

A CPS-Based IIoT Architecture Using Level Diagnostics Model for Smart Factory

Byungjun Park and Jongpil Jeong(✉)

Department of Smart Factory Convergence, Sungkyunkwan University, Suwon, Gyeonggi-do 16419, Republic of Korea
{bjunpark,jpjeong}@skku.edu

Abstract. In this paper, a construction process using a level diagnostic agent was applied to the construction of a smart factory. The current status of the smart factory of the demanding company was measured and the target level was derived, and a cps-based design of the smart factory construction type was proposed. It is suggested that the construction of a CPS simulation based smart factory is more effective in preparation for cloud based smart factory manufacturing in the process of informatization, automation, and intelligence of the smart factory due to the explosive increase of data. In this paper, a Korean-type smart factory adopting an empirical research method that activates the actual construction cases of smart factory level diagnosis according to the basic components of the smart factory, information, automation, and intelligence, and the present examples of each smart factory level as an empirical case.

Keywords: CPS · Industrial Internet of Things (IIoT) · Level diagnostics model · Smart factory

1 Introduction

Smart Factory means a consumer centered intelligent factory that combines next generation digital new technologies and manufacturing technologies that go beyond the existing Factory Automation (FA) level. Various products can be produced in one production line, and it is expected to change from mass customization to individual flexible production system through modularization [1]. The transition to the smart factory is expected to dramatically improve the productivity of the manufacturing industry, and it is also possible to save energy and realize a human centered work environment. It is predicted that it is possible to monitor the manufacturing site in a virtual space and to control it, so that it is easy to manage the plant and to strengthen quality and cost competitiveness [2]. The smart factory, which is a core element of the IIoT(Industrial Internet of Things) trend, aims to realize an intelligent manufacturing factory that finally performs optimization of the smart factory through the informatization and automation of data [3]. Through IIoT, various types of industrial

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equipment are used as production nodes. Smart factories no longer exist as independent data through the generation, accumulation, and processing of big data generated in the field, and data can be converted and upgraded through connection and convergence. The network manufacturing process can be accelerated. The recently built smart factory aims to continuity of manufacturing process production data and accumulation of key process variable data for each process through cloud computing based on the use of the internet [4]. The composition of the thesis is presented in Chap. 2, the current status and target level of the Smart Factory in Korea and the level diagnosis system. In Chap. 3, the CPS-based IIoT smart factory construction model is introduced, and in Chap. 4, the case study. The case of a smart factory running a CPS-based automated production platform is presented, and in the last Chap. 5, the significance of the paper and the direction of future research are presented.

2 Related Work

The establishment of smart factories in Korean SMEs is more appropriate than the system approach, unlike large corporations, where the factory level diagnosis and the smart factory uptake approach are appropriate. Therefore, in this paper, we will diagnose the smart factory basic level, intermediate level and advanced level according to the field level diagnosis, and propose a plan to build the smart factory at the target level.

2.1 Smart Factory in South Korea

Building a Korean smart factory has achieved the quantitative goal of building 30,000 small and medium-sized SME smart factories in 2022 thanks to the government's support policy, and it is necessary to achieve the goal of establishing an empirical Korean smart factory standard construction process. Accordingly, the direction of building a smart factory in Korea presents an effective construction process that implements the characteristics of data informatization, process automation, and autonomous process enablement, which are necessary to convert from a factory oriented factory level to a smart factory, and has a process to achieve this. Smart Factory means a consumer centered intelligent factory that combines next generation digital new technology and manufacturing technology that goes beyond the existing Factory Automation (FA) level. Various products can be produced in one production line, and it is expected to change from mass customization to individual flexible production system through modularization [5]. The transition to a smart factory is expected to dramatically improve the productivity of the manufacturing industry, and it is also possible to save energy and implement a human centered work environment. It is predicted that it is possible to monitor the manufacturing site in a virtual space and to control it, so that it is easy to manage the plant and to strengthen quality and cost competitiveness.

