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Framework and development of fault detection classification using IoT device and cloud environment

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ABSTRACT

While Cyber-physical system (CPS) is considered as a key foundation for cyber manufacturing, many related frameworks and applications have been provided. This research suggests a new and effective CPS architecture for supporting multi-sites and multi-products manufacturing. As target processes, the manufacturing processes for vehicles' High Intensity Discharge (HID) headlight and cable modules are considered. These modules are manufactured with several multi-manufacturing sites consisting of internal manufacturing tasks and intermediate outsourcing processes. In addition, they produce multiple types of HID cable modules with different components. These issues make it difficult to improve the qualities of the overall processes and to control those considering overall manufacturing plants and processes. In order to overcome these limitations, this research provides an Internet of Things (IoT) embedded cloud control architecture. The mixed flow issues are overcome with the cloud control server with the suggested framework. The developed IoT device detects several system status and transmits the signals. The data is analyzed for the fault detection classification (FDC) mechanism using deep learning based analytics. Then, the cyber manufacturing based simulation is executed using the provided multi-products queueing network model. The estimated simulation results is used for generating dynamic manufacturing decisions reflecting the real-time changes of the production environment. The suggested framework and its implementations can be used for various industrial processes and applications.

1. Introduction

Contemporary manufacturing environments have been changed drastically with fierce competitions. These changes are resulted from the fact that customers' demands are being advanced more and new service requirements are being created. In order to meet these demands and to compete against rival companies, the new and effective manufacturing processes and environments [1,2,3] have been suggested in many research studies and industrial applications. While these plans and efforts have received considerable emphasis, several governments proposed the nationwide manufacturing blueprints and their detailed master plans (e.g. Germany's "*Industrie 4.0*", The USA's "*Advanced Manufacturing Partnership 2.0*", and Japan's "*Strategic Innovation Promotion Program*"). The common thoughts in these slogans are the materialization of Smart Manufacturing and Factory. While these plans have been evolved and realized from an immature stage to the detailed execution levels, related hardware/software technologies [4,5,6] accelerated the spread of these blueprints and the speed of the implementations. IoT technologies, data mining/big data methodologies and cloud computing are the leading technologies for Smart Manufacturing.

Cyber-physical system (CPS) and cyber manufacturing are the core concepts for Smart Manufacturing. Compared with the existing factory automation and monitoring/control systems, a general smart factory equips three modules: (1) a physical system, (2) a cyber system with simulation/analytic functions and (3) their integrations. What cyber manufacturing is focusing on is the integrations between both systems (physical and cyber systems). When it is compared with other traditional manufacturing control concepts, the cyber manufacturing emphasizes the simulation and prediction functions. In a smart factory, several manufacturing scenarios and what-if cases are simulated and tested with information gathered from the real physical system. This research elaborates on the architecture and its implementations of the new and effective cyber manufacturing. A CPS with cyber manufacturing functions is implemented using the mentioned embedded system technolo-

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gies and related analytics. As a test bed, this research considers the manufacturing and assembly processes for High Intensity Discharge (HID) cable module, one of the principle components in vehicles. These processes consist of several manual tasks and automated processes. In addition, the production flows includes internal manufacturing operations in a factory and other intermediate outsourcing flows in several subcontractors. As several vehicles use different headlight cable modules, the processes handle many different components modules. It indicates that the overall processes are the multi-products processes. With these exemplary processes, this research suggests a new and effective CPS architecture and provides how cyber manufacturing is achieved using the implemented systems. In particular, this study verifies the effectiveness of the suggested systems with Fault Detection and Classification (FDC) examples.

The following section provides the related backgrounds and literature reviews. Section 3 elaborates on the target processes—the HID manufacturing processes and Section 4 explains the detailed implementations of IoT device and a cloud control environment. Then, Section 5 provides how cyber manufacturing is being performed with the suggested framework and Section 6 explains its FDC contributions using deep learning based analytics.

2. Background and literature review

As mentioned in the previous section, this research suggests a new and effective cyber manufacturing framework with contemporary embedded technologies and analytics such as IoT, Cloud sever and deep learning techniques. This section defines the terms and compares the related existing manufacturing applications with the suggested framework. As CPS is a backbone core in several smart manufacturing architectures, many research studies suggest the various definitions for it and its applications. One of the well-defined definitions is the definition of *National Science Foundation* (NSF). According to NSSF and NSF [7,8], CPS is defined as a system with deeply interacting physical and software components. In general, the roles of the physical components are to monitor real processes and to send meaningful information to the other side (cyber components). The software components or the cyber side platform perform the activities for cyber manufacturing. Cyber manufacturing is a contemporary manufacturing paradigm which focuses on possible risk analyses, what-if manufacturing simulation and scenario-based manufacturing decision makings using on-going data from real physical systems. As most of the factory information is not reflected on the function in real-time, a general simulation software is insufficient for implanting cyber manufacturing. Similarly, as existing factory automations and monitoring systems lack simulation and prediction functions, they are distinguished with a cyber manufacturing system. These integrations and interactions between physical sides and cyber sides are crucial for successful cyber manufacturing. Even though these concepts have been suggested in many academic and industrial fields, there have been the lagging implementations. The main reason is resulted from insufficient technologies for covering overall fields—physical system, cyber system and mutual interactions.

With the startling progress of Information and Communication Technologies (ICT), CPS and cyber manufacturing have been implemented fast. Khaitan and McCalley [5] introduces several CPS applications and their used technologies. Herterich et al. [3] analyzes the impacts of CPS in industrial service fields as well as in manufacturing fields.

Among many ICT, IoT technologies are considered as the core technologies for implementing CPS. According to Evans [9], the early version of IoT device is the system combining RFID and emerging sensing technologies. Zhong et al. [4] developed a real-time manufacturing execution system using RFID technology. In general, IoT device measures several signals using embedded sensors and transmits them to a control severs with data storage. The transmitted signals are analyzed using data mining related analytics. Then, appropriate actions are taken. Many contemporary household devices are equipping with these IoT enabled modules.

These trends are reflected in various industrial fields. The most popular IoT based industrial area is a quality control area [10]. For instance, the processing and defect data are detected using IoT sensors. Then, an analyzing system clarifies FDC mechanisms for improving qualities. Early concepts, methodologies, histories and related applications of FDC are reviewed by Venkatasubramanian et al. [11]. The original purpose of FDC is to monitor the existing manufacturing processes and it is linked to the control stages with the equipped manufacturing execution system (MES). When an abnormal state is detected using FDC systems, several causes might be identified using data mining techniques and controlled to the normal state. These functions are expanded with several prediction techniques. The equipment of these methods makes it possible to predict potential errors and causes. These functionalities help to increase the reliabilities of the processes as well as to decrease prevention costs.

Another popular industrial area is the logistics. Qu et al. [12] applied IoT technologies to a production logistics system with high operational dynamics. Even though there have been many IoT enabled industrial applications, they are limited in cyber manufacturing. The main reasons are the insufficient analytics performances and the inefficient network environment.

The emergence of cloud computing and Big Data Analytics has overcome these issue. Zhang et al. [13] applied a cloud environment to manufacturing applications for high performance computing. Adamson et al. [2] suggests a cloud environment for global manufacturing networks and supply chains. Wu et al., [6] and Wu et al. [14] predicted machine tools' wear using a cloud environment based machine learning method. Wu et al. [15] investigated and reviewed the current trends using cloud environment in several manufacturing systems. The combination between IoT and cloud computing makes it possible to overcome many temporal and spatial limitations in many manufacturing applications. Big Data Analytics can be equipped in the cloud system as analyzing module. As transmitted signals from IoT devices are considered as Big Data in general, the highly efficient analytics are required. Many existing data mining techniques [16,17], simulation based optimization approaches [18] and deep learning methodologies have been used for these analytics. Finally, the analyzed data are used for those applications [19]: (1) storing logistics knowledge repository, (2) decision making with real time data and (3) knowledge-based prediction. This section provides the concept of CPS and cyber manufacturing with several technologies and analytics.

