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CPS MODELING FOR SMART FACTORY IMPLEMENTATION

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Abstract. *In order to realize the fourth industrial revolution, the convergence of digital and physical worlds is highly required. Cyber Physical System (CPS) is an integrated system that combines physical and cyber components where relevant functions are realized through the inter-connection and collaboration among the components. For the successful implementation of a smart factory, connectivity is essential, and thus digital twin plays an essential role in this regard. In this paper, CPS modeling for smart factory is proposed for the domain of production and manufacturing system. A reference model and architecture is reported considering a real system. The CPS model for smart factory is implemented in the laboratory level.*
Keywords: Cyber physical system, Smart factory, Digital twin, Big data analytics

1. **Introduction.** A smart factory is defined as a fully-integrated, collaborative manufacturing system that responds in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs [1]. The key features for implementing a smart factory are near-real time, self-optimization, self-adaptation, automation, and big data analysis. Smart factory can operate not only within the four walls of the physical factory, but also connect to a global network of similar production systems or cyber worlds based on IoT (Internet of Things) infrastructure [2]. In order to realize the smart factory, connectivity and sensor network are essential in the physical and cyber worlds. The concept of Cyber Physical System (CPS) plays a key role for the connection and sensor network.

CPS is an engineered system of synergistically integrating physical and computational components. As the computational components are aware of their physical context, they are intrinsically distributed, (time)-synchronizing, have to cope with uncertainty of sensor input and need to produce real-time reactions [3].

In the smart factory domain, CPS can be implemented via the concept of a digital twin. A digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object or process that helps optimize business performance. The digital twin is based on massive, cumulative, real-time, real-world data measurements across an array of dimensions. The five enabling components of digital twin are sensors and actuators from the physical world, integration, data, and analytics from the cyber worlds [4].

The purpose of this paper is to propose a smart factory CPS model for specific domain based on digital twin. The proposed framework is applied to the manufacturing domain in the laboratory level.

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2. **Previous Research.** CPS model and its implementation have been tried in various perspectives. An analytical description of a digital twin architecture reference model for the Cloud-based Cyber Physical Systems (C2PS) has been described in [5]. In the model, every physical thing accompanies a hosted cyber thing in the cloud. Two things can establish mutual connections either through direct physical communications or through indirect cloud-based digital twin connections. The key properties of CPS are computation, communication, and control [6].

Connected factory is typically characterized by a hierarchical structure, which is an "automation pyramid". It is composed of three layers: data acquisition layer, local control alter, and service layer.

Sensor, actuator data and machine log data in the shop floor are inputs to local control later. In the middle loop, Programmable Logic Controller (PLC), Micro-Controller (MC), and Industrial PC (IPC) are names of mediator. In the service layer, there are Supervisory Control And Data Acquisition (SCADA) networks, Manufacturing Execution System (MES), and Enterprise Resource Planning (ERP) [1]. SCADA is a control system architecture that uses computers, networked data communications and graphical user interfaces for high-level process supervisory management.

Transferring those comprehensive data from the Operational Technology (OT) systems in the shop floor to the Information Technology (IT) systems at the top floor would require special methodologies and techniques for big data analytics. The above mentioned concept of automation pyramid is illustrated in Figure 1.

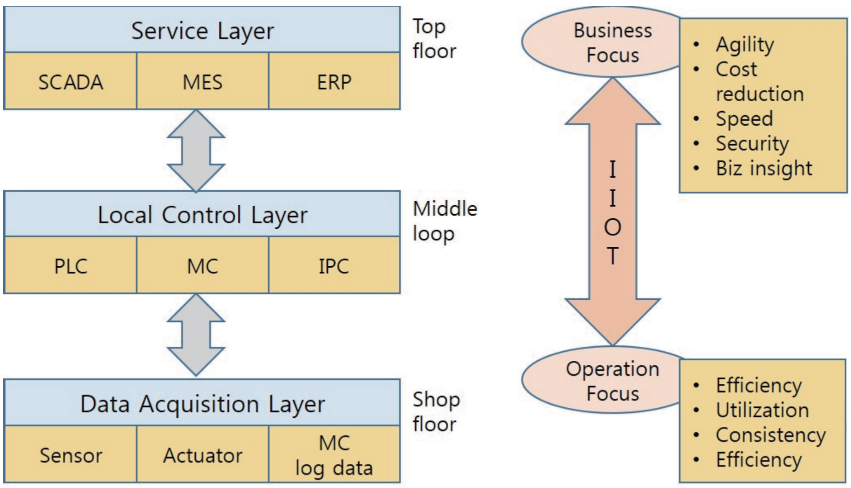

FIGURE 1. Automation pyramid composed of three layers

The above architecture corresponds to computation/communication platform, software platform and physical platform. In CPS, essential system properties such as stability, safety, and performance are expressed in terms of physical behavior [4].