2.2 Level Diagnosis Model

In the CPS-based smart factory construction, the level diagnosis model consists of a total of 6 stages of the smart factory construction stage, the first stage is the ICT non-application stage, the second stage is the partial standardization and management of performance information, and the third stage is real time monitoring of production information. Possible stages, 4 stages are the steps to analyze and control the collected information, 5 stages are possible for proactive response and decision optimization through simulation, and the last 6 stages are intelligent stages that can be operated autonomously from monitoring to control and optimization. Table 1 defines the conditions and construction stages of the smart factory level verification model.

Table 1. Smart factory level confirmation system

Ranking	**R**eference model	**C**haracteristic	**C**onditions (building level)	**S**core
Level 5	Advancement	Customized & Autonomy	Autonomous operation from monitoring to control and optimization	950 above
Level 4	Medium 2	Optimized & Integrated	Optimization and decision making through simulation	950 above
Level 3	Medium 1	Analyzed & Controlled	Control by analyzing collected information	950 above
Level 2	Basic 2	Measured & Monitored	Real-time monitoring of production information	950 above
Level 1	Basic 1	Identified & Checked	Partial standardization and performance information management	950 above
Level 0	ICT not applied	Unrecognized&unapplied	Unrecognized and ICT not applied	950 above

The smart factory level diagnosis model consists of 44 items in 10 categories and 4 areas including leadership and strategy, product development, information system and automation. Table 2 shows the details of the smart factory level confirmation model.

It is organized in 6 grades from level 0 to level 5 from basic level to advanced level. The evaluation according to the Korean smart factory level diagnosis system leads to the leadership and strategy, product development, process information system up to the smart factory upgrade level requested by the demanding company through on-site diagnosis by process by the consultant visiting the site at the request of the demanding company. This is accomplished by cross-checking 44 items in 10 categories and 4 areas including automation.

Table 2. Smart factory level confirmation system

Division	Evaluation area	Main Content	Number of evaluation items
Management system (100)	1. Leadership & Strategy	Leadership, operational strategy, execution management, performance management and improvement	8
Process (400)	2. Product development	Design and production, development management, process development	12
	3. Production Planning	Standard information management, demand and order response, production plan	5
	4. Process Management	Work allocation, work progress management, abnormal management, work management	5
	5. Quality Management	Prevention, correction, screening and standard management, inspection test	12
	6. Facility Management	Equipment operation, equipment maintenance, electronics, mold and jig management	6
	7. Logistics operation	Purchase outsourcing management, warehouse management, shipment delivery	7
System and Automation (400)	8. Information system	ERP, SCM, MES, PLM, EMS etc.	20
	9. Equipment control	Control model, control flexibility, self diagnosis, network method, support equipment	10
Performance (100)	10. Performance	Productivity, quality, cost, delivery, safety and environment, conservation	12
Sum (1,000)	It consists of 95 evaluation items in 10 modules		95

3 CPS-Based IIOT Architecture for Smart Factory

3.1 A. System Architecture

Currently, most smart factories are based on cloud design [6]. Many of the smart factory architectures involved in manufacturing production are based on these designs, and users of these architectures have access to a shared manufacturing platform. Resources needed anytime, anywhere in a smart factory, fast configuration [7]. This is because resource management is essential. In a cloud-based smart factory, the centralized architecture is very weak [8]. That is, if the central node is compromised, all services are suspended. For that reason, we propose a CPS-based IIoT architecture with the goal of building node supervision and distributed systems to back up all service disruptions, and the architecture of these smart factories is shown in Fig. 1.

