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An Internet of Things (IoT)-based Risk Monitoring System for Managing Cold Supply Chain Risks

Abstract:

Purpose – Since the handling of environmentally-sensitive products requires close monitoring under prescribed conditions throughout the supply chain, it is essential to manage specific supply chain risks, i.e. maintaining good environmental conditions, and ensuring occupational safety in the cold environment. The purpose of this paper is to propose an Internet of Things (IoT)-based risk monitoring system (IoTRMS) for controlling product quality and occupational safety risks in cold chains. Real-time product monitoring and risk assessment in personal occupational safety can be then effectively established throughout the entire cold chain.

Design/methodology/approach – In the design of IoTRMS, there are three major components for risk monitoring in cold chains, namely (i) wireless sensor network, (ii) cloud database services, and (iii) fuzzy logic approach. The wireless sensor network is deployed to collect ambient environmental conditions automatically, and the collected information is then managed and applied to a product quality degradation model in the cloud database. The fuzzy logic approach is applied in evaluating the cold-associated occupational safety risk of the different cold chain parties considering specific personal health status. To examine the performance of the proposed system, a cold chain service provider is selected for conducting a comparative analysis before and after applying the IoTRMS.

Findings – The real-time environmental monitoring ensures that the products handled within the desired conditions, namely temperature, humidity and lighting intensity so that any violation of the handling requirements is visible among all cold chain parties. In addition, for cold warehouses and rooms in different cold chain facilities, the personal occupational safety risk assessment is established by considering the surrounding environment and the operators' personal health status. The frequency of occupational safety risks occurring, including cold-related accidents and injuries, can be greatly reduced. In addition, worker satisfaction and operational efficiency are improved. Therefore, it provides a solid foundation for assessing and identifying product quality and occupational safety risks in cold chain activities.

Originality/value – The cold chain is developed for managing environmentally-sensitive products in the right conditions. Most studies found that the risks in cold chain are related to the fluctuation of environmental conditions, resulting in poor product quality and negative influences on consumer health. In addition, there is a lack of occupational safety risk consideration for those who work in cold environments. Therefore, this paper proposes IoTRMS to contribute the area of risk monitoring by means of the IoT application and artificial intelligence techniques. The risk assessment and identification can be effectively established, resulting in secure product quality and appropriate occupational safety management.

Keywords Internet of Things, Cold chain, Risk monitoring, Wireless sensor network, Fuzzy logic

1. Introduction:

Cold chain management has been growing in the past few decades. Unlike traditional supply chain management, the goods in cold chains, such as pharmaceutical products, chilled food and frozen food, generally a have shorter shelf life and higher sensitivity to the surrounding environment, i.e. temperature, humidity and lighting intensity (Gormley et al., 2000). It thus requires certain refrigeration and dehumidification systems throughout the entire cold chain in order to maintain the prescribed environmental conditions. In particular, the ambient temperature for handling goods in a cold chain varies from -25 °C to +10 °C, depending on the type of goods (Lana et al., 2005; Soyer et al., 2010). However, when handling goods in an environment with such a low temperature, special attention should be paid to the potential risks that may directly affect the product quality and operational efficiency. Companies may suffer loss if any potential risks emerge along the cold chain. For instance, in 2017, Lucky's Market tossed all temperature-sensitive food, including cheese, juices and fresh cut meat, because they were stored at 16°C (~60°F), and could not meet the storage requirement for keeping the products below 40°F (Nerbovig, 2017). About 1 in 6 Americans get foodborne illness annually from tainted food which is handled under improper temperature (Wein, 2014). On the other hand, excessive exposure of food handlers to a cold environment may cause serious health effects and contribute to accidents of death and injuries (Rice, 2014). Fifteen workers died and twenty-six workers were injured at a Shanghai cold storage facility due to unexpected ammonia leakage (Laurence, 2013). The above reported cases show that the occurrence of cold chain risks affects not only the product quality and consumer health, but also the safety of personnel who work in the cold environment. Therefore, an effective risk monitoring system, especially for (i) product quality risk and (ii) occupational safety risk, is vital to track and evaluate the levels of risk throughout the cold chain. In general, product quality risk is the degree to which a product does not satisfy customers' requirements that is caused by product deterioration and contamination throughout the cold chain; occupational safety risk is the degree of exposure to workplace hazards, such as an extraordinary cold environment, among different supply chain facilities.

Figure 1 shows a typical cold chain, and the existing problems, for handing frozen food. Among the entire cold chain, it is important to ensure that the products are stored and handled under the proper environmental conditions for maintaining good product quality. Any abnormal environmental changes should be visible and realized by all other cold chain parties. As shown in the figure, each party would perform individual quality checking when receiving goods. However, without the environmental information that is shared by the upstream supply chain parties, only the goods arrival temperature can be measured. There is a chance that the goods have already deteriorated or been contaminated during handling by other parties or during the transportation. Real time environmental monitoring and control is deemed to be essential to increase product visibility and traceability with the related parties in the cold chain. The Internet of Things (IoT) is a global structured network for interconnecting everyday objects which are equipped with intelligence, identification, and sensing technologies (Yang, 2014). By applying the IoT paradigm, products and surrounding conditions in the cold chain can be tracked and traced automatically, resulting in transparent cold chain management. In addition, the quality degradation can be measured in a real-time manner.