A prototype of IoT enabled smart factory in the domain of industrial vinyl film manufacturing has been reported in [7]. The quality problem in the industrial vinyl has been tackled using sensor network. The simulated line is constructed by steel guide, one transparent water bottle, two Arduino boards, three Zigbee and two ultrasonic sensors.

With the rapid development of ICT, network and sensor technologies, there is high demand in the realization of smart factory in the industry [8]. However, the real situation is far behind for the implementation of smart factory in the manufacturing cell and production line because the production line is based on the physical world with many real and physical constraints. In this respect, we can propose a few points to realize the smart factory. They are as the following.

1) What are the key features of a smart factory?

2) What are the components and technologies that comprise the smart factory?
3) What is the methodology?

3. Architecture and Modeling.

3.1. CPS architecture. Key features of smart factory are connectivity, optimization, transparency, proactivity and agility [3]. Smart factories require the underlying processes and materials to be connected to generate the data necessary to make real-time decisions. The optimized smart factory can increase yield, uptime, quality, as well as reducing costs and waste. A transparent network can enable greater visibility across the facility and ensure that the organization can make more accurate decisions by real-time alerts and notifications, and real-time tracking and monitoring. The proactive feature enables advance identifying and warning of anomalies, quality issues, safety and maintenance concerns. Self-adaptation to schedule and product changes is available by agile features.

The scheme of smart factory control and monitoring system based on digital twin works as the following. All the features of smart factory with sensors, network, and legacy system are mirrored in the tablet or PC which is integrated with big data analytics in the cloud or main server. All the actions and tasks in the production and manufacturing cell are monitored transparently in the tablet or PC with real time. Based on big data analytics, quality issue or facility problem is forecasted or prevented proactively. The results of big data analytics are fed back to the industrial field to monitor and control the process.

Figure 2 shows the CPS architecture composed of physical and digital worlds. In the physical world, various sensor data are acquired via wireless and wired sensor network. It is a hardware-dependent processes with embedded system, multi sensors and IIoT (Industrial Internet of Things). In the cyber world, ERP, MES, SCM (Supply Chain Management), QMS (Quality Management System) and data analytics work to implement IoS (Internet of Service). These correspond to legacy in the manufacturing industry.

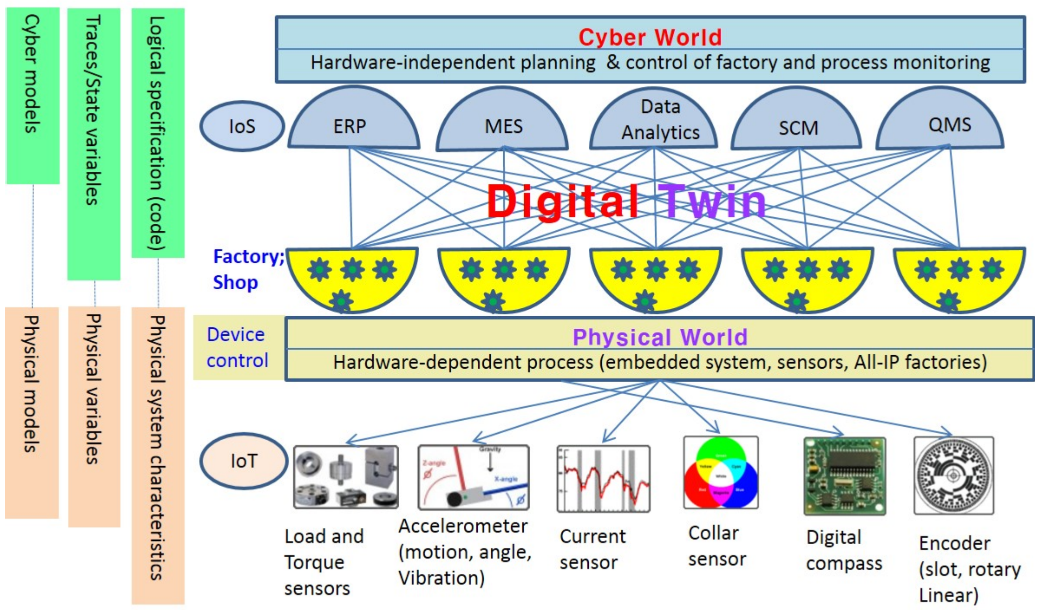

FIGURE 2. Conceptual CPS architecture

3.2. CPS modeling. The proposed CPS architecture can be modeled based on Finite State Machine (FSM). The cyber and physical systems are composed of sensor, actuator, functional unit, event, interface, power and repository [5]. The transition from cyber to physical system is modeled through FSM.