While these innovative technologies have contributed to the development of various manufacturing processes and applications, there have been less studies handling manufacturing processes passing through several manufacturing and assembly sites. Most of existing research studies have focused on FDC based process and quality enhancements in the same company. Even though a company has different and distant manufacturing sites, the implementations using the provided methods and information access are easy comparatively. However, these are limited in manufacturing processes passing through different companies' sites. This research focuses on how these can be achieved and explains why cyber manufacturing and clouding environment are effective mechanisms for enhancing FDC functionalities in a process passing through different companies' manufacturing sites.

3. HID cable manufacturing processes and fault detection issues

3.1. HID cable manufacturing and assembly processes

This research examines the processes for manufacturing High Intensity Discharge (HID) car headlight module which is a core component in the vehicle lighting system. Fig. 1 shows the HID car headlight module which is produced from the target manufacturing processes.

This module is packaged and supplied to *OSRAM©*, then the assembled final light systems are installed on many types of vehicles. Fig. 2 explains the detailed processes for HID cable modules. A HID wire is supplied to the factory and is cut with the fixed specifications. Then, in order to connect a connector to the wire, several processes (Wire trimming, insertion, tapping and so on) are taken. As different types of vehicles require different headlight lamps, various types of HID wires and connectors are handled in the processes.

Fig. A1 shows various types of connectors. After bonding the connector and sleeve with the HID wire, the intermediate assembled module is inspected.

The first inspection tasks are composed of three types of checks (Table 1). These checks are performed using the specially designed test devices considering the characteristics of the modules and acceptable specifications. Fig. A2 shows the inspection and test machines in the processes.

In the inspection stage, the detected defective modules are scrapped without their recycling. The accepted HID wire modules go to the following stages for assembling a retainer and silicon boots. Then, the production information such as *Lot No*, manufacturing date and other information are marked on the module for the product's identification. The final inspection stage performs the tests such as insufficient soldering, poor marking and other quality issues. Then, the accepted HID wire module is assembled with the headlight lamp module (Fig. 1).

The following section explains several issues in the HID cable assembly processes.

3.2. Fault detection issues in HID cable manufacturing processes

Main defect types and their possible causes have been assumed through the accumulated manufacturing knowledge and existing analyses. Fig. 3 provides the relationship between major defect types and the related possible causes with the processes.

As shown in Fig. 3, the defect (insufficient soldering) is resulted from the malfunctions or heat problems of the injecting and compression machines. Fig. 4 shows several injection machines and the compression machines which are used in the HID cable manufacturing and assembly processes.

In particular, the main causes for the insufficient soldering are the misalignment of both roll and the gap widening between both rolls in the injection machine. For instance, injection machine's injecting force (147N) has to be retained. However, the misalignment or widening gap of the injection machine falls the force to 100N–50N. This situation gives result to the insufficient soldering of cable component, shown in Fig. 5(b).

In order to prevent these defects, several sensors for detecting malfunctions might be installed on the machine. Fig. 5(a) shows a gap width and an alignment depth in an injection machine. For instance, a proximity sensor might be installed for detecting the gap width between both rolls. If it detects gap over the specified criterion, the sensor system might give an alarm to a machine operator. Then, the operator might check the torque force and adjust the gap width.

However, the provided solution is limited in these processes. The main reason is the existence of the outsourcing processes. As shown in Fig. 2, the overall processes include several outbound workflows. These outbound workflows are conducted by several cable-related subcontractors. In these processes, the subcontracted works are labor-intensive tasks mainly such as wire's foil removal, tapping and so on. This fact indicates that it is difficult to install sensors in the subcontractors' factories. Even though these were installed, the tracking of sensor signals and continuous quality management activities are limited.

For these reasons, this research suggests a cloud environment using IoT devices and its data analytic framework. The following section provides the suggested IoT sensor devices for detecting processes' status and related defects.

4. Cloud architecture with IoT device

4.1. Cloud architecture for fault detection classification

As explained in the previous section, the existence of outsourcing sites makes it difficult to control several quality factors continuously. In order to overcome this limitation, this research develops IoT devices and installs them in each manufacturing tool and device such as injecting machines, compression machines and the other assembly machine.

A general IoT device sends the detected sensor signals to a control server. The server analyzes these data, sets up an effective control plan using its analytics and re-sends the control commands to the machine tools or the IoT device. While this scenario is suitable in a closed environment, it is limited in the processes with different sites. Cloud computing environment is an effective framework handling this issue. Fig. 6 shows the architecture of the suggested cloud control system. As mentioned in the previous section, the overall tasks are processed in various production sites.

Existing manufacturing knowledge have identified possible defect causes and their related sources/machines shown in Fig. 3. In order to prove the explicit relevance and to prevent defects, IoT beacons are installed in the production machines. The responsibilities of the IoT beacons are to measure manufacturing quality factors in the processes and to send them to the cloud sever. The most important usages of the server are to analyze the signals and is to identify the relationship between the signals and defects. The identified relationship is used for more accurate decisions for FDC.

This study uses *Intel's IoT analytics* [20] as a cloud module. The used module is a part of *Intel©'s IoT Platforms*. The main role of the cloud control server is to gather multiple sensor data, to analyze them and to give alarms or to make the operators take appropriate actions using the cloud environment. The signal gathering is supported using the libraries of *Intel©'s IoT Platforms*. The detailed explanation is provided in the following section. However, the analyzers modules are not supported in the platform. The reason might be given from the fact that different application needs different analytic methods and frameworks. Section 5 elaborates on the issue and the solutions.

This IoT cloud system receives several sensor signals from an *Intel© Atom* chip based *System on Chip* (SoC) computer module. The following section explains the architecture of the IoT device and its implementations. The implemented IoT device is connected to the cloud control server through the related hubs and gateways. The used communication protocol is *IEEE 802.11ac* based *Wi-Fi* wireless network protocol. In order to choose the most suitable communication protocol, several wire/wireless protocols are tested considering the manufacturing processes. While Wire-based serial communication guarantees the signal transmission with minimizing the loss, it is excluded with these reasons: (1) the limited

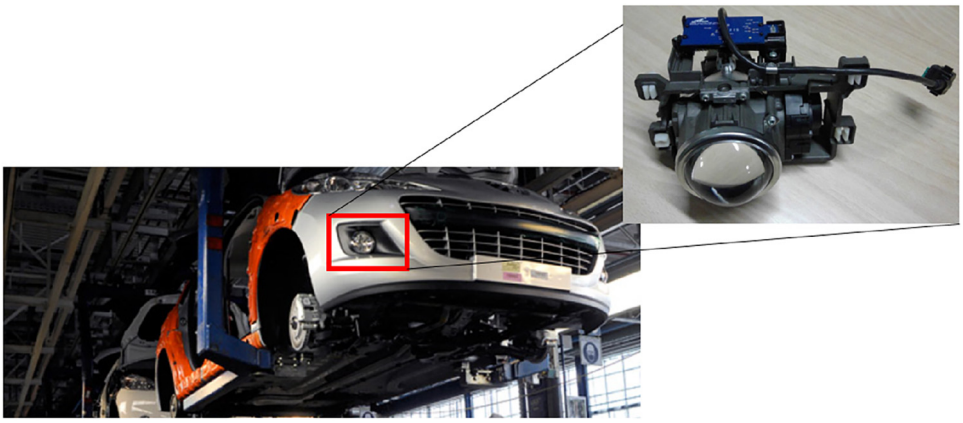


Fig. 1. HID car headlight module.

