

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900

Open access books available

186,000

International authors and editors

200M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



Harnessing IoT Data and Knowledge in Smart Manufacturing

Joseph Shun Ming Yuen, King Lun Choy, Yung Po Tsang and Hoi Yan Lam

Abstract

In the modern digitalized era, the use of electronic devices is a necessity in daily life, with most end users requiring high product quality of these devices. During the electronics manufacturing process, environmental control, for monitoring ambient temperature and relative humidity, is one of the critical elements affecting product quality. However, the manufacturing process is complicated and involves numerous sections, such as processing workshops and storage facilities. Each section has its own specific requirements for environmental conditions, which are checked regularly and manually, such that the whole environmental control process becomes time-consuming and inefficient. In addition, the reporting mechanism when conditions are out of specification is done manually at regular intervals, resulting in a certain likelihood of serious quality deviation. There is a substantial need for improving knowledge management under smart manufacturing for full integration of Internet of Things (IoT) data and manufacturing knowledge. In this chapter, an Internet-of-Things Quality Prediction System (IQPS), which is a mission critical system in electronics manufacturing, is proposed in adopting the advanced IoT technologies to develop a real-time environmental monitoring scheme in electronics manufacturing. By deploying IQPS, the total intelligent environmental monitoring is achieved, while product quality is predicted in a systematic manner.

Keywords: smart manufacturing, Internet of Things, knowledge management, quality prediction, fuzzy logic

1. Introduction

In recent years, the demand on consumer electronics has dramatically increased due to the numerous advanced inventions, such as smartphones and smart city devices. Product quality, which is assessed by the products' features and characteristics, is one of the determinant factors in the sale of consumer electronics [1]. In order to maintain and improve product quality, it's essential that the manufacturing process is under tight control with monitoring of environmental conditions so as to produce electronic devices with high levels of product quality. This area has drawn considerable research interest regarding effective approaches for managing manufacturing conditions, for example, industrial Internet of Things (IoT) applications. However, the electronic manufacturing process is different and more complicated than other general manufacturing processes, including design, development, fabrication, assembly, and testing approaches [2, 3]. Therefore, an effective

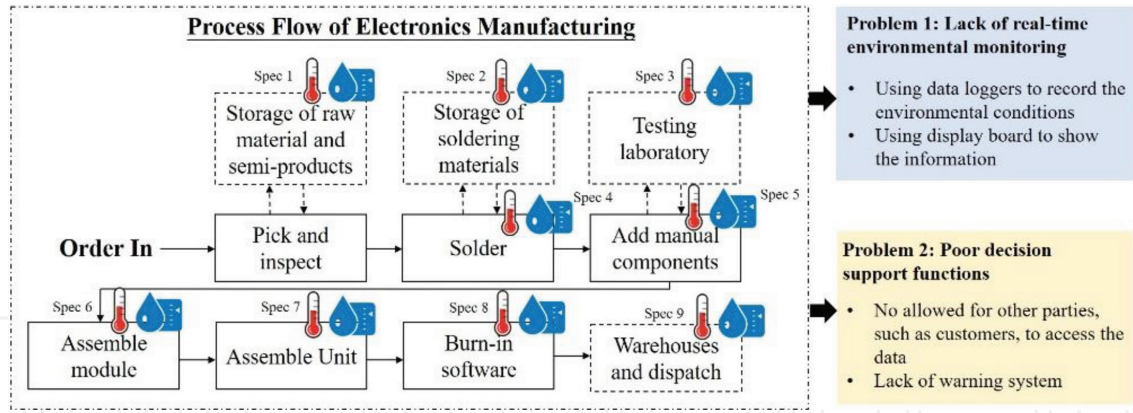


Figure 1.
Process flow of electronic manufacturing and its problems.

environmental monitoring and quality prediction system that fits various manufacturing requirements in the production lines is needed. In electronic manufacturing sites, the arrival of production orders affects the entire manufacturing process, namely, picking, inspecting, soldering, assembling, software burning-in, and dispatching, as shown in **Figure 1**. However, there are two major problems regarding environmental monitoring in manufacturing sites. Firstly, various sections in the manufacturing process have their own requirements on environmental conditions, and data loggers are used to record the environmental conditions, i.e., ambient temperature and humidity, for each section or workshop. On-site supervisors are required to memorize all this information and check it regularly. However, it is time-consuming to record all the data and act accordingly if the conditions do not meet to the requirements. Secondly, traditional environmental control does not allow other parties, such as customers or auditors, to access the data externally, and there is an inefficient warning system when violation of specific environmental conditions occurs. Therefore, the performance of environmental control and monitoring in existing electronic manufacturing is poor, resulting in negative impact on product quality. In order to address the above problems, the development of IoT system in smart manufacturing requires the integration of certain level of domain knowledge, such as the relationship between environmental conditions and quality prediction. In addition, the intelligent environmental monitoring and quality prediction align the business missions and policies of most electronic manufacturing companies. Without such systems, the companies may not be able to formulate operational and business strategies in a proactive manner.

In this chapter, a research methodology for problem identification and knowledge goal definition is presented to connect the academic research and real-world applications with anticipated results in knowledge management. For electronic manufacturing companies, in order to survive in the fiercely competitive business environment, quality management, including quality control and quality assurance, is one of the essential objectives. In the past, the quality problems were identified after production by inspection and testing. By using such a reactive approach in quality management, certain amount of waste in raw materials and company resources are incurred. Therefore, there is room to integrate knowledge from quality management and state-of-the-art technologies, such as IoT technologies and artificial intelligence techniques. An Internet of Things quality prediction system (IQPS) is proposed through making use of the advanced Internet of Things (IoT) technologies and artificial intelligence technique, i.e., fuzzy logic, for monitoring the environmental conditions in a real-time manner and predicting the quality of manufacturing process. Wireless sensor nodes are adopted to collect the environmental data in a specific manufacturing site and transmit the data to local

devices via wireless communication technologies, such as Wi-Fi and Bluetooth. Consequently, the messaging protocol is then applied to publish the data to a specific IoT platform and cloud database for further system development and data management. Under the IoT environment, the sensing devices are interconnected efficiently and effectively such that the various requirements regarding environmental monitoring can be fulfilled. This enables the environmental conditions to be ensured within the specifications, and it can reduce one of the crucial factors which may cause the deviation on product quality. With using the collected monitoring data, the decision support on quality prediction can be established by means of fuzzy logic, and relationship between product quality and some indirect factors can be constructed. Adopting fuzzy logic in real-world application adds the intelligence in learning the knowledge from domain expert in the form of membership functions and fuzzy rules. The resultant knowledge can be managed and stored in the knowledge repository for generating meaningful results, namely, quality prediction, in this chapter. The membership functions can define the fuzziness of input and output parameters, while fuzzy rules are used to connect input and output to generate appropriate adjustments and evaluations in specific circumstances.