On the other hand, depending on the product type, the condition of working environment has to be kept constantly at a low temperature. For example, chilled food should be kept at 0-10 °C while frozen food should be kept below -15 °C. To work under such environment with low temperature, there is a high likelihood of certain occupational safety risks, including cold-related illnesses (e.g. asthma and rhinorrhea), cold-related symptoms (e.g. wheezing and chest pain), and cold injuries (e.g. frostbite and trench foot) (Mäkinen and Hassi, 2009). The occurrence of occupational safety risks would directly affect the working performance of staff, resulting in a decrease in operation efficiency, workplace comfort and safety. The industrial common practice "ISO11079" is currently adopted for improving the ergonomics in cold environments. It is an ergonomics measurement to determine the thermal stress with exposure to a cold environment, called cold stress (ISO/TC 11079, 2007). The required clothing insulation (IREQ), recommended exposure time (D_{lim}) and recovery time are calculated when working in the cold environment. However, this practice does not consider the personal health status so that the formulated risk management may be inappropriate for assessing and identifying the risks in the workplace. Under the IoT environment, certain sensor nodes, such as wearables and environmental sensors, can be applied to collect personal health data to enhance the existing occupational safety measurement. Consequently, the risk assessment and identification regarding occupational safety can be formulated through the use of artificial intelligence (AI) techniques.

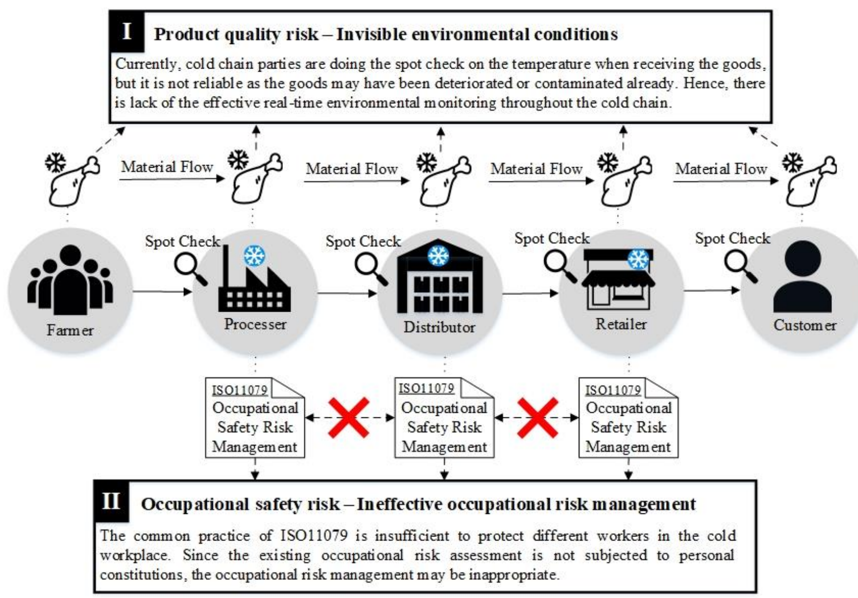


Figure 1. Existing problems in risk management of cold chain parties

With the structured infrastructure of the sensor network in IoT and robust computations in AI, the integration of IoT and AI is a promising way to establish risk monitoring systems in the cold chain. In this paper, an IoT-based risk monitoring system (IoTRMS) is proposed to fill the research gap of ineffective risk monitoring and management for product quality and occupational safety in cold chains. The purpose of this study is (i) to formulate an IoT system framework to measure product quality, and (ii) to integrate an effective fuzzy logic approach with the IoT system to enhance the practice of ISO11079. Cold chain parties will then be able to check the report on all previous environmental data regarding the products, after receiving the goods. In addition, each cold chain party can establish its own occupational safety risk management plan based on the specific ambient environment and workers' health status. Through the adoption of IoTRMS, the product quality can be ensured throughout the entire cold chain, and the personal occupational safety risk can be effectively mitigated for the cold chain parties. The significance of this study is to integrate IoT paradigm and AI techniques in the field of cold chain risk management. In addition, this study contributes to all cold supply chain parties involved, including the farmer, processer, distributor and retailer, so as to manage its product quality risk and occupational safety risk through measuring the product quality degradation and enhancing ISO11079 practice under the IoT environment. Therefore, workplace ergonomics are improved, while the product quality throughout the cold chain is maintained and is measurable.