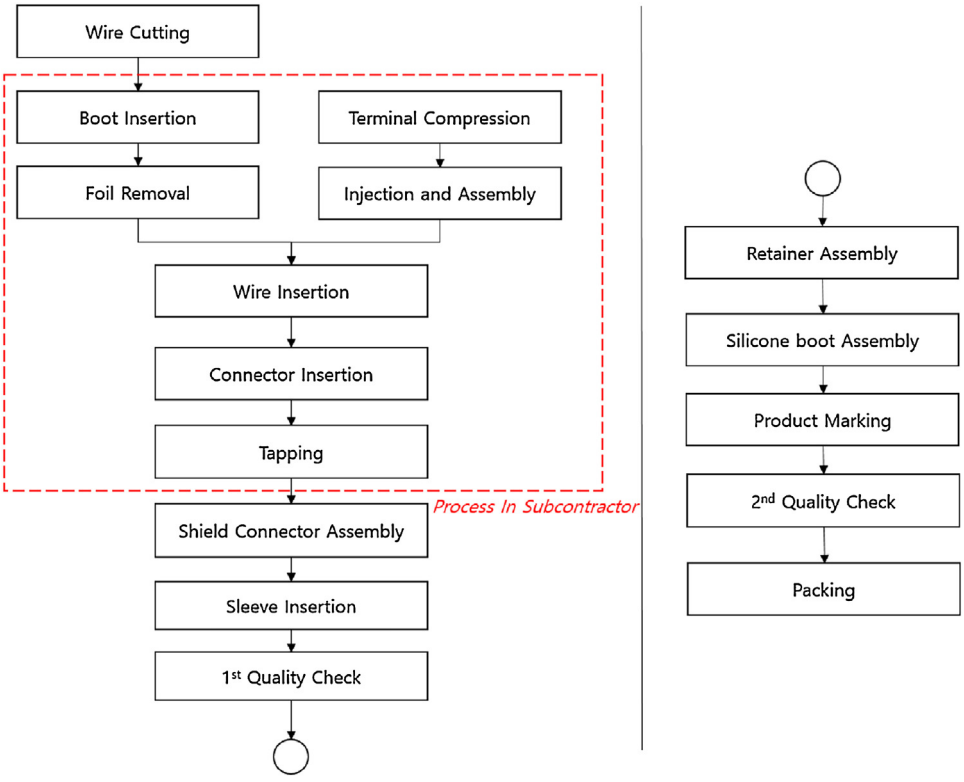


Fig. 2. HID cable manufacturing and assembly processes.

Table 1
Inspection items and methods in the first quality check.

Sequence	Inspection	Test machines/Acceptable Specification
1	Shield Gage Check	Shield Gage Tester Kit (Fig. 4(a))
2	Incorrect Wiring Test	Incorrect Wiring Tester Kit (Fig. 4(b))
3	Withstand Voltage Test	Withstand Voltage Test Machine (Fig. 4(c))/1800 V ± 20 mV, Last for 2 s

mobility, (2) the difficulties of configurations and 3) the distance of the electric sources. In addition, *IEEE 802.15.1* and *IEEE 802.15.4* based protocols are excluded among various wireless communication protocols due to the inefficient connecting performances such as the short transmission distance and small number of fairings. With the consideration of these comparisons and the real sites' conditions, *IEEE 802.11ac* is chosen for the factories' communication protocol. This protocol supports 5 GHz frequency and 160 MHz bandwidth with *Multiple input, multiple output-orthogonal frequency division multiplexing* (MIMO-OFDM). It indicates that the implemented IoT beacon can send multiple signals and receives multiple orders from the cloud control server.

The following section explains the detailed architecture and its implementation of IoT beacons.

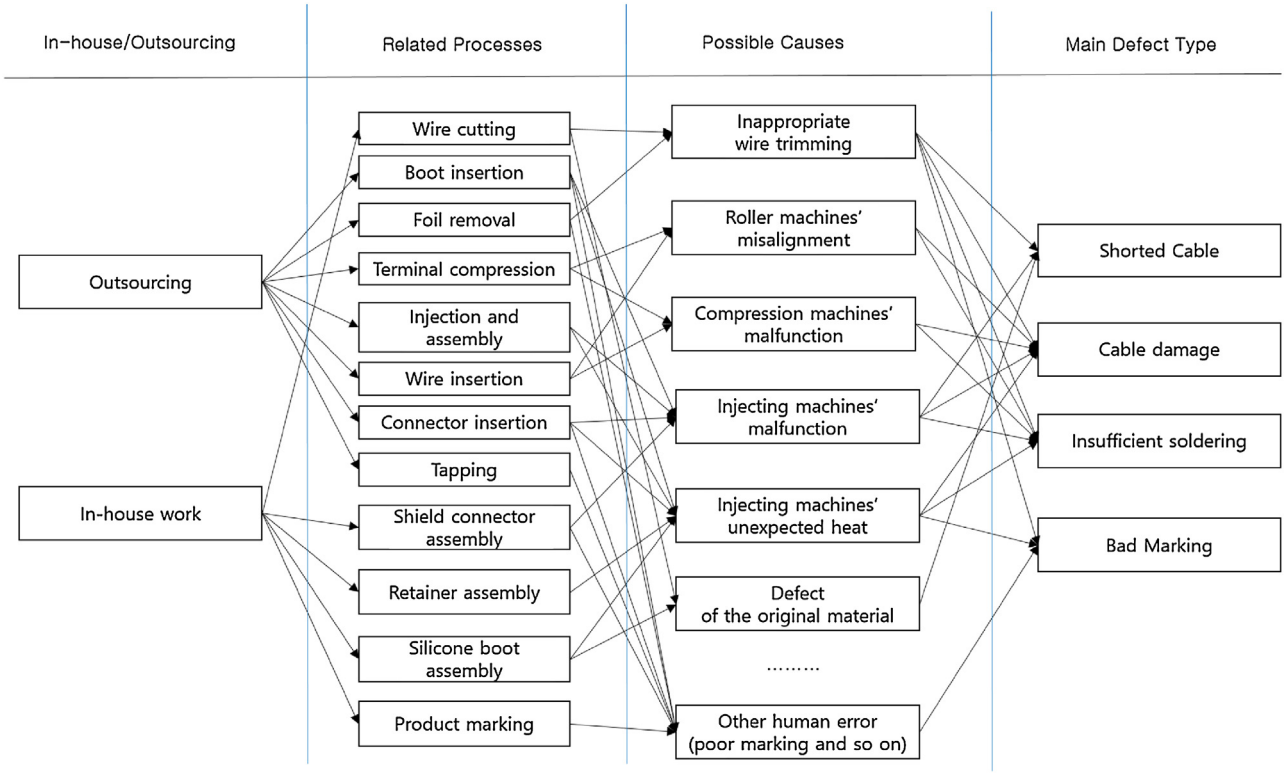
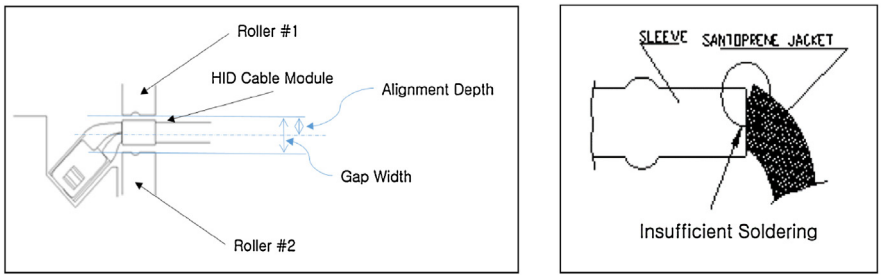


Fig. 3. Defect types and the related causes/processes.

(a)Several injection machines. (b) An example of compression machines.

Fig. 4. Injection and Compression machines.



(a) Injection mechanism. (b) Occurrence of "insufficient soldering".

Fig. 5. Injection mechanism and insufficient soldering.

4.2. Design and implementation of IoT device

The developed IoT device fulfills both functions: (1) Detecting torques of a compression machine and (2) Detecting gap between the components and a related part in the machines. The former beacon detects the force signals using the magnetic based torque sensor and the latter uses the proximity sensors. The torque sensor measures the magnetic field and its degrees in a compression motor. When the motor's compression torque is changed, it influences on the related magnetic field and the sensor detects the