The architecture has three tiers. Data detection layer generated in the field of factory, data hub that senses and manages this data through Raspberry Pi, and storage layer that stores it, and firm ware application layer that utilizes various data for processing and purpose through visualization. It consists of 3 layers. The first layer, the data-sensing layer, includes various types of sensors, and one or more microcomputers with specific computing power can obtain various equipment and preprocessing information. The second layer, the data collection and storage layer, stores the collected data, while in conjunction with the management hub layer, analyzes the uploaded data and packages the data

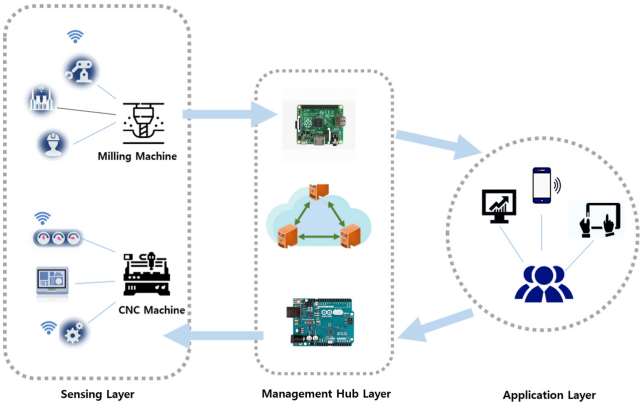

Fig. 1. CPS-based IIoT architecture for a smart factory

to store it in a database. The third layer is a data utilization layer that provides users with various data processing services such as visualization and equipment failure prediction that can be monitored in real time.

3.2 Description of Components

The proposed architecture is divided into two types: intranet and extranet. The intranet aims to collect and store data generated at the manufacturing site, and the extranet aims to use the collected data to provide other data users for visualization data or failure prediction purposes. Intranet consists of data detection layer, data storage and management layer. The data generated by manufacturing equipment at the manufacturing site stored in the intranet is managed by the management hub of each equipment node. Data flow information that is input to the manufacturing line and processed along the line is measured and stored in connection with the sensing node. Figure 2 describes the user friendly data processing analysis road that occurs in intranets and extranets according to data generation, accumulation, and processing in smart factory construction.

The extranet has a major difference between the data management and storage layer and the application layer. Extranets are intended for users who utilize data collected and accumulated, while intranets are intended for data production equipment at the manufacturing site. Therefore, what is required in the extranet is to secure the stability connected to the Internet to always detect the generated data inside the smart factory, and through this, provide services to users such as visualization programs that can utilize data and reasonably access it. It is to provide a variety of ways to provide. Through this, the data user can obtain various processing information related to the production information of the manufacturing site according to the user's demand, and guarantee the high quality of service reflected in real time. Figure 3 displays intra extranet process flowchart.