This paper is organized as follows. Section 1 is the introduction. Section 2 reviews the literatures related to cold chain, risk management, IoT applications and AI techniques. Section 3 presents the system architecture of IoTRMS. A case study of the proposed system and implementation roadmap are presented in Section 4. Section 5 gives the results and discussion of the advantages and limitations of the proposed system. Finally, conclusions are drawn in the Section 6.

2. Literature Review

Supply chain management is an extended concept of logistics management, which aims at enhancing the linkage and coordination between various interdependent parties, such as suppliers, processers, distributors and customers (Christopher, 2016; Chung et al., 2016). The key objective of logistics and supply chain management is to plan and coordinate the material and information flow from the source to users in an integrated and effective manner. Catering to environmentally-sensitive products in the material flow, cold chain management (CCM) is established to maintain the desired product quality so as to achieve specific handling requirements by using particular refrigeration and dehumidification systems (Joshi et al., 2011). According to the 2016 Top Markets Report of Cold Supply Chain issued by International Trade Administration, the refrigerated warehouse and transportation are two significant components in the cold chain (Miller, 2016). The refrigerated warehouse capacities in India, China and Mexico were increased by 43%, 35%, and 27% from 2008 to 2014 respectively, implying that the demand for cold chain services is sustainably increasing globally. Inside the cold chain, technologies for controlling the environment play an important role in providing ideal conditions for products so that the likelihood of product deterioration and contamination can be reduced. However, the supply chain is vulnerable due to internal and external risks, including supply risk, demand risk, process risk, control risk and environmental risk (Christopher, 2016). The assessment of the vulnerability can be evaluated by multiplying the probability of disruption and impact, and the results can be used in identifying the risk profile of a company. Hence, the appropriate control measures and possible consequences can be formulated. Regarding cold chain activities, there are two additional risk considerations compared to the general supply chain management, namely (i) maintaining products under specific ranges of environmental conditions and (ii) occupational safety in the cold environment. Laguerre et al. (2013) summarized seven major stages for the material flow in cold chains, namely transportation, warehousing, logistics hub, cold room, retail display cabinet, and the domestic refrigerator of customers. On the one hand, warehousing is an important section among all cold chain parties, and is a closed environment applying refrigeration systems to meet the handling requirements. The workers are at risk in completing all warehousing operations when exposure to a cold environment. On the other hand, without real-time traceability, it is difficult to ensure that the products which are moved along the cold chain are maintained in stable prescribed environmental conditions (Aung and Chang, 2014). Therefore, the risk assessment, identification and monitoring for product quality risk and occupational safety risk in cold chains is particularly essential.

In cold chains, risk management should prevent exposure to undesired temperature and humidity, as product deterioration and contamination may result. Tse and Tan (2011) stated that the product quality risk is harmful to consumers in producing unsafe products in the supply chain, and, in fact, exists at any tier of the supply chain network. The visibility of the risk in the supply chain is important to enhance the product quality. The importance of real-time inventory monitoring and asset visibility is emphasized in maintaining appropriate levels of product quality and determining minimal managerial costs (Kelepouris et al., 2007; Montanari, 2008; Nakandala et al., 2016). Furthermore, recent research discussed the development of cold chain monitoring systems by means of radio frequency identification (RFID) technology for beverages, fruits, horticultural, and fishery products (Abad et al., 2009; Lao et al., 2012; Lam et al., 2013; Ting et al., 2014; Kim et al., 2016). It shows that the product categories in cold chain are varied, and the products themselves are environmentally-sensitive. Although RFID technologies are able to identify the products and record ambient environmental conditions, the product quality in terms of shelf life may worsen due to changes of temperature (Rong et al., 2011). Expired shelf life may cause product deterioration and contamination leading, for example, to foodborne illness. Product quality degradation is a main concern in customers' acceptance, and it should be seriously controlled in the cold chain (Ling et al., 2015), otherwise, the product quality can be below the acceptance level, resulting in wastage and spoilage issues. Besides, storage and transportation environmental conditions are sometimes extraordinarily low, according to the handling requirements, and there is a potential risk in the workplace related to occupational safety. Human factors and occupational safety risks are important, but receive limited consideration in supply chain management (Skjoett-Larsen, 2000; Gowen, 2003; Chan and Chan et al., 2011). As cold chain facilities operate at a low temperature, the comfort design and operational processes should be focused on maintaining productivity and the operators' safety. Occupation safety risk management is used to prevent workplace hazards which can lead to physical and emotional hardship (Kitt and Howard, 2013). The ergonomics of the thermal condition is an essential workplace hazard factor impacting on the efficiency and effectiveness of the logistics operations (Epstein and Moran, 2006; Balaras et al., 2007). Mäkinen and Hassi (2009) generally defined temperature range of cold work at/below +10 to +15°C. In real-life situations, the temperature of cold chain facilities may vary from -40 to +10°C, depended on the type of inventory handled. Apart from the climatic factors, the safety and health effect of the cold conditions is also contributed by physical activity, clothing, individual constitution, and socioeconomic factors. Inappropriate risk management for cold exposure may trigger cold-related diseases and aggravate the symptoms of chronic diseases. The above studies focused on state-of-the-art technologies to provide functionalities on incident management, cold chain monitoring, and traceability in order to maintain the desired product quality. However, there was a lack of the consideration of risk mitigation related to product quality risk throughout the entire cold chain. In addition, there have been limited studies on occupational safety risk management in cold chains, particularly considering of individual constitutions, i.e. health status.