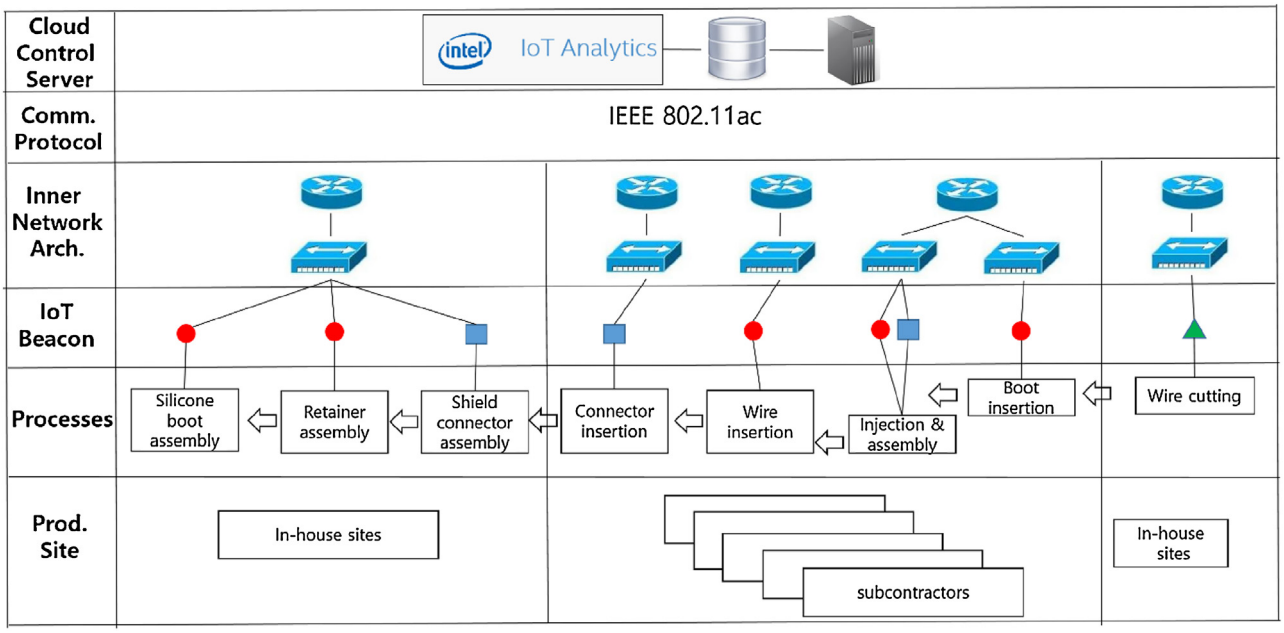


Fig. 6. The architecture of the suggested cloud system.

degree and sends it to the cloud server. Similarly, the micro-level proximity sensor detects the gap or approaching products. Fig. A3 shows the used the proximity sensors —*Panasonic(c)'s GXL-8 sensors*: the flat-on type proximity sensor and the head-on type proximity sensor.

The used proximity sensor has an ability to detect the distance from 40 μm–5000 μm as the gap ranges from 100 μm to 2000 μm. The detecting mechanisms of the sensor are explained in Fig. 7(a) and (b). Fig. 7(a) shows the gap distance between both rollers before the insertion of the HID cable module. The other figure shows the detection of the gap between the upper roller and the inserted HID cable module. If the gap between both rollers is widening over the allowed width, the sensor detects the gap and sends the signal to the cloud server. In addition, the sensor detects the gap between the roller and inserted cable component. If an insufficient insertion occurs, the sensor detects it and send the signal to the control server.

The implemented IoT beacon has multiple LEDs and an alarm buzzer for indicating alerts and alarms. As explained in the previous section, the device is connected to the network hubs using *IEEE 802.11ac*. Table 2 shows the detailed hardware specifications of the IoT beacon.

As described in Table 2, the processor [21,22] is a SoC processor including *Intel© Atom* processor. It has LPDDR3 memory and communicates using Bluetooth or Wi-Fi. Due to its expansion abilities, many IoT applications [23,24] have used the processor. Fig. A4 shows the block diagram of the implemented IoT beacon. As shown in Fig. A4, the CPU is connected to Analog and Digital control boards through *Serial Peripheral Interface* (SPI), *Multiplexer* (MUX), *Inter Integrated Circuit* (I2C) and so on. Then, LEDs are installed on the digital control board and the other sensors such as a magnetic torque sensor and an inductive proximity sensor are bonded on the analog control board with an alarm buzzer.

The beacon detects the designated signals and sends them to the cloud control server. The following section explains the functions of the control server using the cloud environment.

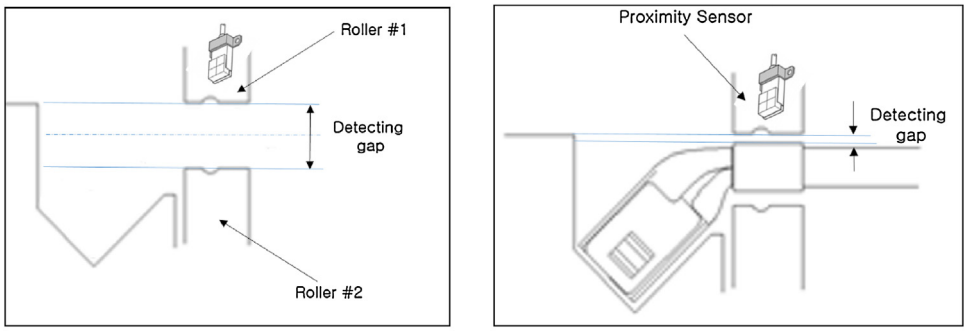
Table 2
Hardware specifications of the IoT beacon.

Component	Specifications
Core Processor	• *Intel © Edison Processor*
Sensor Connecting Block	• Arduino based expansion block • Analog 6 pins • Digital 13 pins
USB and Connectors	• Micro USB Device port (UART) • Micro USB 2.0 Device port (USB OTG)
ADC module	• Analog Input with 20 MHz clock rate • 12-bit A/D conversion
Basic I/O units	• User LED/Power LED/System LED • Reset switch/System switch
Battery and Power	• 4.4 V Power Supply • Battery recharger battery header • External power adapter jack for 7V ~ 15 V DC input with 500 mA
Dimension	• 180 mm X 125 mm X 15 mm

5. Cyber manufacturing and cyber-physical architecture

According to Rajkumar et al. [25] and Gunes et al. [26], CPS is defined as a physical and engineering system with functionalities: (1) monitoring/observation, (2) coordinating, (3) communication, (4) integrating and (5) controlling. Many related research studies attempt to define CPS with the concepts of "Roles in Physical manufacturing model", "Roles in cyber/simulation/meta models" and "their mutual integrations and communication".

In order to set up CPS for the processes, this research borrows the definitions and insights from the mentioned existing research studies. The roles of the cloud control server are categorized to several missions: (1) Information database of processing data, (2) Monitoring processing status, (3) To identify the hidden relevance between defects and possible causes, (4) To give alarms in case of detecting abnormal state, and (5) To simulate the processes with multiple



(a) Gap detection between both rolls.

(b) Gap detection between the upper role and the wire module.

Fig. 7. Detecting mechanisms using the proximity sensor.

Table 3
The functions of the cloud control server.

Functions	Activities & Missions
Information Sharing	• Database of overall process data from IoT beacons • Collecting rule-based control models
Monitoring	• Monitoring current status in each machine • Monitoring other processing data (e.g. Current working Lots, Machines' availability, Factory utilization) • System performance monitoring • Detecting abnormal machine status
Estimation	• Identify the relationship between defects and processing data (Fault Detection Classification) • Identify the relationship among processing data
Control	• Give alarms to machine operators in case of detecting abnormal status • Request rescheduling of manufacturing plans, in case of tardy processing
Simulation & Prediction	• Manufacturing simulation using Cyber physical interface • Multiple scenario test and validation • Prediction of system performance indices (e.g. WIP, Cycle Time, Throughput and so on)

scenarios and to prevent the possible risks. Table 3 explains the detailed functions of the cloud control sever.

The cloud control server is used as a core module of the overall CPS in the newly innovated processes. As shown in Fig. 6, the server consists of three parts: (1) Data gathering part, (2) Storing unit and (3) Analyzing unit. The data gathering part is established using *Intel© IoT Analytics* cloud module. Fig. 8(a) shows the connecting procedures between IoT beacons and the analytics sever. Fig. 8(b) shows the gathered sensor data and their time-series plots.

Even though the system is useful for gathering sensor data using the cloud module, it is limited in the fact that the analyses and control functions are supported less in the system. In addition, the server lacks the simulation and prediction functions. This fact indicates that the cloud module, itself is unsuitable for implementing CPS.