This chapter is organized as follows. Section 1 is the introduction. In Section 2, the related work and literature in the aspects of electronic manufacturing, Internet of Things (IoT), and its applications are described. Section 3 presents the system architecture of IQPS. A case study in implementing the proposed system is illustrated in Section 4. Section 5 gives the results and discussion related to the benefits and limitations of the proposed system. Conclusions are drawn in Section 6.

2. Related works

Electronic manufacturing is a series of activities for designing, developing, fabricating, assembling, and testing of electronic parts, tools, products, and systems [4]. There are three epochs in the evolution of electronic manufacturing, namely, the vacuum tube era, the transistor era, and the integrated circuit era. Current electronic manufacturing falls under the integrated circuit era, focusing on producing small and reliable electronic devices and components at low cost. However, the complexity and dynamics in electronic manufacturing processes have rapidly increased in recent years due to short product life cycle and efficient new product development [5, 6]. Since the initial investment for manufacturing technologies is high and talented professionals in process engineering and quality are required, there is a great barrier for most start-up electronic manufacturers to enter the fiercely competitive market. In addition, effective and comprehensive control on the production environment, without which product quality deviation, occupational injuries, and low productivity may occur, should consider four major elements, i.e., equipment, process, ambient factors, and job procedures [7]. Most studies have covered the elements of equipment, process, and job procedures, such as advanced inkjet printing equipment, process optimization, job shop scheduling, and lean manufacturing [8–11]. Moreover, in order to manage the manufacturing process effectively, some new manufacturing systems have been developed. For example, an advanced concept of cyber-physical system (CPS) architecture where the information from all related perspectives in the manufacturing process are closely monitored and synchronized was proposed so as to standardize the development process for Industry 4.0 [12]. However, the ambient factors in electronic manufacturing are a less-touched research area due to the technology barriers in the past. The control and monitoring of the ambient factors, for example, lighting, relative humidity, and temperature, can be completed under the environment

and paradigm of Internet of Things (IoT). In addition, the concept of knowledge management can be integrated in the system development process so as to improve the machine learning process and the expected results from the system.

The ontology of knowledge management (KM) has drawn huge attention in the modern research and business sectors, with the aim of creating value for stakeholders [13]. In recent years, KM is well-defined as the processes and practices in an organization with the aim of enhancing the effectiveness and efficiency in managing its knowledge resources [14]. To facilitate the development of knowledge management, technology adoption is a crucial element to provide functionalities of knowledge sharing and process innovation, such as business process reengineering. An et al. [15] presented a KM framework to drive collaboration, communication, and connectivity in three directions, namely, (i) rearrangement of KM roles by people, (ii) reengineering of KM activities by processes, and (iii) reconfiguration of KM artifacts by technology. In other words, the effective KM approach requires the integration of people, process, and technology in a systematic manner. Dehghani and Ramsin [16] summarized several methodologies used in the development of knowledge management systems, which should cover the stages of identification, assessment, classification, and knowledge goals. Also, the development of KM needs to focus on adaptability, analysis, and maintenance so as to develop a practical and beneficial application for the industry. In the world of smart manufacturing, it refers to adopting pervasive applications and ubiquitous computing, in which traditional facilities are transformed to knowledge-embedded facilities, enabling functions of predictive approach, incident prevention, performance enhancement, and decision-making capabilities [17]. Thus, the role of KM for knowledge-embedded facilities in smart manufacturing is inevitable. Papazoglou et al. [18, 19] proposed a knowledge-based model for smart manufacturing with integrating advanced technologies, including IoT, to establish manufacturing analytics and resource integration. Its knowledge structures covered partner, product, process orchestration, and quality assurance blueprint controlled by various knowledge repositories. Therefore, the value of quality assurance in smart manufacturing by means of KM is proven, and the integration of state-of-the-art technologies and KM is the preferred approach.

IoT is an emerging concept in which objects equipped with certain sensors, actuators, and mobile devices are able to interact with each other so as to achieve a specific goal [20, 21]. IoT technologies are developed from the extension of radio-frequency identification (RFID) technologies. In recent years, the IoT-related solutions and applications have dramatically increased in many industries, such as smart health, smart home, and smart manufacturing. The IoT solutions are basically developed with three technology stacks, namely, thin layer, connectivity layer, and IoT cloud layer [22]. The above three stacks clearly describe the requirements on the sensor nodes, the process of using protocols to connect the sensor nodes and cloud services, and the system development in the IoT cloud platform. In view of the detailed IoT elements, IoT consists of six major elements to create various functionalities in the applications and solutions, i.e., identification, sensing, communication, computation, services, and semantics. Da et al. [23] presented six key considerations in building a new IoT solution, i.e., energy consumption, data latency, throughput rate, scalability, topology, and security. For evaluating the industrial IoT applications, the aforementioned factors are used to establish the key performance indicators (KPIs) to ensure designated level in quality of service (QoS) and appropriate structure of service-oriented architecture (SOA). With appropriate system configuration and deployment, IoT applications can be developed which are applied into numerous application areas, including the healthcare service industry, food supply chain, safer mining production, and

logistics [24–27]. The above applications show that IoT technologies have sufficient capability in monitoring the conditions of an indoor environment. Therefore, there is room to extend the advanced IoT concepts, methods, and technologies for building an environmental monitoring system in electronic manufacturing. After IoT monitoring application is established, the data analytics by means of artificial intelligence can be followed. To achieve the goals of quality assurance and quality prediction, fuzzy logic, which is able to process linguistic variables and terms and mimicking human thinking process, is selected [28]. The knowledge from domain experts is managed in the knowledge repository in the form of if-then rules, and it can connect input and output attributes which may be subjective and uncertain to provide decision support in quality assurance.

With the above study, it is concluded that electronic manufacturing plays an essential role in our society for producing the latest electronic devices. Since the end users require a high level of product quality, control and monitoring in the electronic manufacturing process are one of the key elements for improving product quality and productivity. In order to achieve the above objective, IoT technology is feasible for developing a real-time and automatic monitoring system in electronic manufacturing and formulating an intelligent quality prediction for manufacturing process. Therefore, an intelligent environmental monitoring and quality prediction system is proposed, and a knowledge-based approach is used to design the framework of entire system development and implementation in this chapter.