Under the IoT environment, smart objects with integrating wireless communication technologies, sensors and actuators can connect to the Internet and share their data, in order to provide real-time data acquisition in supply chain management (Wortmann and Flüchter, 2015; Yan et al., 2016). The fundamental architecture of IoT consists of four layers, namely the sensing layer, gateway/network layer, management service layer, and application layer (Dweekat et al., 2017; Rezaei et al., 2017). Compared with RFID technology, IoT is an expanded concept that emerged from the prerequisite of RFID foundation (Jia et al., 2012). Apart from developing the automatic data capturing technology, an IoT-based system has a structured network infrastructure for connecting both physical and virtual objects in order to enhance the capability of data capturing, event transfer, network connectivity and interoperability. Wearable technology has been developed to reflect the actual personal health status for further analytics, while several sensors are integrated to collect real-time bio-signals, such as heart rates, body/skin temperature and blood pressure (Pantelopoulos and Bourbakis, 2010). Other sensor technologies, such as temperature sensors, can be applied to build a wireless sensor network in order to monitor warehouse environmental conditions (Wu et al., 2015). In recent years, the feasibility of M2M protocols, such as IPv6 over Wireless Personal Area Network (6LoWPAN), Message Queueing Telemetry Transport (MQTT) and Extensible Messaging and Presence Protocol (XMPP), on BLE links have been investigated, while the sensors in such networks can directly communicate to the Internet. By doing so, the sensor network can be operated in a scalable and efficient manner with increasing interoperability and standardization (Higuera and Polo, 2011).

Recent research shows that different AI techniques have been applied in occupational safety management to aid domain experts in making decisions, including case-based reasoning, analytic hierarchy processing and association rule mining (Virkki-Hatakka and Reniers, 2009; Chen et al., 2010; Liao and Chiang, 2012). Among the above AI techniques, there was lack of capability in handling vague and uncertain variables, such as personal health status. Fuzzy logic is another promising AI technique for generating acceptable reasoning with uncertainty and vagueness by mimicking human thinking and decision-making processes. In practice, fuzzy logic has been widely applied in various scenarios. Markowski et al. (2009) explored the fuzzy logic approach in process safety analysis for accident risk assessment due to uncertain input data and inaccurate output process risk level. Beriha et al. (2012) proposed the adoption of fuzzy logic for prediction of various accidents in an uncertain environment. Saravanan et al. (2014) developed a fuzzy-based risk rating system to predict accident risk on road networks based on road condition, driver-based risk and the number of pedestrians crossing the road. Hence, it is deemed to be a suitable technique to enhance ISO11979 practice by combining personal constitutions to evaluate the appropriate levels of occupational safety risk.

With the above study, it can be summarized that product quality and occupational safety risk management are critical to the effectiveness and efficiency in cold chains. The existing ISO11079 measurement can be enhanced to provide a customization of occupational safety measurements, resulting in improvement of productivity. Hence, this study attempts to develop an IoT monitoring system integrated with the fuzzy logic approach, in which real-time environmental data can be collected, and personal occupational safety risk plans can be formulated for cold chain operators.

3. Design of the IoT-based risk monitoring system (IoTRMS)

This section proposes an IoT-based risk monitoring system (IoTRMS) for dynamic occupational safety management and real-time environmental monitoring. It can further estimate the occupational safety risk level and accident frequency rate so as to schedule an appropriate workforce level. The proposed system is divided into 4 modules, i.e. automatic data capturing, IoT service management, fuzzy occupational safety risk assessment, and dynamic risk management, as shown in Figure 2.