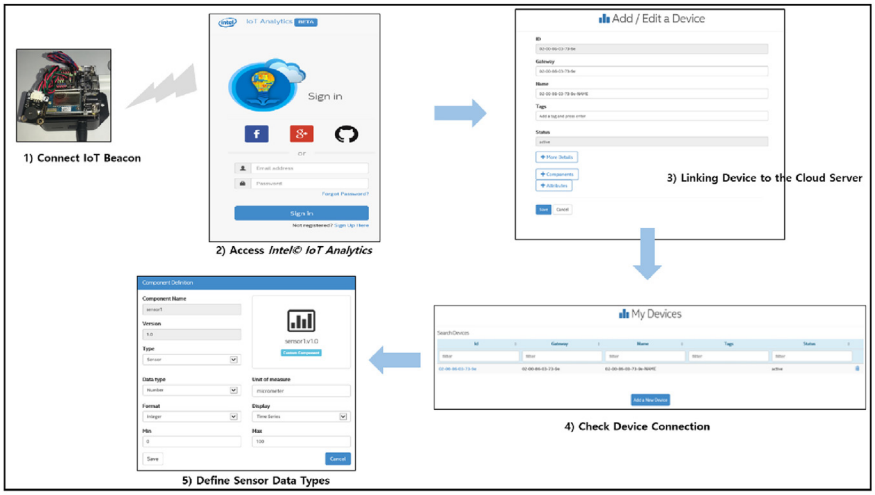
In order to overcome these limitations, a database system and an analytic functions are equipped, shown in Fig. 6. The data is stored from *Intel© IoT Analytics* to the database system in the cloud system. Then, the data is analyzed and used for simulations and predictions. The control sever performs the functions which are provided in Table 4. As a monitoring and control function, a control chart module is implemented and used for detecting abnormal status of manufacturing machines. Fig. 9 shows the $\bar{X} - R$ control chart using an inductive proximity sensor.

As explained in Section 3.2, the sensor detects the gap between both rollers. If the gap is widened over 135 μm, an insufficient soldering might occur. As shown in Fig. 9 ($\bar{X}$ control chart), the X axis indicates the product ID and the Y axis means the gap between both rollers in the process. When the 125th HID cable module is processed, the widen gap (136.593 μm) is detected and the alarm signal is sent to the machine operator. After its maintenance, it is checked that the gap is controlled normally.

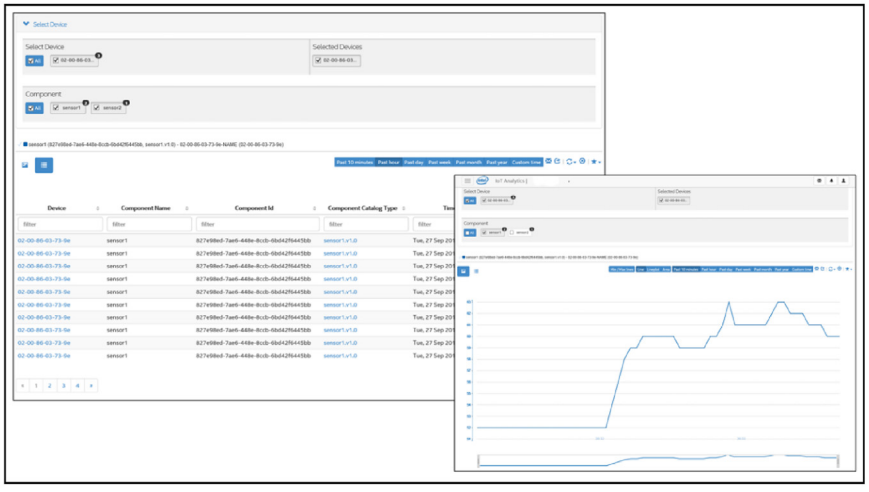
Simulation and production modules are implemented with these implemented monitoring and control modules. The main objectives of these modules are to evaluate the processes' performances considering the current information and assumed future scenarios. For example, the detections of abnormal status might give rise to additional delay due to their maintenances. Then, it might be difficult to deliver the HID cable modules to a following manufacturing site on time. In this case, the tardiness is measured using a simulation model and the new manufacturing plan is established for minimizing the tardiness. There are many control strategies [27] for minimizing tardiness or maximizing other system performances.

As a prerequisite stage for the controls, the simulation is needed and it is considered as the most important function in CPS. Wu et al. [28] uses a stochastic Petri Net based model for representing a cloud-based manufacturing model and allowing its simulation. While these Petri Net-based CPS approaches have several advantages in monitoring and simulation, their main limitations are in (1) the complicated representations from many status and (2) the discontinuity with other control strategies. In addition, the processes handle different types of cable modules, shown in Fig. A1. It indicates that the processes have to be modeled using a multi-products production model. When the Petri Net methodology is applied to the modeling, the colored stochastic Petri Net model is required and its analyzing loads are increased.

Considering these issues, this research uses a multi-product queuing network [29] based approach. As shown in Fig. 2, the overall processes consist of 11 serial connections and 1 merging connection. As there is no batch processes, a single process is modeled with G/G/1 model. The overall manufacturing processes in a



(a) Connecting procedures between IoT beacon and cloud module.



(b) Gathered sensor data and time-series based plot.

Fig. 8. Data Connection between IoT beacon and the cloud system.

Table 4
An exemplary simulation result.

Contents		Scenario #1	Scenario #2
Situation		• All machines are working properly	• The 2nd IoT beacon detect abnormal situations • The machine's maintenance is needed
Parameters' estimation methodology		• All parameters are captured using Sensors' signals	• $E[S_2]$is changed from historical data and what-if analyses
Simulation using Queuing Network	CT (Time)	1 h 15 min	1 h 53 min
	WIP (Each)	56	39
	Throughput (Each/min)	0.746	0.317
Possible Decision Makings		–	• Tardy delivery of several types of HID cable is expected • Sequence changes and control

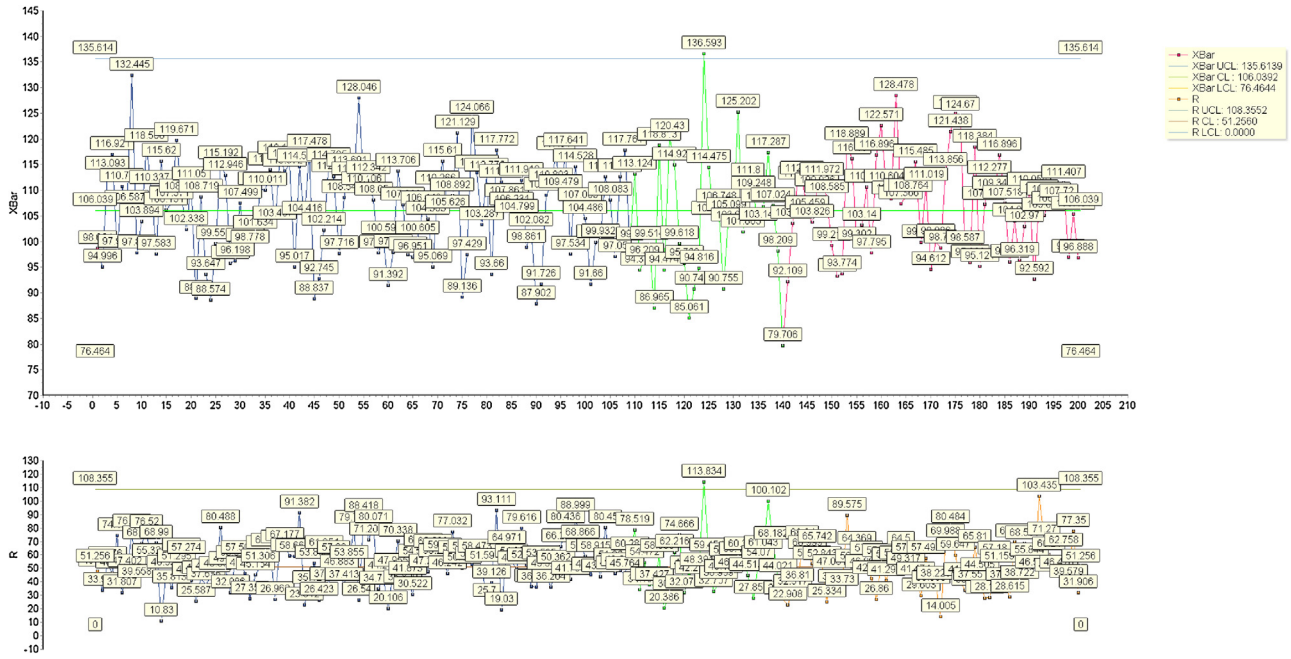


Fig. 9. $\bar{X} - R$ control chart using a proximity sensor.

