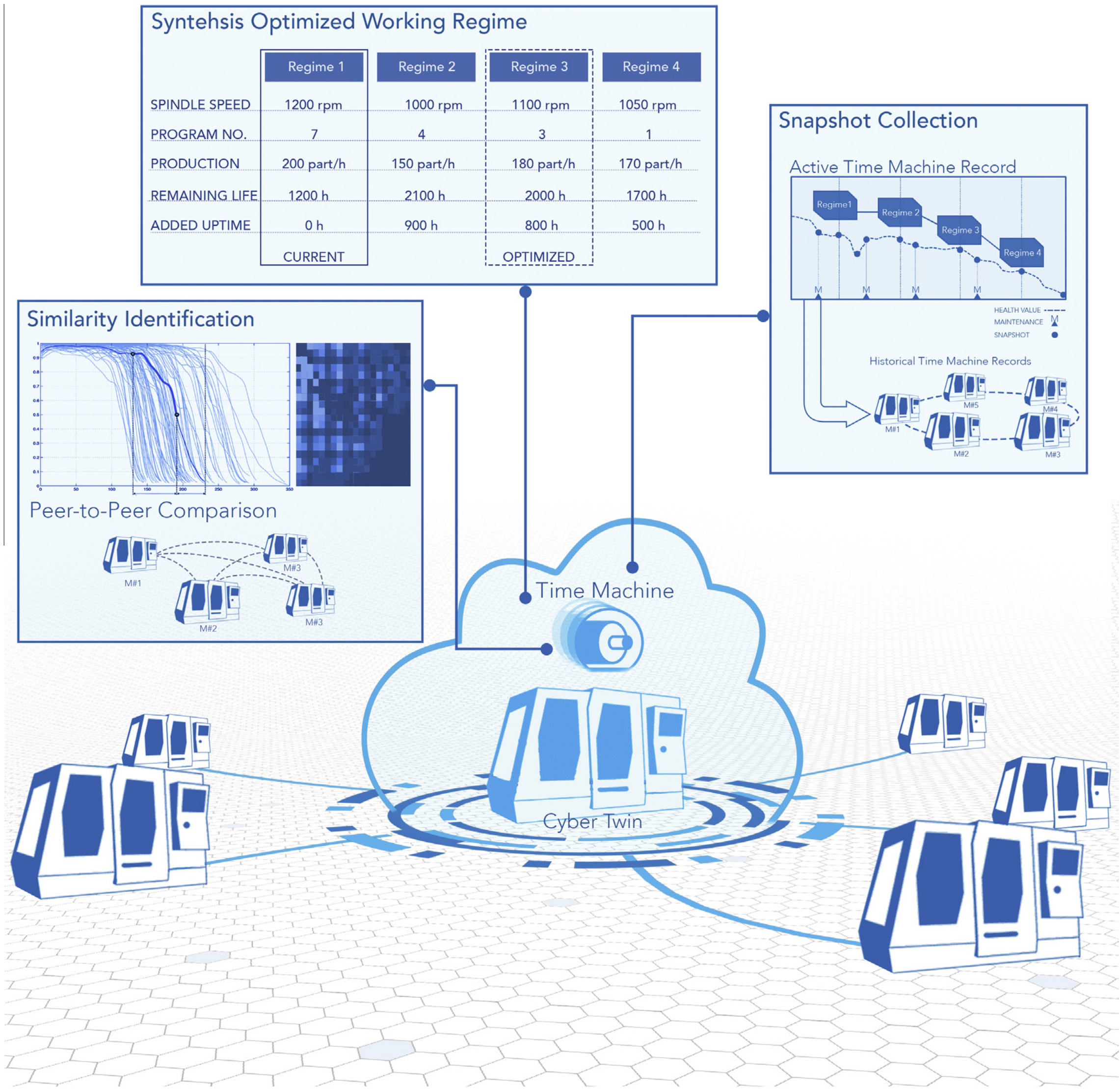

Fig. 3. Time machine approach for Cyber-Physical PHM.

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 has 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.

II. *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, trajectory similarity method [11] or various stochastic methods. Once the patterns are matched, future behavior of the monitored system can be predicted more accurately.