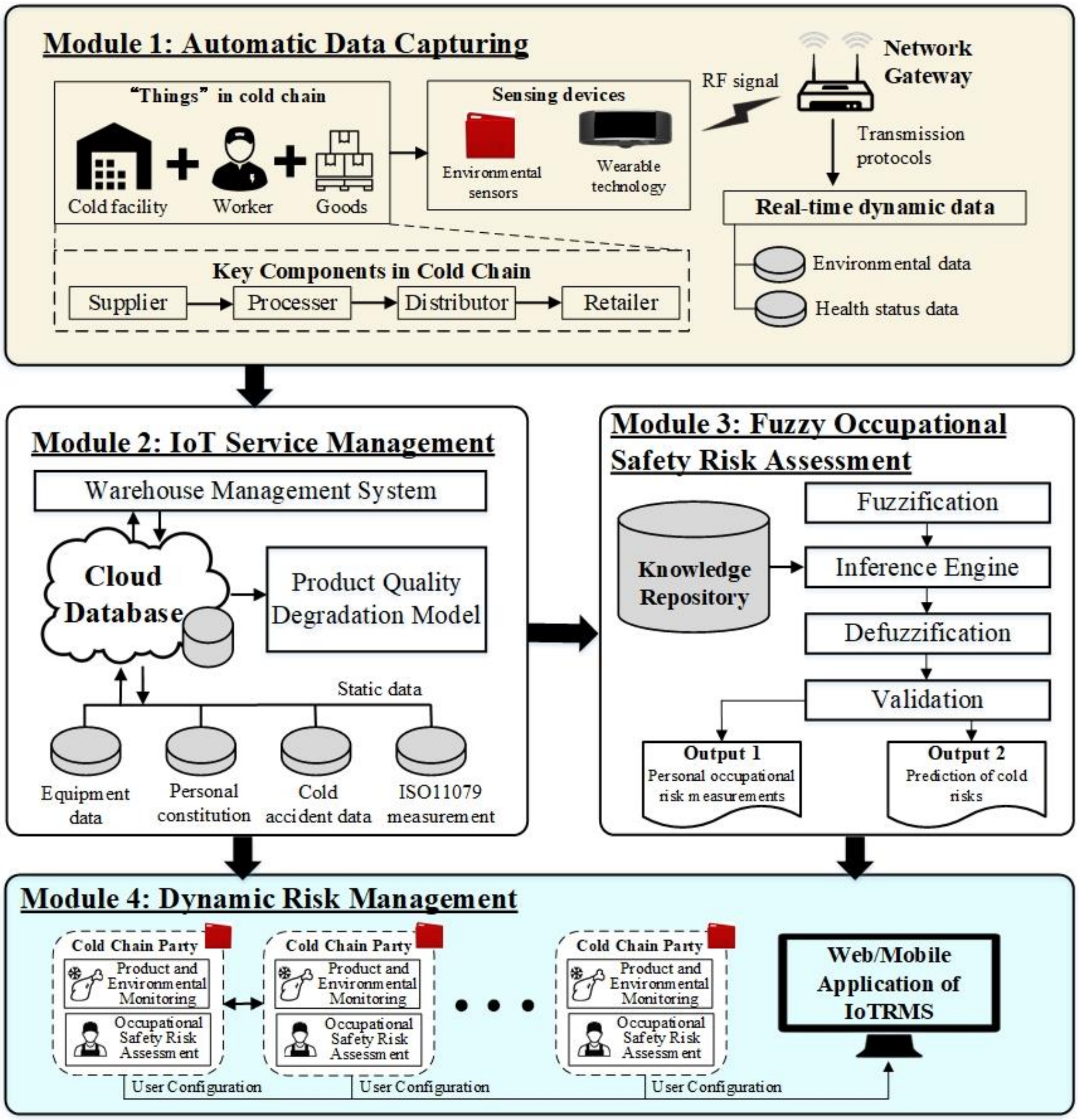


Figure 2. System architecture of IoTRMS

3.1. Module 1: Automatic data capturing

This module shows the structure for collecting real-time data related to the operators' health status and ambient environmental information. In the entire cold chain, cold facilities, workers and goods are three major elements, called "Things" in the IoT paradigm, among suppliers, processers, distributors and retailers for handling environmentally-sensitive products, such as frozen meat and seafood. The environmental sensor, i.e. SensorTag CC2650, is deployed in every cold facility and cargo pallets so as to monitor the degree of temperature, humidity and light intensity. The real-time monitoring of the product and cold facility can be formulated throughout the cold chain. Moreover, the workers are equipped with wearable devices, i.e. Microsoft band 2, in order to monitor their health status in real-time. The SensorTag CC2650 and Microsoft band 2 are selected as the sensor nodes due to the high capability of cloud application programming interface (API) so as to convert real-time data in JavaScript Object Notation (JSON) format, and integrate the data into a cloud-based Platform as a Service (PaaS). Data from SensorTag CC2650 and Microsoft band 2 can be transmitted to the proposed system through IBM IoTF registered service and Microsoft Health Cloud APIs respectively. In addition, they are manufactured for collecting the ambient environment data, for example ambient temperature and humidity, and health data, for example heart rate. Hence, the IoT monitoring application is established to collect sensor data automatically for further analysis by means of AI techniques. As illustrated in Figure 3, the IoT technology stack for data acquisition is divided into three major layers, namely device layer, connectivity layer, and IoT cloud layer, called as the IoT technology stack.