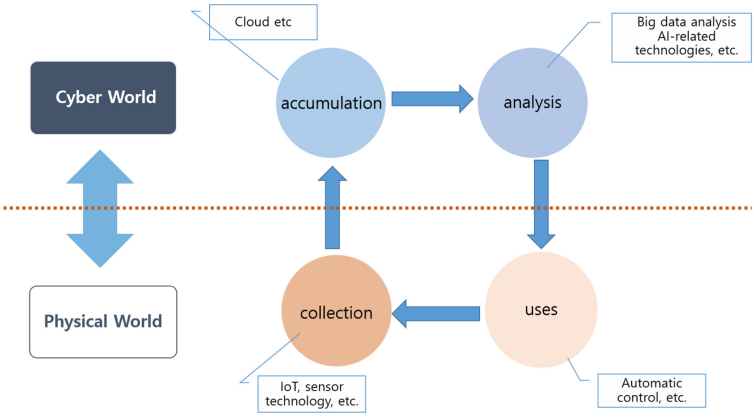

Fig. 2. Intra-extranet data analysis process

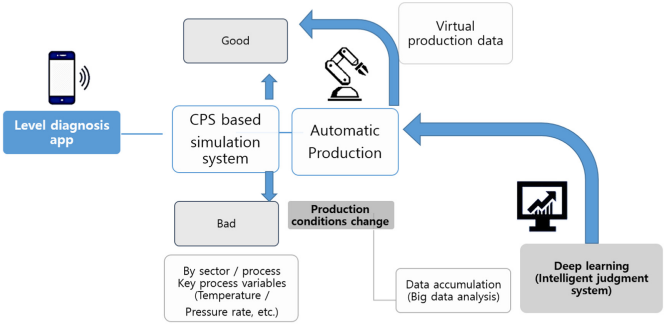

Fig. 3. Process flowchart

In the CPS(Cyber Physical System)-based smart factory building system, a series of processes appearing in the production consistent process line are linked to other smart factories' regional hub factories that perform the same process through data monitoring and real time hub layer data storage and sharing, and the production work is performed in parallel. Twin system technology is attracting attention as a core technology that can solve various social problems and is promoting the growth of related industries [9,10]. Figure 4 explains about CPS relating to Twin System.

The 'digital twin system', a technology that creates the same digital twins as the physical world, is becoming one of the essential technologies for building a smart factory along with AI(Artificial Intelligence), blockchain, and IoT(Internet of Things) [10]. The decline in price is acting as a catalyst to accelerate the convergence of manufacturing and ICT in the 'trillion sensor era' where more than 1 trillion sensors exist by expanding the grafting area of the digital twin. The digital twin is prominent in the 'manufacturing industry' with the trend change of 'personalized production' [11]. The CPS in the manufacturing field is composed

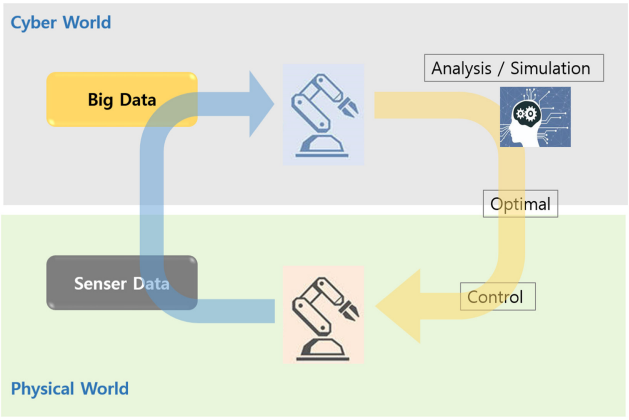

Fig. 4. CPS (Twin System)

of structured digital data such as Operation Technology (OT) systems, namely production information systems (PLM, MES, etc.) and enterprise operating systems (ERP, SCM, CRM, etc.) [12]. By collecting data generated in real time in the production process as a platform, data management system and smart factory self optimization should go beyond the level of managing data by partitions such as each machine, worker, process, and department. The ultimate form of smart factory using cyber physical system technology is digital twin, which is realized by perfectly synchronizing the production activities of the virtual space and the real space [13]. This means that production activities in the real space are accumulated as digital data, and AI analysis technology is applied to it, and intelligent autonomous production activities, that is, defects caused by differences caused by process specific core variables through machine learning, etc. It means that it is possible for factories to learn the patterns themselves and find the optimal solution to defects through accumulated defect data.

4 Case Study: A CPS-Based Automatic Production

4.1 Case Study Overview

T company, which is introduced in Case Study, is a manufacturer of equipment for automobile powertrain (engine/transmission) automatic precision measurement and assembling machines. It is a manufacturing company that manufactures and delivers precision measurement granulators for automobile manufacturing. It is a company that is trying to innovate quality and productivity by converging. In order to build a CPS-based smart factory, we present the process of sensing and storing the data controlled by the line in a digital twin method in the same way as the actual manufacturing process in multiple factories.

First, we diagnosed the current level of T company's smart factory through the smart factory level diagnosis app for manufacturing managers of T company,

and then established the process by deriving the target level of smart factory through site visits to the factory and promoting the process improvement direction for this.