III. *Synthesis optimized future steps:* Predicting remaining useful life of assets helps to maintain just-in-time maintenance strategy in manufacturing plant. In addition, life prediction along with historical time machine records can be used to improve the asset

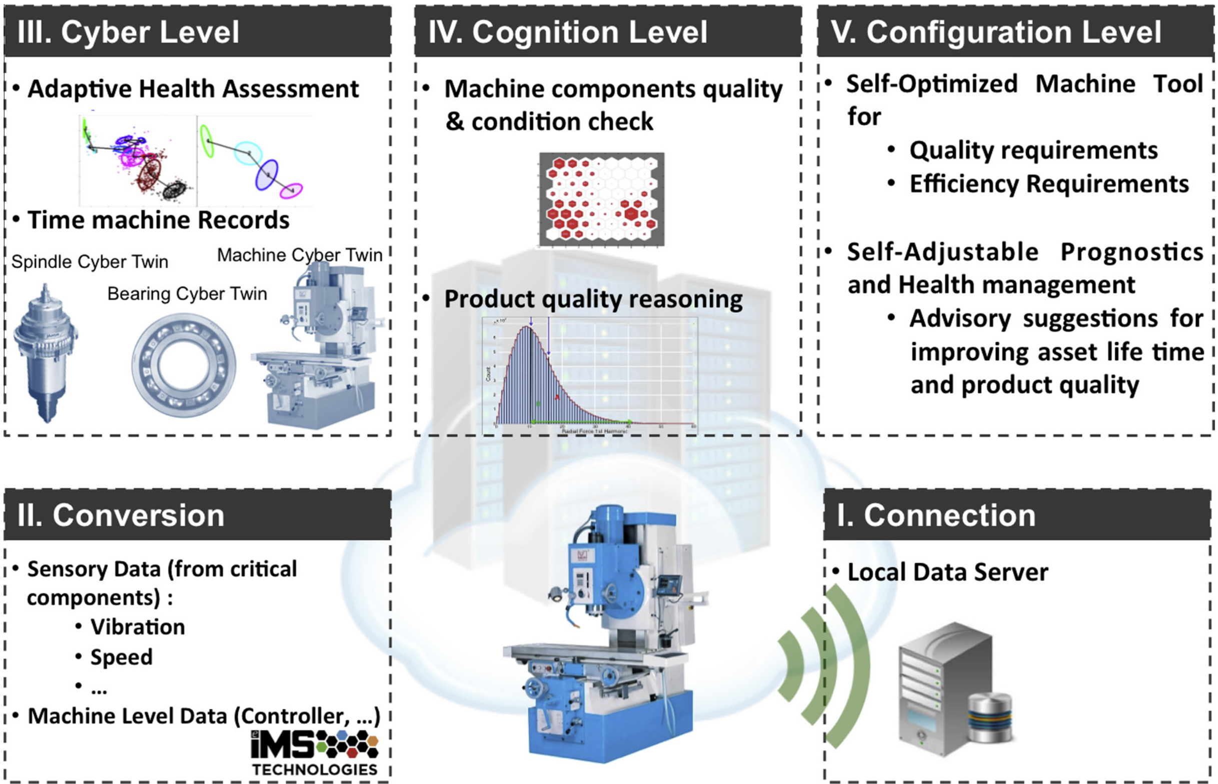

Fig. 4. The flow of data and information in a CPS enabled factory with machine tools in production line based on 5C CPS architecture.

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.

4. Implementation of 5C CPS architecture for factories

Implementing CPS in today's factories offers several advantages that can be categorized in three stages of component, machine and production system that have been introduced in Table 1. Considering a production line consists of a numerous amount of machine tools, the advantages of a CPS enabled company at the aforementioned stages can be observed. At the component stage, once the sensory data from critical components has been converted into information, a cyber-twin of each component will be responsible for capturing time machine records and synthesizing future steps to provide self-awareness and self-prediction. At the next stage, more advanced machine data, e.g. controller parameters, would be aggregated to the components information to monitor the status and generate the cyber-twin of each particular machine. These machine twins in CPS provide the additional self-comparison capability. Further at the third stage (production system), aggregated knowledge from components and machine level information provides self-configurability and self-maintainability to the factory. This level of knowledge not only guarantees a worry free and near zero downtime production, but also provides optimized production planning and inventory management plans for factory management (Fig. 4).

5. Conclusions

This paper presents a 5C architecture for Cyber-Physical Systems in Industry 4.0 manufacturing systems. It provides a viable and practical guideline for manufacturing industry to implement CPS for better product quality and system reliability with more intelligent and resilient manufacturing equipment.

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