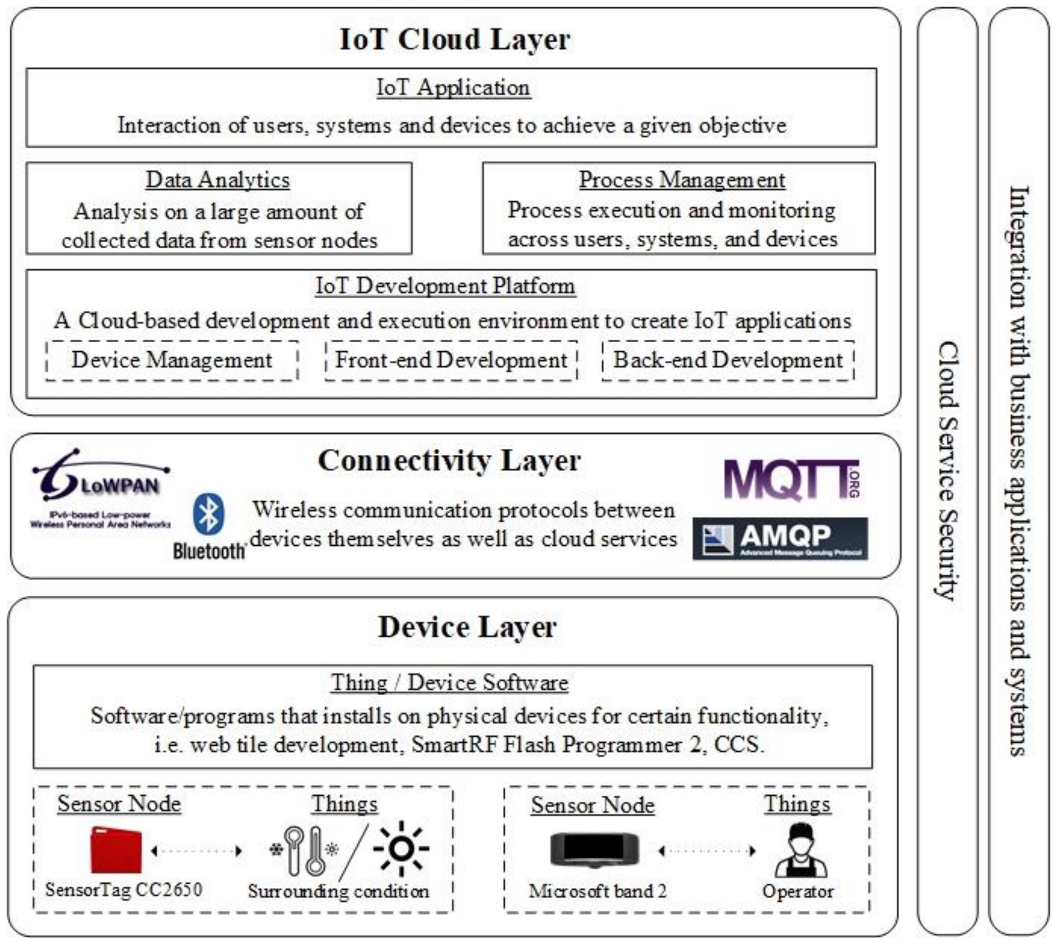


Figure 3. IoT technology stack for IoTRMS

In the device layer, the SensorTag CC2650 and Microsoft band 2 play the role of sensor nodes to collect real-time data, such as ambient temperature, humidity, light intensity, heart rate, and burned calories. Certain software and programs are flashed on the sensor nodes to operate the requested functionality, for example sensor listening frequency and data measurement intervals. The real-time collected data is then transmitted to the IoT cloud layer through M2M transmission protocols in the connectivity layer. The proposed sensor nodes are embedded in the Bluetooth wireless module for effective short-range data exchange. Particular to SensorTag CC2650, it also enables the capability of 6LoWPAN for handling local data exchange and connection to the Internet by using an arbitrary link, such as Wi-Fi and 3G/4G network. In addition, transmission protocols are developed for asynchronous messaging queues and point-to-point communication from sensor nodes to both front-end and back-end applications, for example MQTT and XMPP. In the IoT cloud layer, the IoT development platform, such as IBM Bluemix and Exosite, is applied to standardize the system development through providing device management, front-end and back-end development sources. Through registering the sensor nodes in the IoT platform, the collected data can be loaded in the cloud database with two additional functions, namely data analytics and process management, so the data pre-processing can be simply completed. By integrating the static data, including personal constitutions, cold accidents and ISO11079 measurement, a tailor-made IoT application is then developed to achieve the proposed objectives of IoTRMS, namely product monitoring reporting and occupational safety risk assessment. Consequently, cloud service security and integration with other business applications, such as Warehouse Management System (WMS), by using APIs are used to formulate a total IoT application. Therefore, the wireless sensor network with adopting low power sensing technologies, can be established.