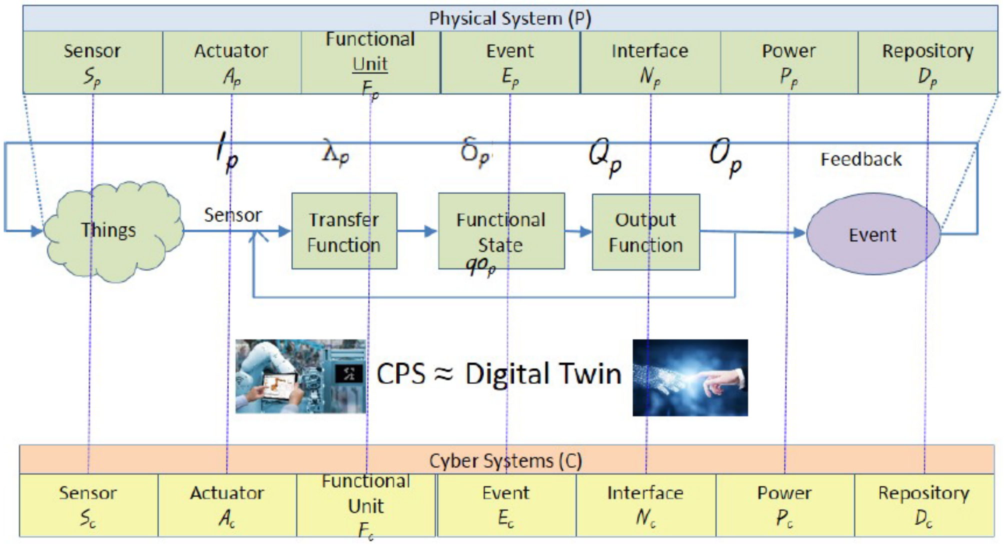

FIGURE 3. CPS modeling expressed in FSM

The FSM is composed of input, transition function, functional states, output function, and event (output). The cyber world is connected with physical world through FSM and vice versa. The concept of CPS modeling described above is shown in Figure 3.

The CPS modeling is composed of physical system (P), cyber system (C), and hybrid system (H). Each model is described as the following.

- Physical System (P)

Physical things $p \in P$ is composed of seven components.

$$p = (S_p, A_p, F_p, E_p, N_p, P_p, D_p)$$

where S_p: Sensor, A_p: Actuator, F_p: Functional unit, E_p: Events, N_p: Interfaces, P_p: Power supply, D_p: Data storage.

$$P \equiv \{p_i,\ i = 1, 2, \ldots, |P|\}$$

Following the definition of Moore's Finite State Machine,
Functional unit, f_p ($f_p \in F_p$) is defined as follows;

$$f_p = \left(Q_p, I_p, O_p, q_p^0, \lambda_p, \delta_p\right)$$

where Q_p: Infinite states, I_p: Input function, O_p: Outputs, q_p^0: Initial states, λ_p: Transfer function, δ_p: Output function.
Event $O_p \subseteq E_p$

$$\lambda_p : Q_p \times I_p \to Q_p$$
$$\delta_p : Q_p \to O_p$$

- Cyber System (C)

Cyber things $c \in C$ can be modeled similar with the physical system.

$$c = (S_c, A_c, F_c, E_c, N_c, P_c, D_c)$$

Functional unit, $f_c = (Q_c, I_c, O_c, q_c^0, \lambda_c, \delta_c)$.

- Cyber-Physical Hybrid System (H)

Cyber-physical things $h \in H$ and functional unit f_h can be modeled similar with physical system and cyber system.

$$h = (S_h, A_h, F_h, E_h, N_h, P_h, D_h)$$
$$f_h = \left(Q_h, I_h, O_h, q_h^0, \lambda_h, \delta_h\right)$$

The key technology in the architecture is big data analytics utilizing sensor data. Data mining and big data analytics methodology will be utilized to analyze big data with fast process. Prediction, classification, association algorithms will be adopted for big data analytics. Visualization of big data helps decision makers for capturing the quality problems and management issues quickly.

The implementation steps of smart factory based on CPS are sensor data creation, communication between physical process and digital platform, data aggregation, analysis and visualization, insights from analytics, action back to the physical world. The above steps are repeated over different processes or operations.