single G/G/1 model, the cycle time (CT) of the node (i) is calculated as (1).

$$CT_i = \left(\frac{U}{1-U}\right) \cdot E[S] \cdot \left(\frac{C_a^2(i) + C_s^2(i)}{2}\right) + E[S] \tag{1}$$

In a process, the input (a HID cable module)'s arrival rate is λ and the machine's service rate is μ. These parameters are measured using the sensor data from the IoT beacons. With these parameters, the utilization rate of the process ($U = \lambda/\mu$) and the average service time in one process ($E[S] = 1/\mu$) is calculated. Then, the *squared coefficient of variation* (SCV) for the arrival distribution ($C_a^2(i)$) and SCV for the service distribution ($C_s^2(i)$) are driven for calculating the cycle time in the ith process. However, the processes produce 14 types of HID cable modules. For this reason, different types of arrival information and service information have to be considered. It indicates that the average arrival rate ($\bar{\lambda}$) is calculated using each type' arrival rate (λ_i) using (2).

$$\bar{\lambda} = \sum_{i=1}^{k} \frac{\lambda_i}{k} \tag{2}$$

Then, SCV for the average arrivals ($C_a^2(n)$) in the nth process is driven from each squared coefficient ($C_{a,i}^2(n)$) using (3).

$$C_a^2(n) = \sum_{i=1}^{k} \frac{\lambda_i}{\bar{\lambda}} C_{a,i}^2(n) \tag{3}$$

Due to the different type of components, the service times are different in the provided processes. The average service time and SCV for the average service are calculated using (4) and (5).

$$E[S] = \sum_{i=1}^{k} p_i E[S_i] \tag{4}$$

Where, p_i = the ith product' portion in service

$$C_s^2(n) = \frac{\sum_{i=1}^{k} p_i (C_{s,i}^2(n) + 1) \cdot E[S_i]^2}{E[S]^2} - 1 \tag{5}$$

Then, the cycle time considering multi-products can be calculated using (1)–(5). As the overall processes consist of 16 processes, the process model is represented using the queuing network. In the model, the connections are categorized into two types, shown in Fig. 10. Fig. 10(a) shows a serial connection handling multi-products.

In these serial queues, the cycle time of the previous process (the ith process) is calculated using the mentioned equations. However, the calculation of the post process (the jth process) needs the calculation of $C_a^2(j)$. As $C_a^2(j)$ is interpreted as SCV for departing the previous process ($C_d^2(i)$), this research calculates the value using (6) [30]. As it is the multi-products model, $C_a^2(i)$ and $C_s^2(i)$ are calculated using (3) and (5), respectively.

$$C_d^2(i) = (1 - U^2) \cdot C_a^2(i) + C_s^2(i) \cdot U^2 \tag{6}$$

The remaining issue is the calculation of a merging connection. As shown in Fig. 2, the processes contain one merging connection (Connection from "Foil Removal process" and "Injection and Assembly" to "Wire Insertion Process"). As shown in Fig. 10(b), the cycle time CT_o is calculated using the provided equations. During the calculation, $C_a^2(o)$ is obtained considering the previous processes using (7).

$$C_a^2(o) = \frac{(\bar{\lambda}_1 \cdot m) \cdot C_d^2(i) + (\bar{\lambda}_2 \cdot (n - m + 1)) \cdot C_d^2(j)}{\sum_{i=1}^{n} \lambda_i} \tag{7}$$

With the provided multi-products queuing factory model, the total cycle time is calculated. The other system performances such as WIP or Throughput are driven using *Little's law* [31]. The provided simulation framework is used for cyber manufacturing in the CPS. Then, the simulated cycle time, WIP and Throughput information are utilized for factory decision makings. The estimated

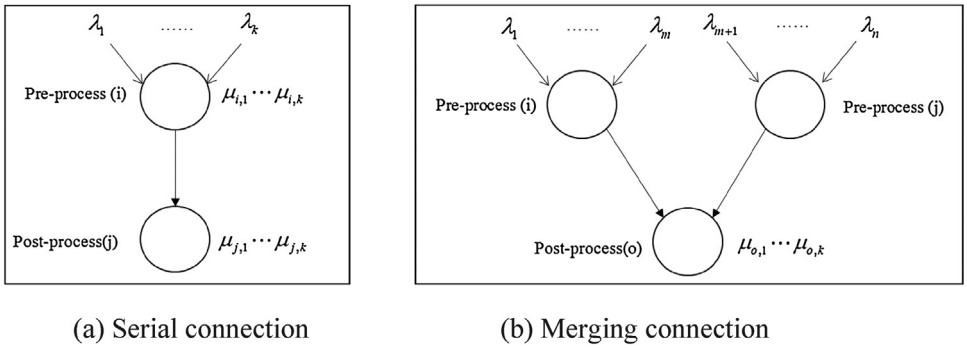


Fig. 10. Serial and merging connections in the provided processes.

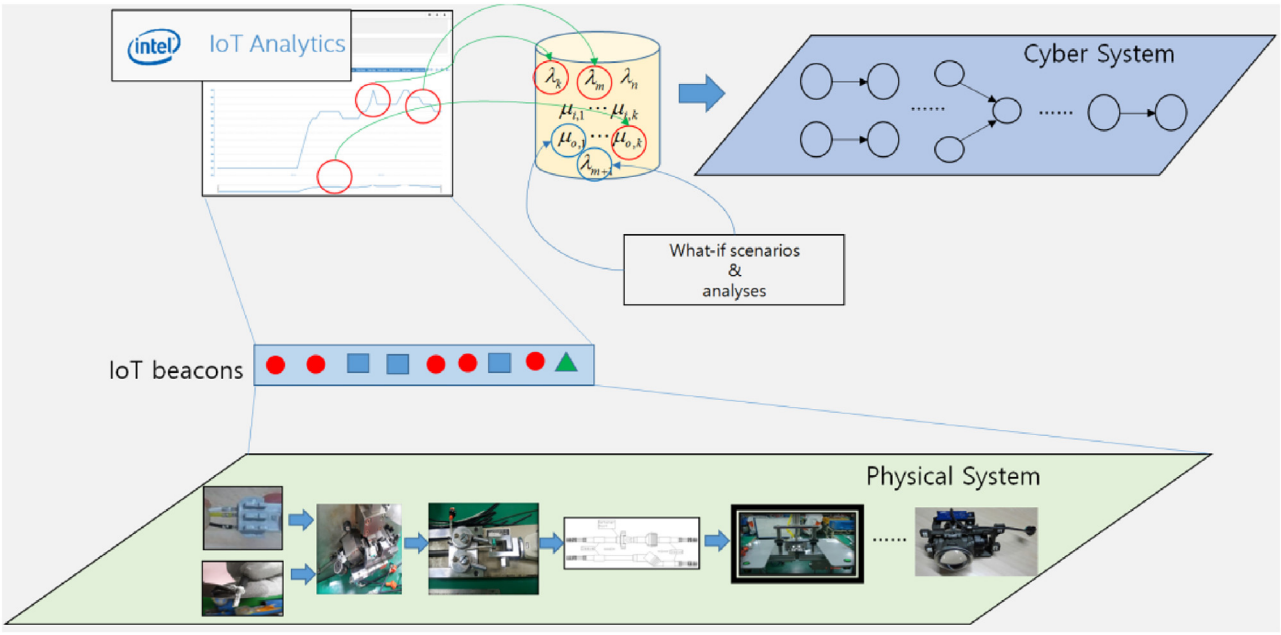


Fig. 11. The architecture of CPS.

manufacturing performances can be used for the factory decision plans in case of an abnormal status. As the detailed cycle time and WIP of each product are simulated, manufacturing sequences may be changed with various objectives (e.g. minimizing tardiness of designated products or handling sudden orders). Fig. 11 shows the cyber-physical system for the provided processes.

Table 4 shows the exemplary simulation results with the implemented CPS.

This section elaborates on the cloud control system. This system is a core module in the implemented cyber manufacturing. As the provided processes handle multi-products and have various connections, the related queuing network model is used for its simulation and decision making. The following section provides the other important function—FDC, among those functions in Table 3.