3.2. Module 2: IoT Service Management

In this module, the real-time dynamic data is integrated with the static data in a cloud database under the IoT services. The cloud database is then connected to the existing warehouse management system in order to create a product monitoring report by using specific time ID and product ID. Figure 4 shows the process of IoT system implementation starting from the sensor nodes to the end application. The sensors and corresponding devices are registered in the specific IoT service platform such that the data capturing function can be enabled. The data is then transmitted to the platform in the formats of JSON/XML/HTML which are the common data formats for real-time data transmission. Through the authenticated cloud API service and certain logic building in the back-end process, the collected data can be managed in a cloud database. It is also capable of integrating with other data which has been pre-loaded in the database. Consequently, it can support the development of the proposed system in occupational safety risk management, including handling web event and querying. The cloud database contains not only dynamic sensor data, but also static data from real-life cold chain operations. Figure 5 shows the diagram for database structure for IoTRMS development, covering both dynamic and static data in the workplace. There are eight major data tables, namely product information (prodInfo), cold accident record (ColdAccident), personal constitution (Worker), ISO11079 measurement (ISO11079), environmental sensor data (ESensor), and personal health data (Health), equipment data (Clothing), and WMS. Apart from the typical data extraction, transformation and loading, the IoT service platform also enables usage monitoring and is integrated with NoSQL for achieving the complicated data transmission and management tasks. Therefore, all loaded data can be managed in an organized manner for formulating dynamic risk management in cold chains.

As the real-time environmental data is collected through the above IoT system, the product quality degradation model is embedded in this module to estimate the quality change for a specific time period. The proposed product quality degradation model is derived from the generic quality prediction as equation (1) (Rong et al., 2011).

$$\frac{\Delta q}{\Delta t} = kq^n \tag{1}$$

,where q is the product quality, t is the time, k is the rate of quality gradation, and n is the order of degradation reaction. The generic quality prediction model can be further derived by using the Arrhenius equation. Since a zero-order reaction is suitable to describe the temperature-dependent quality degradation, the product quality degradation model is therefore established with activation energy E_a and gas constant R to calculate the quality change, as equation (2). In other words, the relationship between quality and time is linear.

$$\Delta q(t, T) = -k_0 t e^{-\frac{E_a}{RT}} \tag{2}$$

The products in cold chains are moved along with supplier, processer, distributor, retailer and other sub-parties involved. Assuming that $q_i(t,T)$ and shelf life s_i are partitioned into i equally sized, the maximum rate of product quality degradation is assigned and minimum shelf life is selected despite the fact that the ambient temperature fluctuates in the cold chain, i.e. $\max\{ q_i(t,T) \}$ and $\min\{ s_i \}$.