4. **Implementation.** The proposed CPS model will be realized as the following process. First, choose a production or manufacturing process in which site monitoring is required. Second, according to the requirement of the process, needed sensor type is decided and attached to the process. This is the realization of IoT techniques. Third, the sensor data is gathered and transferred to the cloud where data is gathered and analyzed. Fourth, real-time monitoring is executed through sensor network process and management. At the same time, big data analytics is performed based on cumulative sensor data with statistical analysis. Fifth, through the real-time monitoring process, if any anomaly or strange data is recognized through the monitoring process, a warning message is transferred to the system manager or operator.

This process is implemented as the following. In the factory operation site, multi sensors are attached in the machining center or assembly process. Some sensor data are gathered and processed within the sensor system with embedded capabilities. Most of the data are transferred to the fog layer. This framework is tested using an IoT system module which is available in the market. Figure 4 shows the CPS architecture composed of three layers. By analyzing the multi sensor data in the fog or cloud level, an alarm or warning message is provided if the sensor data reach the predefined level or line.

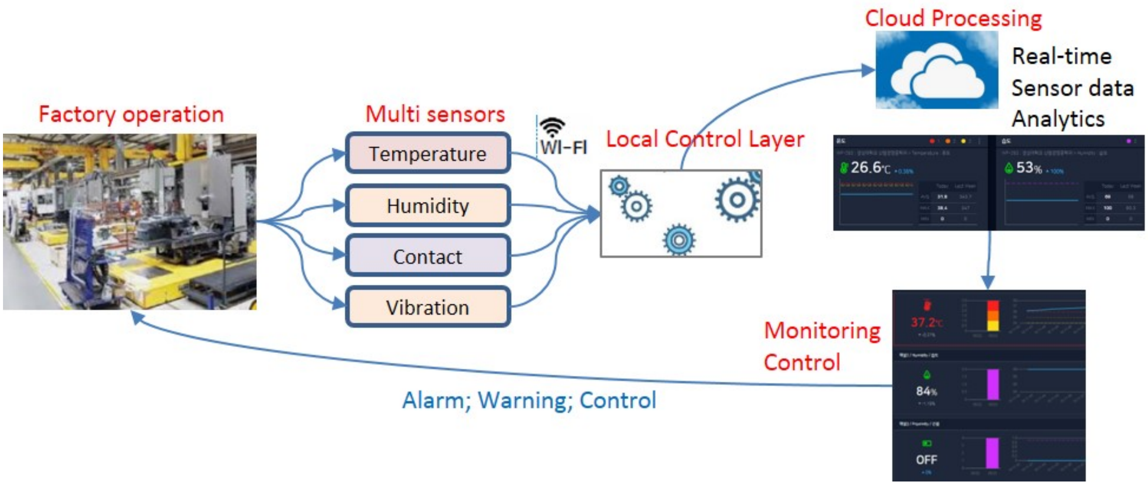

FIGURE 4. CPS implementation architecture composed of three layers

Figure 5 shows multi sensor system with four sensors. They are temperature, humidity, contact and vibration sensors. Figure 6 provides monitoring results from multi sensors via cloud computing.

Measuring the validity of smart factory implementation is not an easy work because the result is shown by the realization of smart factory framework. Even though, a few approaches are reported for the validity of implementation. One is maturity model for leveraging digitization [9]. Under three overarching areas such as people, process, and technology, four levels of maturity model are proposed. They are connected technology,

FIGURE 5. Sensor monitoring system (Temperature, Humidity, Proximity, Vibration)