3. Integrating KM and IoT data in smart manufacturing

To achieve the goals of quality assurance and prediction in smart manufacturing, a knowledge-based approach is used to formulate the practical system with three phases, as shown in **Figure 1**. They are (i) problem identification and knowledge goal definition, (ii) design of IQPS, and (iii) performance measurement. It takes advantage of KM approach in developing and deploying the IoT systems in the real-world situations [29]. Apart from merely collecting the IoT data, the fusion between IoT data and human knowledge from domain experts is then exploited to generate decision support in smart manufacturing. With the systematic way to manage such knowledge, the effectiveness and efficiency of an organization can be further improved. Consequently, the projection of expected quality defects can be quantified in a systematical manner (**Figure 2**).

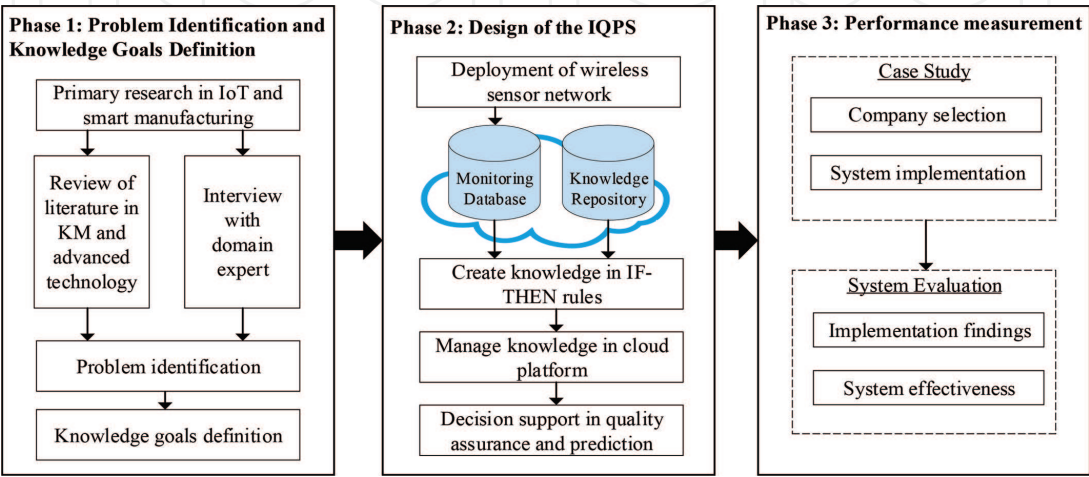


Figure 2.
Process flow of electronic manufacturing and its problems.

3.1 Phase 1: problem identification and knowledge goal definition

To harness IoT data and knowledge in the environment of smart manufacturing, the primary research in the fields of IoT and smart manufacturing is required to select the appropriate IoT technologies and techniques. However, merely deploying systematic solutions is insufficient for success, and KM approaches are needed to consider other angles in the organization. The literature related to KM and interviews with the industrial experts are then conducted to explore research gaps in the real-world situations. The interview and even site visits can truly reflect the existing situations in the organization, by investigating the workflow and discussing with the frontline operators. This generates the information for identifying the practical problems for manufacturing companies. Once the problem scenarios are built, the knowledge goals can be defined for effectively managing the knowledge in the entire system environment.

3.2 Phase 2: design of IQPS

This section describes an Internet-of-Things (IoT) quality prediction system (IQPS) to automatically collect ambient factors, namely, ambient temperature and relative humidity in production lines, and to predict in-process quality by using fuzzy logic. **Figure 3** shows the system architecture of the proposed system, IQPS, which consists of three modules, namely, the sensor node deployment module, the cloud connectivity module, and the quality prediction module. It aims at developing an automatic and real-time environmental monitoring system so that it can assist the regular recording and checking process for the indoor ambient factors. As a result, the collected data are analyzed to formulate decision support in quality prediction regarding manufacturing quality defects.

3.2.1 Sensor node deployment module

The SensorTag CC2650 is selected for the use in the sensor nodes in the proposed system due to low cost, capability of using multiple communication protocols, and low energy consumption. It is placed in various workshop environments so as to collect, at most, 10 different types of data, including ambient temperature and relative humidity. In order to deploy the sensor nodes effectively, target coverage and sensor node connectivity are two key elements, which are achieved by using the deterministic approach [30]. Firstly, the target coverage, which implies that sensor nodes at the target point get the optimal coverage level, is done by a binary coverage model and coverage algorithm. It ensures that the deployed sensor nodes are able to reach all the target nodes within the sensing reading range. In addition to controlling the number of sensor nodes, sensor s_i which covers the most target points is selected in a specific grid m , as in Eq. (1). When considering multiple grids simultaneously in a Cartesian coordinate system, the grid n is selected where the distance to the farthest target node $d_{i,t}$ is minimized among all the considered grids, as in Eq. (2). P denotes the grid set with the same number of target nodes, and Q denotes the set of target nodes covered by the sensor nodes:

$$m = \arg \max (s_i) \quad (1)$$

$$n = \arg \min_{i \in P} \max_{t \in Q} (d_{i,t}) \quad (2)$$

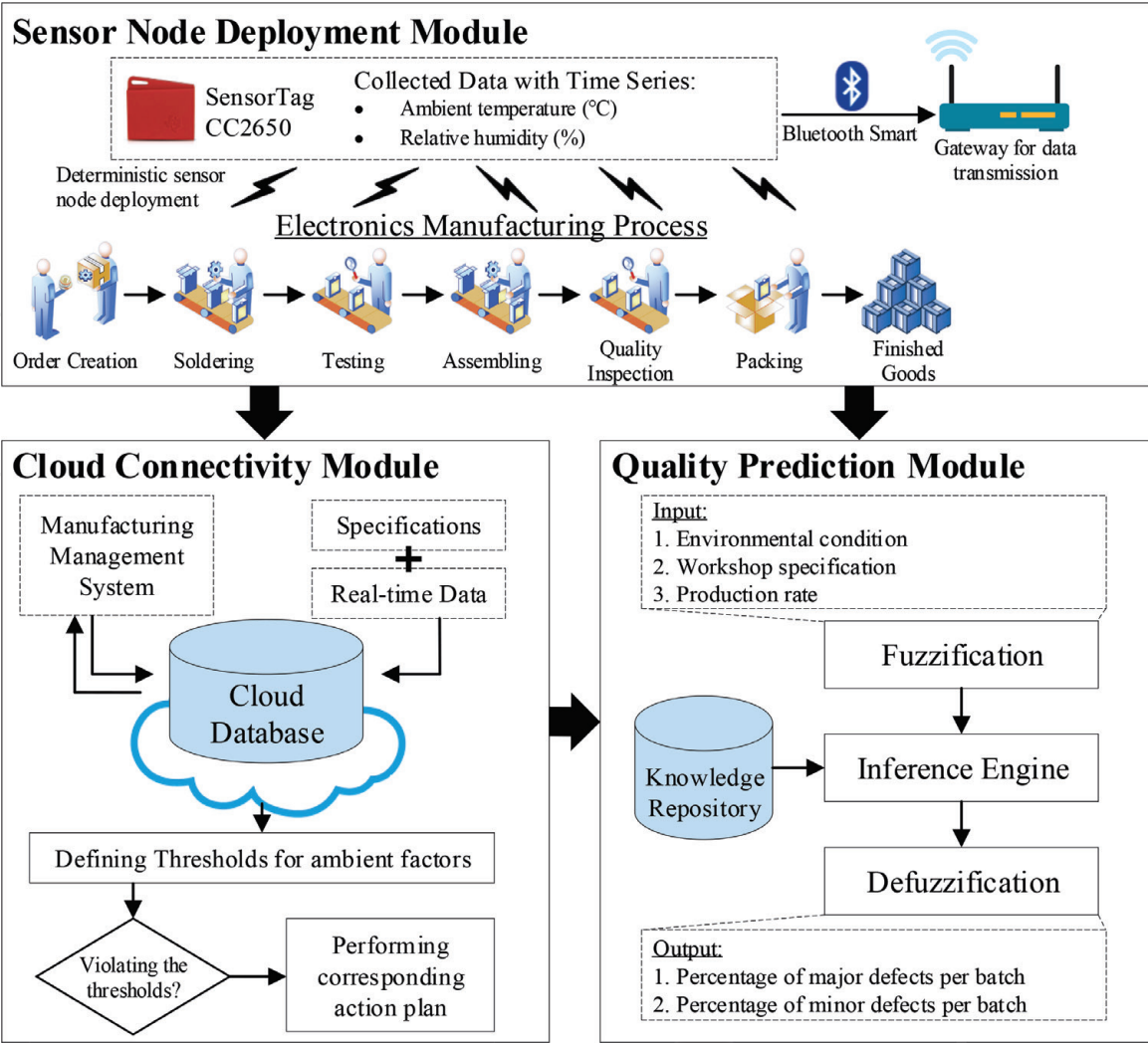


Figure 3.
System architecture of IQPS.

Secondly, for the sensor node connectivity, relay nodes should be placed in the indoor environment so as to transmit the collected data to specific host computers. Sensor node grouping and group connectivity are two major factors for placing the relay nodes. Firstly, relay nodes are required when there are some unconnected groups of sensor nodes, and the relay nodes are used as the node neighbor in each unconnected group. In addition, the number of relay nodes should be controlled through minimizing the relay node r_i and sensor node s_k in group j in a specific grid, as in Eq. (3). When considering more than one grid, the relay nodes $r \in R$ should connect the various groups of sensor nodes $t \in P$ as far as possible, as in Eq. (4):

$$d_{rj} = \min[d(r_i, s_k)] \quad (3)$$

$$f_n = \arg \max \min[d(r_i, t)] \quad (4)$$

3.2.2 Cloud connectivity module

In this module, all the collected data are then transmitted to the cloud services or host computers through the transmission protocols, for example, Message Queuing Telemetry Transport (MQTT). In order to effectively create the IoT applications, the data are stored in the cloud database under an IoT development platform, such as

IBM Cloud. The sensor nodes have to be registered in advance for configuring and authenticating data queries and messaging to the pointed web services. In the cloud platform, the real-time data and specifications for ambient factors are integrated to formulate a monitoring application. In addition, the collected data stored in the cloud database can be linked to the existing manufacturing management system so as to enable suppliers and customers to view the reports on indoor ambient factors. If the collected ambient environmental conditions are violated, corresponding action will be taken to maintain stable and appropriate environmental conditions.

3.2.3 Quality prediction module

In the IBM Cloud, some development tools are well-designed for creating a customized IoT application, for example, Node-RED. They embed the major programming environment and capability of using multiple programming languages. It offers the advantage to freely design an appropriate solution for meeting a specific goal. The proposed system, apart from real-time monitoring and alert management, is also able to generate a report with time series data and to build customized user interfaces for displaying the collected data to the suppliers and customers. Last but not least, the proposed system is also able to record the number of quality deviations under the controlled indoor environment in order to access the system performance.

On the other hand, the fuzzy logic approach is used to evaluate the quality in the manufacturing process by making use of the real-time data and other static data, namely, workshop specification and production rate. In the fuzzy logic approach, the percentage of major and minor defects per batch can be evaluated by the environmental information, i.e., ambient temperature and relative humidity; workshop specification, i.e., workshop area; and production rate. In order to formulate the relationship between input and output attributes, there are three generic steps in fuzzy logic approach, namely, fuzzification, inference engine, and defuzzification. In the step of fuzzification, the linguistic input attributes are converted into fuzzy sets, where the fuzzy set F is defined by membership function $\mu_F(x)$ with element x as shown in Eq. (5):

$$F = \sum_{i=1}^n \frac{\mu_F(x_i)}{x_i} \quad (5)$$

The fuzzy sets are then processed to the inference engine in which Mamdani's method is used to integrate the fuzzy-rule-based knowledge stored in the knowledge repository. Therefore, the crisp input values are estimated and aggregated to be an appropriate adjustment of output values. The fuzzy rules used in this process are stated in the format of if-then rule which contains antecedent and consequent statements. The rules in the fuzzy logic are the knowledge which is collected from domain experts intuitively to express the relationship between input and output attributes. The inference engine is connected with the knowledge repository to facilitate the computation and conversion. Thus, the inference engine can be customized according to the extracted knowledge related to input and output attributes in different manufacturing environments. After aggregating the membership values in consequent membership functions, the OR operator is used for handling multiple attributes, and thus the bounded area can be formed, and the defuzzification process can be used consequently so as to obtain estimated output values. In the step of defuzzification, the centroid method which measures the center of gravity of the bounded area is applied to obtain the crisp output value y as shown in Eq. (6). Therefore, the average number of major and minor defects per batch can be predicted and estimated:

$$y = \frac{\int \mu_F(y) \cdot y dx}{\int \mu_F(y) dx} \quad (6)$$

3.3 Phase 3: performance measurement

To measure the performance of the proposed method, a case study and performance evaluation are two major approaches. To conduct a case study, two major steps are involved, i.e., company selection and system implementation. In the case study, the company should be the active practitioner in the electronic manufacturing industry, and the quality assurance is one of its business objectives. The selection criteria cover the company size, capability on quality management, and product variety. Thus, operators and staff at management level can be actively engaged in the quality assurance to provide high level of knowledge quality, and the value of decision support by using expert knowledge can be guaranteed. After implementing the system, the results need to be analyzed, and the effectiveness and satisfaction should be evaluated through conducting a survey. The results can be used to formulate the strategic quality planning in future production schedule to adjust the controllable factors for maximizing yield rate. Also, the proposed system advocates the domain experts to input their own expertise and knowledge for the inference engine to improve the quality of results.

4. Case study in an electronic manufacturing company

In order to validate the proposed system, a case study was conducted in an electronic manufacturing company, called Innovation Sound Technology Co. Ltd., which mainly produces headsets, headphones, and earphones. The company has 10 working and storage areas with various requirements on ambient temperature and relative humidity. The areas, with specifications as shown in the bracket, are the mold workshop (21–28°C; 40–60%), laboratory (21–28°C; 40–60%), processing workshop (21–28°C; 40–70%), dust-free workshop (21–28°C; 40–70%), packaging workshop (21–28°C; 40–70%), assembly workshop (21–28°C; 40–65%), chemical warehouse (10–25°C; 40–80%), electronic warehouse (15–28°C; 40–60%), glue warehouse (5–21°C; 40–60%), and general warehouse (15–32°C; 40–70%). The section supervisors and managers are required to remember all the above specifications and to check it regularly, but this manual approach is not effective in monitoring the ambient factors and in providing alert management. Due to growing technologies and solutions under the IoT environment, a real-time environmental monitoring system can be used to address the above challenges in electronic manufacturing sites. In order to implement the proposed system in the case company, there are three milestones in the entire implementation process, namely, (i) sensor node deployment, (ii) IoT system deployment, and (iii) quality prediction development.

In the first milestone, the sensor nodes, i.e., the SensorTag CC2650, are deployed according to the consideration of the target coverage and sensor node connectivity. The sensing radius for the sensor nodes is around 50 m in using Bluetooth Smart for data transmission. In the workshop environment, the sensor nodes are placed in the corners to collect temperature and humidity data at specific points, and the relay nodes have to be placed within sensor nodes' sensing radius so as to transmit the data to the cloud services. This method not only collects the data at the specific locations but also computes an average value to express the entire environmental conditions in the workshop environment. After placing the sensor nodes and relay nodes correctly, the sensor nodes and relay nodes are registered in the IoT development platform, i.e., IBM Cloud, in the second milestone. In this milestone, the service "Internet of Things Platform

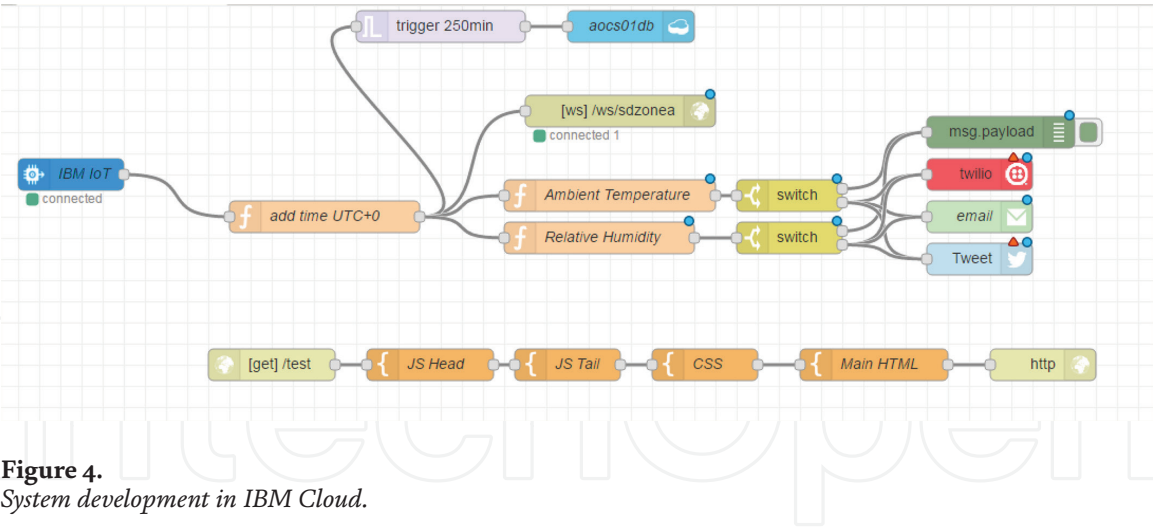


Figure 4.
System development in IBM Cloud.