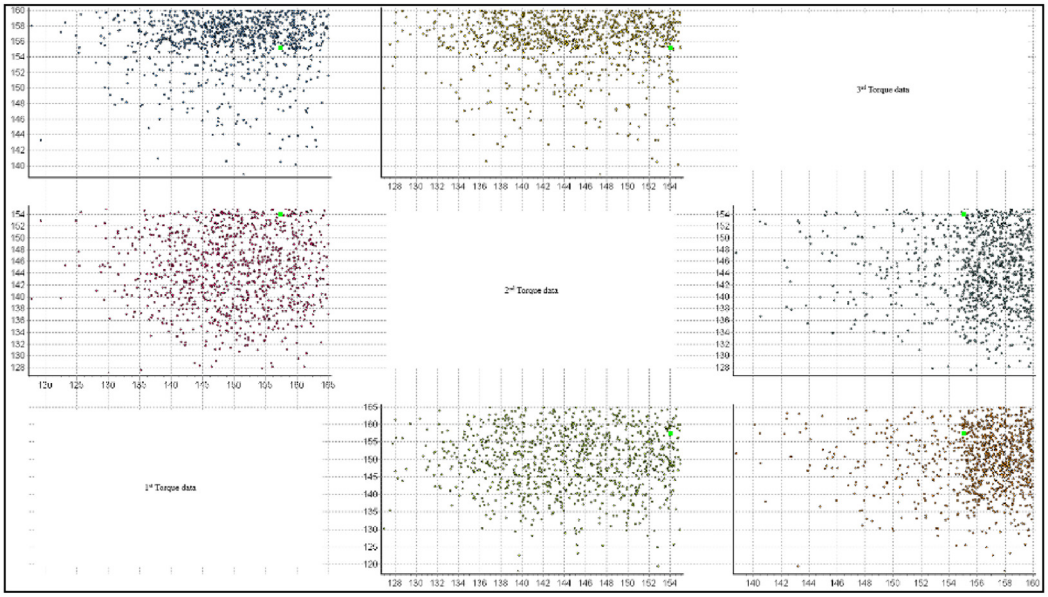
6. Fault detection and classification using deep belief network

As explained in the previous section, one of important function in CPS is to identify the relationships among possible cause-effect variables more clearly. FDC is one of these tasks. As a prerequisite condition for effective FDC execution, the relationship explained in Fig. 3 has to be verified. It is difficult to identify the mapping before the implementation of cyber manufacturing framework. These reasons are resulted from (1) the mixed product flows with in-flow and multi-outsourcings, and (2) the absence of information gathering mechanism.

The implementation of CPS makes it possible to gather the relate data automatically using IoT beacons as well as to analyze them using the cloud environment. The usages of the cloud control server overcome the mixed flows' limitation.

As shown in Fig. 3, several types of defects, possible causes and their sources have been identified. However, it includes inaccurate inferences and analogies. It is resulted from the difficulties of exact matching between defect data and process data. As there is the time disparity between the machines' malfunction and the detection of the defects, an exact *Lot* and the time tracking are needed. The implementation of CPS makes it possible to track and match them exactly. As shown in Fig. 6, the *Lot* information is assigned the cable component and each detected sensor signals are transmitted with the *Lot ID*. When a defects is detected, the *Lot ID* is tracked and the related sensor signals and defect types are mapped.

After matching the data set exactly, the following task is to clarify the cause-effect relationship of defects. For this classification, eight signals (three from torque sensors and five from proximity sensors) are used for input nodes. Then, three dependent variables (binary values for shorted cable, cable damage and insufficient soldering, respectively) are used for output variables. For instance,



(a) Matrix plot of input data from three torque sensors.

Output variables	Data Size	Binary Variable	Frequency	Percentage (%)
Variable for Shorted cable	1,000	0	970	97
		1	30	3
Variable for cable damage	1,000	0	944	94.4
		1	56	5.6
Variable for insufficient shouldering	1,000	0	917	91.7
		1	83	8.3

(b) Specification of defect data.

Fig. 12. Data for FDC gathered from the IoT based cloud system.

(1,0,1) indicates that a tested HID cable has two types of defects: shorted circuit and insufficient soldering between the cable and a connector. Fig. 12(a) shows a part of input data (three torque sensor signals) with the matrix chart. In order to investigate the relationship, a processing data (data size = 1000) is used. Fig. 12(b) shows the frequencies and percentages of three output variables.

This research uses and compares three learning algorithms for matching inputs and outputs: (1) Support Vector Regression (SVR), (2) Radial Basis Function (RBF) and (3) Deep Belief Learning based deep learning (DBL-DL). Table 5 explains the configurations and parameters of three learning model.

This research uses a data mining software—*ECMiner*© for testing SVR and RBF. As the deep learning function is supported less in the commercial data mining software, it is implemented using [32]. As shown in Fig. A5, the overall architecture of DBL-DL consists of 4 layers: one visible layer, two hidden layers and one output layers. The visible layer is considered as an input layer for handling inputs ($x = \{x_1, \cdots, x_D\}$) from several IoT sensors in multi-sites. Both hidden layers has four nodes $h^1$and h^2, respectively. The role of these layers is to extract more suitable classification features with the less prior knowledge. Each layer has its own bias vector, b for input layer, c^1 and c^2 for both hidden layer. While other neural network methods depend on the input features heavily, most deep learning approaches have an advantages of extracting relevant features as well as of classifying objects. For training hidden layers, this model uses the contrastive divergence method [32] and the back propagation method is used for training the output layer.

The reasons using DBL-DL are explained with the ambiguity of extracted features and the accumulated data size. While several sensors' inputs are effective for detecting defects, their interdependent relations or other potential causes are explained less. In addition, this framework uses a cloud environment considering multi-production sites. For these reasons, DBL-DL is used for training and classifying potential defects.

In order to compare the effectiveness of DBL-DL with other models, three learning approaches are tested. Table 6 shows the validation and the results of three models with the test data. Among the overall data, the 90% of data is used for training set and the other are used for test set.

Table 5
Parameters of three learning model for FDC.

	SVR	RBF	DBL-DL
Size of Training data	900		
Size of Test data	100		
Parameters	• SVM type: C-SVM • Kernel: RBF type • Degree: 3 • C-value: 1	• Center Size of RBF: 10 • Regularization parameter: 0.01	• # of Hidden layer: 2 • # of MLP layer: 1 • Optimization method for MLP: Steepest Descent • # of Nodes in each layer: 4

Table 6
Test results of three FDC learning models.

	SVR	RBM	DBL-DL
Error rate of training data set	7.67%	8.01%	7.80%
Error rate of test data set	8%	9%	7%

As shown in Table 6, the DBL-DL model is considered as a more suitable model for explaining the relationship between the sensor signals and the defect types. The monitoring and control functions can works more accurately with the validation model. This learning machine is used for FDC in the overall processes, then it is expected that the overall quality level will be improved with the provided CPS architecture.

7. Conclusions

This research provides the framework of a new and effective cyber-physical system and its architecture for the manufacturing processes with multi-products and mixed internal tasks/outsourcing flows. The issues from internal/outsourcing processes are overcome with the cloud computing environment. And, the multi-products manufacturing issues are resolved using the equipped several simulation and control functions in CPS. As the exemplary processes, the manufacturing and assembly processes of the HID cable module for vehicles' headlight parts are provided. In order to use the cloud computing environment, the IoT devices are developed. The implemented IoT beacons have roles of detecting the status of machines and processes, and of sending them to the cloud control server.

The transmitted data is used for identifying the cause-effect relationship for FDC more clearly with the embedded learning model using a deep learning technique. These analytics contribute to the improvement of the processes' qualities.

In addition, the simulations considering various manufacturing scenarios are allowed using the cyber and cloud environment. As the provided processes consists of various connections and handles multiple products, a multi-products queuing network model is considered as a basic simulation model. Through the modeling and its simulation, the processes' performances are predicted under several what-if scenarios. Then, these results can be used in the following decision making stages.

This research verified the effectiveness of the cyber manufacturing and its architecture through the development of IoT device, transmission protocol and architecture, the implementation of the cloud control server and the analytic functions. The suggested framework and implementations can be used in various types of industrial fields and processes.