4.2 Level Diagnosis Results

As a result of the level diagnosis of T company, it was found to be at a level of 3 levels, which showed a relatively high level in the process management technology and logistics operation technology field compared to the industry. The evaluation factors of level comparison are 10 categories, such as leadership strategy, product development ability, production planning, process management technology, quality management technology, facility management technology, logistics operation technology, system information level, facility automation level, management performance. Figure 5 explains T company smart factory level diagnosis result. The areas that showed the highest position were the process management technology field and the facility management technology field, which are identified as the main reason for T company's CPS-based process construction. The results of the diagnosis were found to be relatively vulnerable in the areas of product development capability and business performance. This is attributed to the fact that the product portfolio of a single type of manufacturing industry is monotonous and the weakness of aggressive sales activities. Accordingly, T company is constructing a smart factory with the goal of level 4 level diagnosis in the direction of expanding the smart factory construction project based on the accumulated technology in the process management technology field, which is a strength.

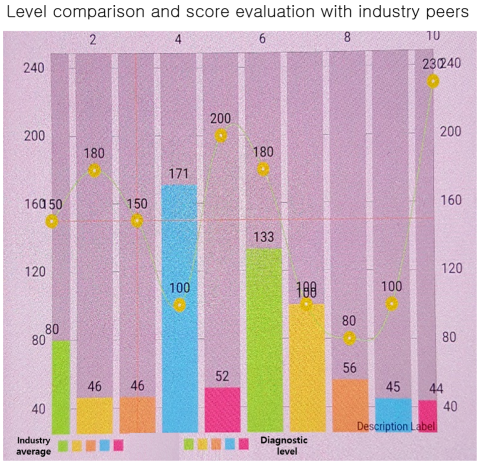

Fig. 5. T company smart factory level diagnosis result

4.3 CPS-Based System Construction

Based on the proposed construction model, the manufacturing production line automation process verified the effectiveness of CPS-based smart factory construction in industrial manufacturing sites. This company has been producing various quality and productivity innovation facilities for a long time in the field, and now has developed the artificial intelligence smart factory platform, which can produce and connect various data by integrating ICT technology with facilities. This platform acts with the goal of quality and productivity innovation by interacting together with products, organizations, companies, technologies, cultures, etc., each with its own value. Figure 6 explains an automatic production platform according to the proposed architecture.



Fig. 6. Automatic Assembly Line

Figure 7 displays architecture of the automatic production platform. Raspberry Pi is attached to a production node that senses data in a field in an automated assembly process line. It can be seen that the data is accumulated in the management hub, and the process is efficiently improved by accumulating temperature and process working time delays or poor process occurrence phenomena such as pressure differential generated in this process and visualizing it through visualization processing.

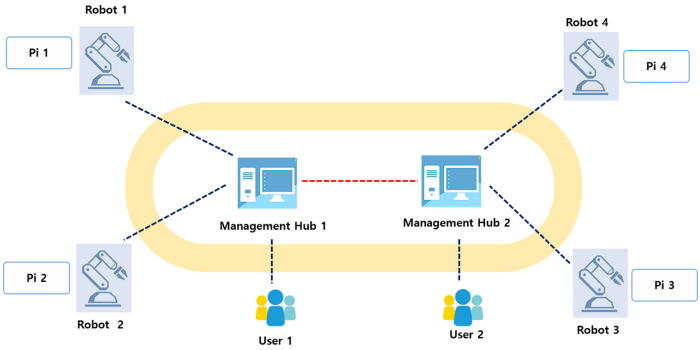

Fig. 7. Example of the automatic production Line platform

5 Conclusion

The CPS-based smart factory construction model using the proposed level diagnostic system shows that it is possible to build a more effective intelligent smart factory compared to the existing cloud based construction. The main contribution of this work is an innovative production oriented approach to CPS-based system. In particular, in the expansion of smart factory construction, the key process variables for each production and manufacturing process through data management which is the process of intelligent smart factory construction, through data informatization and big data analysis through data accumulation and analysis. Through the simulation system, it is shown that the intelligent judgment system enables customized manufacturing processes through virtual production data. Future research tasks include proactive response and decision making through simulation to increase the probability of preliminary preservation. It will be a process identification for the smart factory intelligent process from smart factory monitoring to control and optimization operation, such as scenario optimization.

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