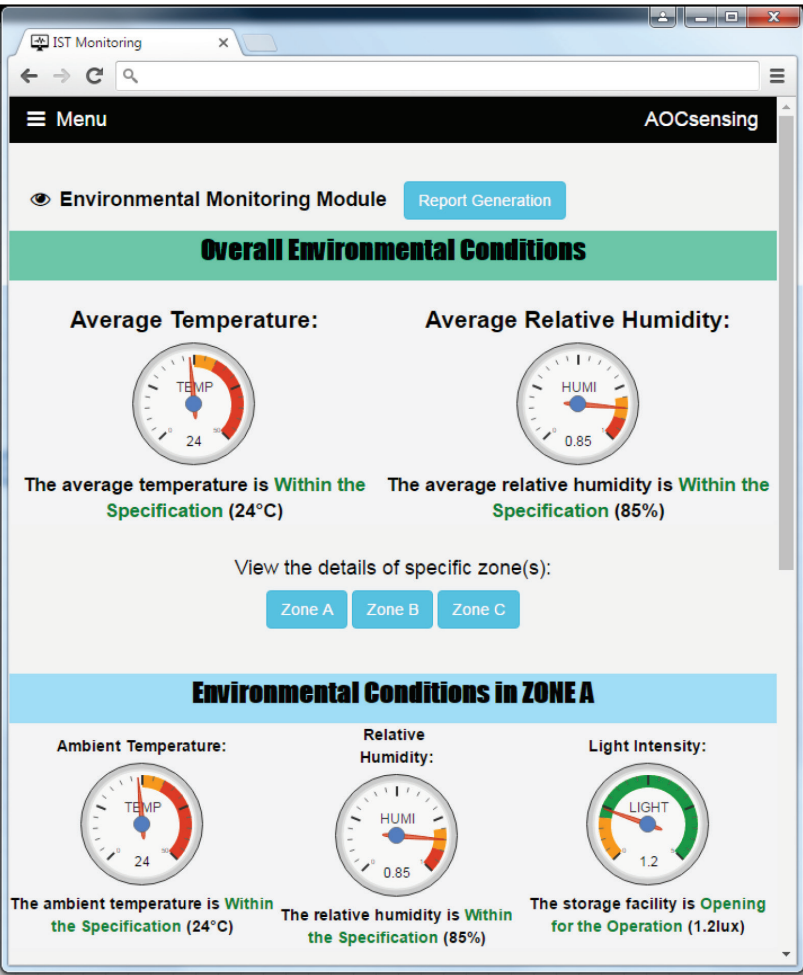


Figure 5.
User interface of IQPS.

Starter,” which consists of a standard development kit (SDK) for Node.js, Cloudant NoSQL database, and Internet of Things platform, is used. First and foremost, the sensor nodes are required to register in the Internet of Things platform with returning the authentication and configuration information. The sensor nodes can be connected to the Internet of Things platform by setting the configuration information in the relay nodes using IoT-registered services. After successfully connecting the sensor nodes, the system development is done in the Node-RED platform, including environmental monitoring, alert management, reporting, user interface development, and quality deviation analysis. **Figure 4** shows the entire system development to achieve all the

above functionalities. The node IBM IoT is the input from the sensor nodes where the data is transmitted in the format of JavaScript Object Notation (JSON). The data can be stored in the Cloudant NoSQL database effectively for further messaging and querying functions. In addition, a rule-based mechanism can be set to detect any violation of the collected data by comparing with the specifications. If there is a violation in either temperature or humidity, it will activate the services of Twilio, email, and tweet to alert supervisors and managers via SMS, email, and Twitter. Therefore, such alerts are transparent to all the corresponding parties. These functions are limited to a certain number of stakeholders with controlling security settings and system environment variables in the Node-RED platform, and therefore the leakage of personal information can be prevented. In addition, an add-on system monitoring plug-in is used to keep track of the IPs of access and usage of Internet traffic.

On the other hand, the collected data can be sent to a web application by using WebSocket, i.e., /ws/sdzonea in the proposed system. **Figure 5** shows the user interface for displaying the collected data in a user-friendly manner. All the stakeholders, including supervisors, managers, and customers, can gain access right to the web application for checking the environmental conditions at specific zones.

In the third milestone, the fuzzy logic approach is implemented in the case company so as to predict the product quality in the electronic manufacturing process. Under the Python programming environment, skfuzzy 0.2, which is the Python module of fuzzy logic approach, is applied where the fuzzification, Mamdani's inference, and defuzzification are included. First of all, the maximum and minimum values of attributes are defined in advance. The membership function of input and output attributes in the triangular shape are presented by `fuzz.trimf(attribute name, [x1, x2, x3])`, where `[x1, x2, x3]` represents the

| Attributes | Range | Fuzzy class | Membership function |
|--|-------------|--------------------|------------------------|
| Input attributes [Abbr.] (Unit) | | | |
| Ambient temperature [AT] (°C) | [10, 35] | Low | [10, 15, 20] |
| | | Medium | [15, 20, 25, 30] |
| | | High | [25, 30, 35] |
| Relative humidity [RH] (%) | [0, 1] | Low | [0, 0.1, 0.2] |
| | | Medium | [0.1, 0.4, 0.7] |
| | | High | [0.4, 0.7, 1.0] |
| Workshop area [WA] (m ²) | [100, 5000] | Small | [100, 400, 500] |
| | | Medium | [400, 500, 1500, 2000] |
| | | Large | [1500, 2000, 5000] |
| Production rate [PR] (unit/hour) | [50, 500] | Slow | [50, 70, 100] |
| | | Medium | [70, 100, 270, 300] |
| | | Fast | [270, 300, 500] |
| Output attributes | | | |
| Percentage of major defects per batch [MD ₁] (%) | [0, 1] | Low | [0, 0.2, 0.4] |
| | | Medium | [0.2, 0.4, 0.6] |
| Percentage of minor defects per batch [MD ₂] (%) | | High | [0.4, 0.6, 0.8] |
| | | Significantly high | [0.6, 0.8, 1] |

Table 1.
Fuzzy logic specifications for input and output attributes.

| Fuzzy inputs | | | | Fuzzy outputs | |
|--------------|--------|--------|--------|---------------|--------------------|
| AT | RH | WA | PR | MD1 | MD2 |
| Low | Low | Small | Low | Low | Low |
| Low | Low | Small | Medium | Low | Low |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Low | Low | Medium | Medium | Low | Medium |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Medium | Low | Medium | Medium | Medium | Medium |
| Medium | Medium | Medium | Medium | Medium | Medium |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| High | Medium | Medium | Medium | Medium | High |
| High | High | Large | Medium | High | Significantly high |

Table 2.
Knowledge of fuzzy rules for manufacturing quality prediction.

vertexes of the triangular membership function. For the trapezoidal membership function, `fuzz.trapmf(attribute name, [x1, x2, x3, x4])` is used, where `[x1, x2, x3, x4]` represents the vertexes of the trapezoidal shape. After that, the fuzzy rules stored in the knowledge repository is controlled by using `ctrl.Rule(antecedent, consequence)` and `ctrl.ControlSystem([rule1, rule2 ... rulen])`. Consequently, when the values of the input attributes are input properly, the fuzzy logic engine is then able to estimate the values of the output attributes. **Table 1** shows the range and membership function of the attributes for the fuzzy logic approach.

Moreover, the fuzzy rules for the Mamdani’s inference is collected from domain experts and summarized as **Table 2**. The fuzzy rules, or core knowledge in the proposed system, are expressed by using the defined fuzzy classes in **Table 1**. They are stored in knowledge repository and activated when the input parameters match the antecedents of the rules. The quality and quantity of stored knowledge determine the quality and accuracy of the results in quality prediction.