As further studies, more accurate and fast analytics are required in the cloud layer. The detailed monitoring level, a number of sensing points and shorten sensing periods may lead to the enormous size of data and the exponential scaled computation loads. This situation might give result to the useless of a developed cyber-physical system. In order to prevent the situation, more effective techniques for big data and related architectures are considered.

Acknowledgements

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Appendix A.

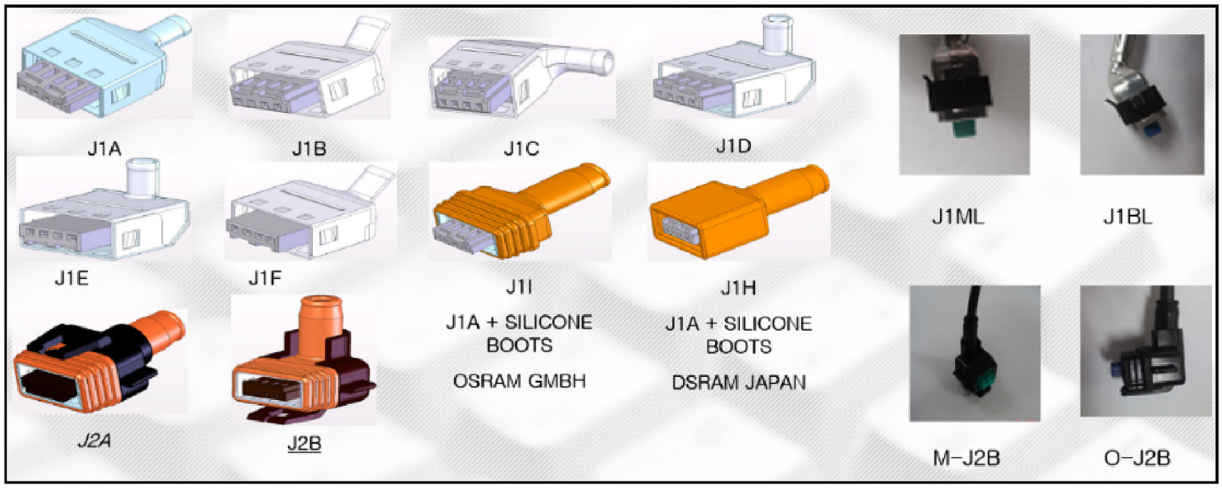
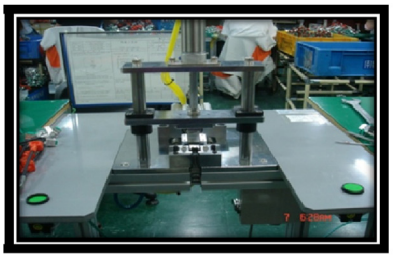
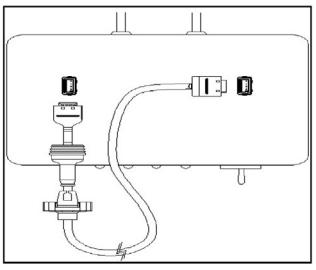


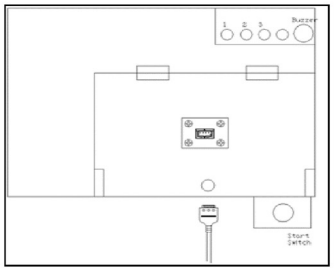
Fig A1. Various types of HID cables and connectors.



(a) Shield gage tester.



(b) Incorrected wiring tester kit



(c) Withstand voltage tester

Fig. A2. Inspection machines in the intermediate quality check process.

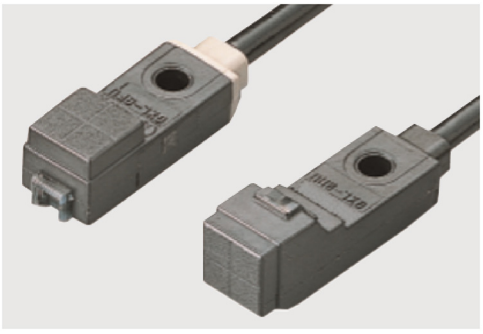


Fig. A3. The embedded proximity sensors.

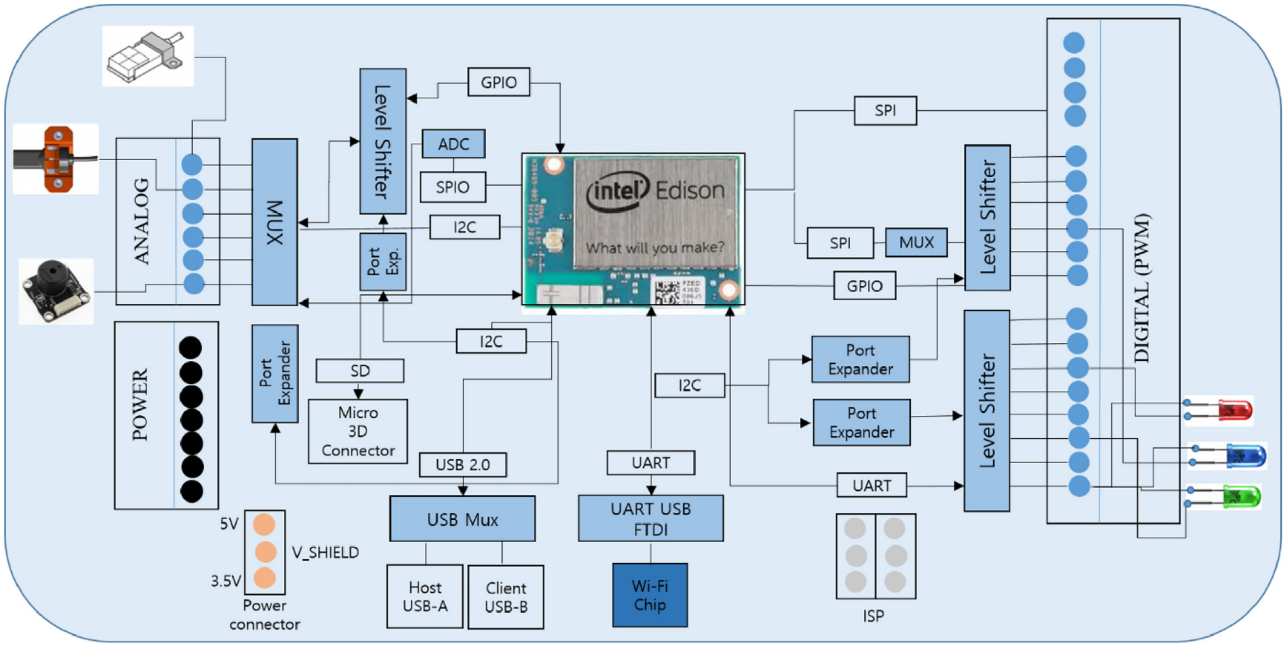


Fig. A4. The implemented IoT beacon's system block diagram.

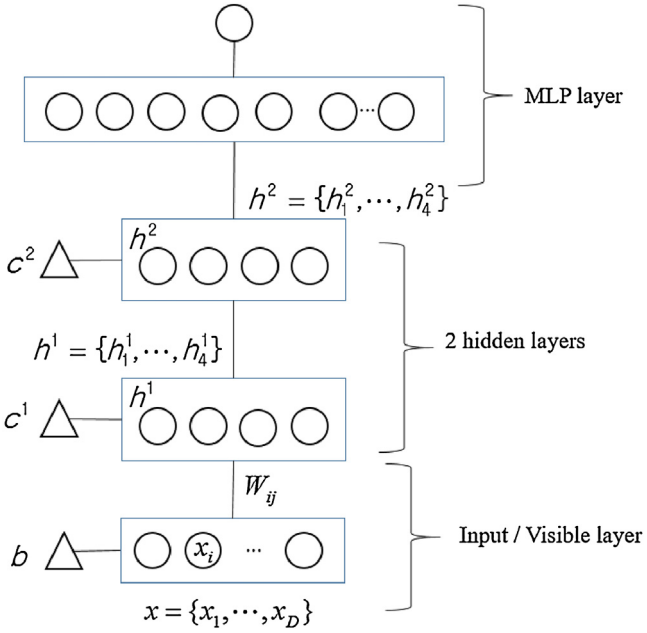


Fig. A5. The architecture of DBL-DL.

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