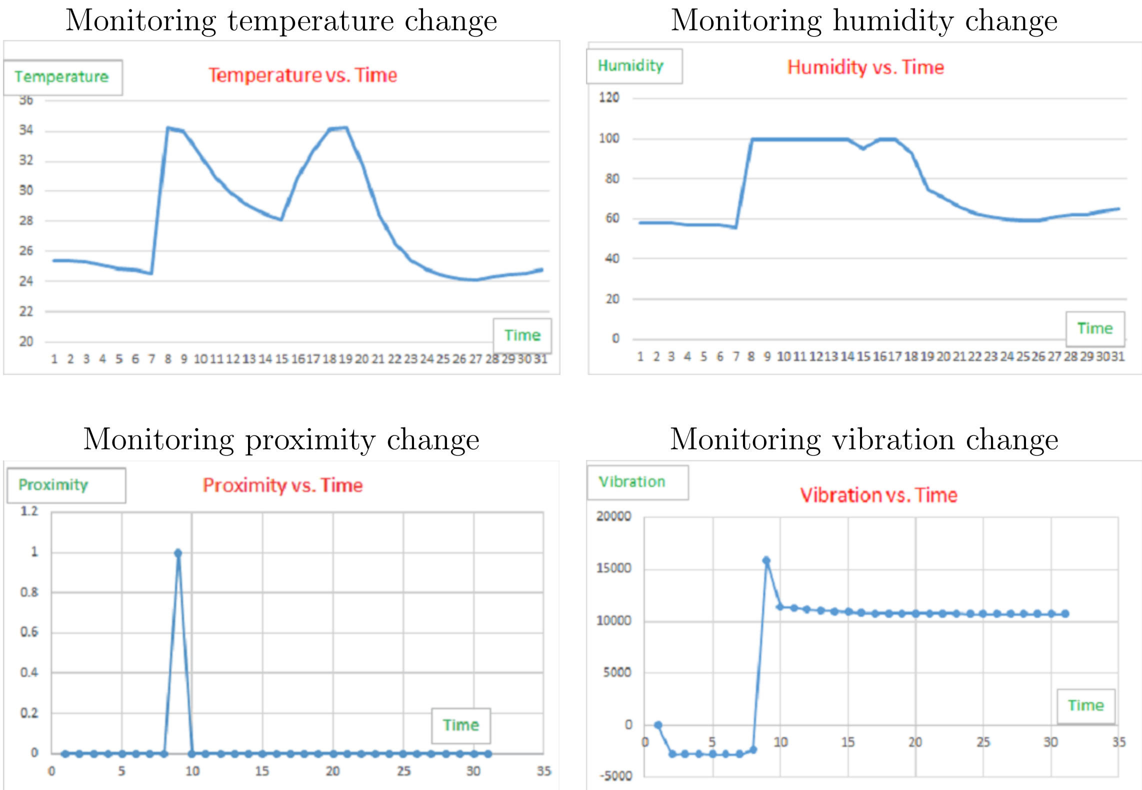

FIGURE 6. Monitoring data anomaly from multi sensor data

structured data gathering and sharing, real-time process and optimization, and smart predictable manufacturing. Another approach is smartness assessment based on ANP (Analytic Network Process) [10]. They proposed assessment framework which consistes of 4 criteria, 10 sub-criteria, 48 assessment items. The ANP model is applied for the 20 SMEs in Korea. Thus, the validity of smart factory implementation of this paper can be proved if several use cases are added based on this framework in the near future.

5. **Conclusions.** A CPS architecture and modeling for smart factory is proposed. The model is implemented with four sensors, namely, temperature, humidity, proximity and vibration in the laboratory level. The sensor data are gathered and transferred to the cloud, where big data analytics has been performed. If any data with significance is

identified for the process, the status can be fed back to the process and any control action can be performed immediately.

The proposed system can be implemented in the production and manufacturing domain in the real world. The IoT and sensor network are essential for the realization of smart factory and industry 4.0.

Further research is required that the smart factory CPS model need to be more generic and applicable architecture. The production and manufacturing fields differ according to the domain. The model will be revised through iterative testing and implementing for the industry sensor data in the manufacturing field. A generic model can be applied in various domains with a minor customization.

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REFERENCES

[1] IIC, Smart factory applications in discrete manufacturing, *White Paper*, 2017.
[2] Y. Lu, K. C. Morris and S. Frechette, Current standards landscape for smart manufacturing systems, *NISTIR 8107*, pp.1-39, 2016.
[3] H. Giese, B. Rumpe, B. Schatz and J. Sztipanovits, Science and engineering of cyber-physical systems, *Reports from Dagstuhl Seminar 11441*, www.dagstuhl.de/11441, 2011.
[4] G. Karsari, Modeling cyber physical systems: Challenges and recent advances, *Working Seminar Mateiral*, 2015.
[5] K. M. Alam and A. E. Saddik, C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems, *IEEE Access*, vol.7, pp.2050-2062, 2017.
[6] E. A. Lee and S. A. Seshia, *Introduction to Embedded Systems: A Cyber Physical Systems Approach*, 2nd Edition, The MIT Press, 2017.
[7] H. Lee and T. Kim, Prototype of IoT enabled smart factory, *ICIC Express Letters, Part B: Applications*, vol.7, no.4, pp.955-960, 2016.
[8] Deloitte, *Industry 4.0 and the Digital Twin*, Deloitte University Press, 2017.
[9] D. R. Sjodin, V. Parida, M. Leksell and A. Petrovik, Smart factory implementation and process innovation: A preliminary maturity model for leveraging digitalization in manufacturing, *Research-Technology Management*, vol.61, no.5, pp.22-30, 2018.
[10] J. Lee, S. Jun, T. Chang and J. Park, A smartness assessment framework for smart factories using analytic network process, *Sustainability*, vol.9, no.5, pp.1-15, 2017.