5. Results and discussion

This chapter presents IQPS for formulating a real-time environmental monitoring and quality prediction system for managing the environmental conditions and manufacturing process in electronic manufacturing sites with the adoption of advanced IoT technologies. According to the implementation of IQPS in Innovation Sound Technology Co. Ltd., routine work regarding regularly recording and checking the environmental conditions by using data loggers can be eliminated. All the relevant parties can access and view the environmental conditions for all the zones in a web application, and the site supervisors and managers can receive an alert message via either SMS, email, or Twitter, when any violation of environmental specifications occur. Besides, all the collected data is stored in a cloud database such that this can be used to generate a report about the workshop’s environmental condition with a defined timeframe. On the other hand, the results of the quality prediction in manufacturing process by means of fuzzy logic approach are shown in **Table 3**. Five processing workshops are

| Workshop | AT | RH | WA | PR | MD1 | MD2 |
|----------|----|------|------|-----|------|------|
| 1 | 25 | 0.55 | 1000 | 210 | 0.06 | 0.11 |
| 2 | 23 | 0.58 | 850 | 180 | 0.01 | 0.05 |
| 3 | 29 | 0.66 | 1650 | 480 | 0.12 | 0.20 |
| 4 | 26 | 0.49 | 600 | 200 | 0.01 | 0.03 |
| 5 | 26 | 0.52 | 1500 | 480 | 0.09 | 0.31 |

Table 3.
Results of fuzzy logic approach.

| Parameters | Before implementing IQPS | After implementing IQPS |
|---------------------------------------|--------------------------|-------------------------|
| Average % of quality defects | | |
| • Major quality defects | 0.11 | 0.07 |
| • Minor quality defects | 0.19 | 0.12 |
| QM staff satisfaction (scale of 1–10) | 6.8 | 7.9 |
| Average production yield rate | 98.5% | 99.1% |
| Time for environmental monitoring | 1 hr./day | Real-time |

Table 4.
Comparative analysis before and after implementing IQPS.

selected to conduct the inspection to investigate the quality performance during the manufacturing process. Through the proposed system, the environmental conditions and quality performance can be visualized for all the staff involved in the electronic manufacturing process. The high percentage of estimated defects can be an indicator to the line supervisors and manager to adjust the operations and other manufacturing processes.

Through implementing the IQPS, the expert knowledge is constructed in the form of the if-then rules to generate expected quality defects in electronic manufacturing operations. The results can be used to evaluate the system effectiveness, and a survey is conducted to compare the performance and satisfaction before and after implementing the proposed system in the case company. **Table 4** shows the findings of the comparative analysis for implementing IQPS in the case company. It demonstrates a positive impact on reduction of average quality defects and improvements in quality management staff satisfaction and average production yield rate. Also, the environmental monitoring is done by IoT technologies instead of the manual recording approach. Thus, the time for recording environmental conditions manually can be minimized.

As a consequence, two advantages can be gained after implementing the proposed system, namely, (i) better visibility of environmental conditions in the manufacturing sites and (ii) systematic approach to analyze the relationship between quality deviation and ambient factors. Firstly, since the regular recording and checking of environmental conditions are not the core business in electronic manufacturing sites, the time taken for these tasks is regarded as wasteful and redundant. Through adopting the IQPS, the operators don't need to keep recording and checking data regularly, such that they pay more attention to the electronic production. In addition, the proposed system also gives a better visibility regarding environmental conditions for all the stakeholders as the data can be accessed in a simple web application. Secondly, as a report on environmental factors in various

workshops can be generated, managers are able to conduct an analysis to investigate the relationship between quality deviation and ambient environmental factors. Incidents on quality deviation, including major and minor defects in production, are of great concern, and management aims at minimizing all possible causes of product defects. The above analysis is helpful to the management level to predict future quality deviation and to improve the existing manufacturing facilities.

6. Conclusions

Due to increasing demand and higher-quality level of electronic products all over the world, attention on quality improvement and monitoring has attracted considerable attention in the research field of electronic manufacturing. In manufacturing sites, there are numerous workshops and facilities for producing the electronic products, such as laboratory and assembly lines, but the requirements for environmental conditions in workshops vary according to the technical specifications. In order to ensure that the environmental conditions inside the manufacturing site are met, an environmental monitoring system is needed, but the traditional approach, which relies on data loggers and manual recording, is ineffective. With the rapid growth of IoT in recent years, the environmental monitoring system can be integrated with advanced IoT technologies. However, only relying on advanced technologies cannot develop and deploy the practical and mission-critical systems for the companies. Knowledge-based approach is considered in providing the systematic framework for the system development and performance measurement. Apart from that, the knowledge and information from the companies can be managed in the knowledge repository to enhance the computing systems by mimicking human thinking and logic. This chapter proposes an Internet of Things quality prediction system (IQPS) where SensorTag CC2650 is used to collect the environmental data and to transmit the data through wireless communication protocols to the cloud services. The sensor nodes and relay nodes are deployed by satisfying the target coverage and sensor node connectivity and are registered in the IBM Cloud so as to develop a customized system in the Node-RED platform. All the collected data is stored in the Cloudant NoSQL database with complete messaging and querying functions. With the adoption of IQPS, the manual recording and checking work can be eliminated, and automatic environmental monitoring and alert management can be provided. In view of the managerial perspectives, IQPS not only provides the real-time environmental monitoring inside manufacturing sites but also can be applied to investigate relationships between quality deviation and ambient environmental conditions. The fuzzy logic is thus applied in this situation for predicting the product quality along the entire manufacturing process. The expert knowledge stored in knowledge repository is extracted for the use of inference engine, and thus the proposed system can reflect the on-site relationship between input and output attributes in quality assurance. The possibility of major and minor defects per order batch can be estimated and visualized, and the workshop supervisors and managers are able to take any control actions to maintain the product quality at an appropriate level. Therefore, the visibility of environmental conditions inside manufacturing sites can be enhanced, while the quality deviation can be predicted and reduced.

Acknowledgements

The authors would like to thank the Faculty of Engineering of the Hong Kong Polytechnic University through the engineering doctorate program for supporting this project.

IntechOpen


IntechOpen

Author details

Joseph Shun Ming Yuen, King Lun Choy*, Yung Po Tsang and Hoi Yan Lam
Department of Industrial and Systems Engineering, The Hong Kong Polytechnic
University, Hung Hom, Hong Kong

*Address all correspondence to: kl.choy@polyu.edu.hk

IntechOpen

© 2020 The Author(s). Licensee IntechOpen. Distributed under the terms of the Creative Commons Attribution - NonCommercial 4.0 License (<https://creativecommons.org/licenses/by-nc/4.0/>), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited. 

References

- [1] Holbrook MB. Product quality, attributes, and brand name as determinants of price: The case of consumer electronics. *Marketing Letters*. 1992;**3**(1):71-83
- [2] Mason SJ, Cole MH, Ulrey BT, Yan L. Improving electronics manufacturing supply chain agility through outsourcing. *International Journal of Physical Distribution and Logistics Management*. 2002;**32**(7):610-620
- [3] Lau JH, Wong CP, Lee NC, Lee SR. *Electronics Manufacturing: With Lead-Free, Halogen-Free, and Conductive-Adhesive Materials*. New York: McGraw-Hill, Inc; 2003
- [4] Landers TL, Brown WD, Fant E, Malstrom EM, Schmitt NM. *Electronics Manufacturing Processes*. New Jersey: Prentice Hall; 1994
- [5] Stark J. Product lifecycle management. In: *Product Lifecycle Management*. Vol. 1. Cham: Springer; 2015. pp. 1-29
- [6] Salgado EG, Salomon VA, Mello CH. Analytic hierarchy prioritisation of new product development activities for electronics manufacturing. *International Journal of Production Research*. 2012;**50**(17):4860-4866
- [7] Helander MG, Burri GJ. Cost effectiveness of ergonomics and quality improvements in electronics manufacturing. *International Journal of Industrial Ergonomics*. 1995;**15**(2):137-151
- [8] Abbel R, Teunissen P, Rubingh E, van Lammeren T, Cauchois R, Everaars M, et al. Industrial-scale inkjet printed electronics manufacturing—Production up-scaling from concept tools to a roll-to-roll pilot line. *Translational Materials Research*. 2014;**1**(1):015002
- [9] Doniavi A, Mileham AR, Newnes LB. A systems approach to photolithography process optimization in an electronics manufacturing environment. *International Journal of Production Research*. 2000;**38**(11):2515-2528
- [10] Gupta AK, Sivakumar AI. Job shop scheduling techniques in semiconductor manufacturing. *The International Journal of Advanced Manufacturing Technology*. 2006;**27**(11-12):1163-1169
- [11] Abdulmalek FA, Rajgopal J. Analyzing the benefits of lean manufacturing and value stream mapping via simulation: A process sector case study. *International Journal of Production Economics*. 2007;**107**(1):223-236
- [12] Lee J, Bagheri B, Kao HA. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*. 2015;**3**:18-23
- [13] Rubenstein-Montano B, Liebowitz J, Buchwalter J, McCaw D, Newman B, Rebeck K, et al. A systems thinking framework for knowledge management. *Decision Support Systems*. 2001;**31**(1):5-16
- [14] Inkien H. Review of empirical research on knowledge management practices and firm performance. *Journal of Knowledge Management*. 2016;**20**(2):230-257
- [15] An X, Bai W, Deng H, Sun S, Zhong W, Dong Y. A knowledge management framework for effective integration of national archives resources in China. *Journal of Documentation*. 2017;**73**(1):18-34
- [16] Dehghani R, Ramsin R. Methodologies for developing knowledge management systems: An evaluation framework. *Journal of Knowledge Management*. 2015;**19**(4):682-710

- [17] Davis J, Edgar T, Porter J, Bernaden J, Sarli M. Smart manufacturing, manufacturing intelligence and demand-dynamic performance. *Computers and Chemical Engineering*. 2012;**47**:145-156
- [18] Papazoglou MP, Elgammal A. The manufacturing blueprint environment: Bringing intelligence into manufacturing. In: *International Conference on Engineering, Technology and Innovation, ICE/ITMC*. 27-29 June 2017. Madeira: IEEE; 2017
- [19] Papazoglou M, van den Heuvel WJ, Mascolo J. Reference architecture and knowledge-based structures for smart manufacturing networks. *IEEE Software*. 2015. DOI: 10.1109/MS.2015.57
- [20] Wortmann F, Flüchter K. Internet of Things. *Business and Information Systems Engineering*. 2015;**57**(3):221-224
- [21] Al-Fuqaha A, Guizani M, Mohammadi M, Aledhari M, Ayyash M. Internet of Things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys and Tutorials*. 2015;**17**(4):2347-2376
- [22] Porter ME, Heppelmann JE. How smart, connected products are transforming competition. *Harvard Business Review*. 2014;**92**(11):64-88
- [23] Da Xu L, He W, Li S. Internet of Things in industries: A survey. *IEEE Transactions on Industrial Informatics*. 2014;**10**(4):2233-2243
- [24] Pang Z, Chen Q, Tian J, Zheng L, Dubrova E. Ecosystem analysis in the design of open platform-based in-home healthcare terminals towards the internet-of-things. In: *2013 15th International Conference on Advanced Communication Technology (ICACT)*. IEEE; 2013. pp. 529-534
- [25] Tsang YP, Choy KL, Wu CH, Ho GTS, Lam HY, Tang V. An intelligent model for assuring food quality in managing a multi-temperature food distribution centre. *Food Control*. 2018;**90**:81-97
- [26] Qiuping W, Shunbing Z, Chunquan D. Study on key technologies of Internet of Things perceiving mine. *Procedia Engineering*. 2011;**26**:2326-2333
- [27] Tsang YP, Choy KL, Wu CH, Ho GTS, Lam HY, Koo PS. An IoT-based cargo monitoring system for enhancing operational effectiveness under a cold chain environment. *International Journal of Engineering Business Management*. 2017;**9**:1-13
- [28] Klir GJ, Yuan B. *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. New Jersey: Prentice Hall PTR; 1995
- [29] Choy KLT, Siu KYP, Ho TSG, Wu CH, Lam HY, Tang V, et al. An intelligent case-based knowledge management system for quality improvement in nursing homes. *VINE Journal of Information and Knowledge Management Systems*. 2018;**48**(1):103-121
- [30] Guo XM, Zhao CJ, Yang XT, Sun C, Li M, Li W, et al. A deterministic sensor node deployment method with target coverage based on grid scan. *Chinese Journal of Sensors and Actuators*. 2012;**25**(1):104-109