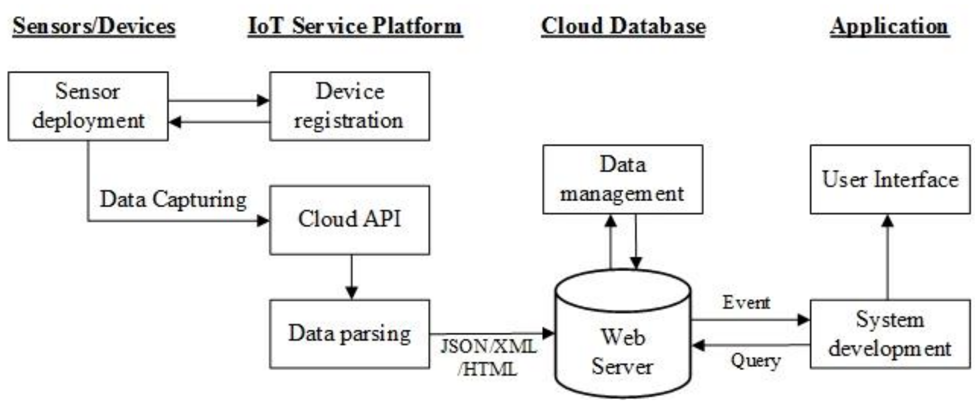


Figure 4. Process of IoT system implementation

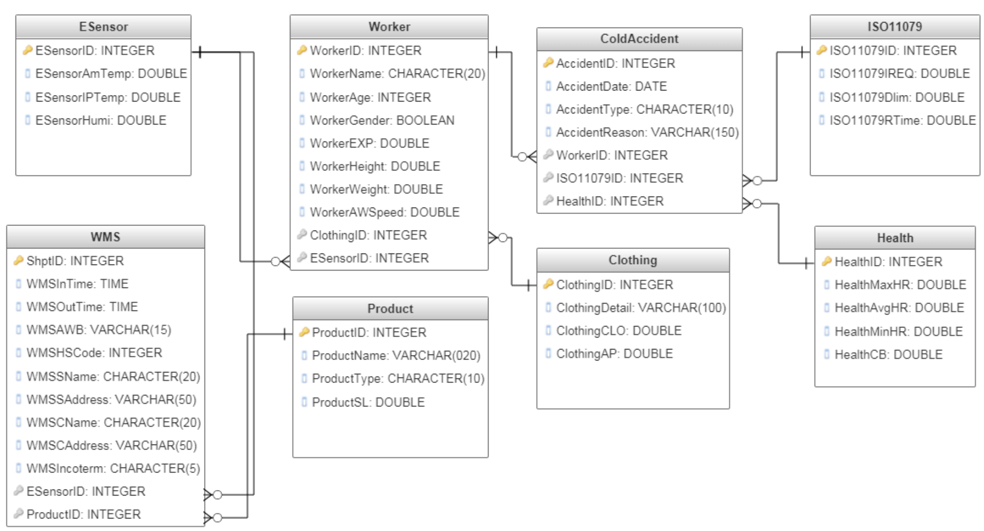


Figure 5. Data structure of IoTRMS

3.3. Module 3: Fuzzy Occupational Safety Risk Assessment

Since the cold chain operators have varying personal constitutions and work under extraordinary conditions, companies face challenges in providing adequate ergonomics design and risk assessment. This module proposes a fuzzy logic approach on occupational safety risk management, which is able to consider uncertain information in the system design. The input and output parameters in the assessment are related to personal constitutions, work experience, ISO11079 measurements and occupational safety risk. Decision makers in cold chains conveniently use linguistic terms, such as "high and "low", to express the relationship between the above input and output parameters. For instance, the occupational safety risk should be large for warehouse workers who are old and have poor in health. However, there is no detailed deterministic approach to judge the exact quantities on age and health conditions. The process in occupational safety risk assessment involves a range of possibilities of inputs to achieve the definite outputs. Therefore, the simple rule-based or non-fuzzy system may not be applicable such that the proposed system should be capable of handling the fuzziness of data to determine a personal ISO11079 measurement and occupational safety risk assessment for the cold chain service providers. The inference mechanism of adopting fuzzy membership functions and fuzzy rules is able to imitate human reasoning to provide a certain flexibility and levels of possibilities when integrating knowledge from domain experts in the companies. The required data is extracted from the cloud database under the IoT service platform so as to provide a real-time and dynamic fuzzy logic assessment. In addition, useful data assimilation and knowledge are jointly referred to and stored in the knowledge repository, where they are collected by interviews with domain experts and the data mining of historical data. The membership function of the specific fuzzy sets can be defined and used in the fuzzy rules, while it also contains the fuzzy IF-THEN rules for supporting fuzzy logic assessment. Overall, this module consists of three stages: fuzzification, inference engine, and defuzzification, in order to establish a dynamic occupational safety risk measurement for cold chain operators.

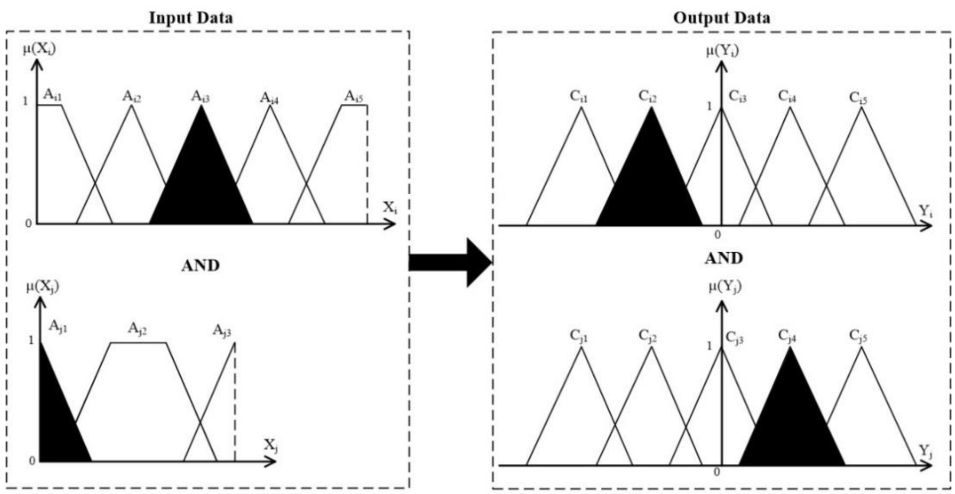
In the stage of fuzzification, the real-life input and output data are converted to the fuzzy data sets with a defined fuzzy class, such as "low", "medium", and "high" etc., and degree of belongingness from 0 to 1, typically. In other words, there are two sets of data, namely input data with $I = \{I_1, I_2, I_3 \ldots I_n\}$ and output data with $O = \{O_1, O_2, O_3 \ldots O_n\}$. The fuzzy set I_i of data set X is illustrated with its membership function as shown in (3).

$$I_i = \sum_{i=1}^{n} \frac{\mu_A(X_i)}{X_i} \tag{3}$$

,where X_i shows the entire data set with all element $\{x_1, x_2, x_3 \ldots x_n\}$; $\mu A(X_i)$ is the corresponding membership function of fuzzy class A of X_i; n is the total number of sub-elements.

In the inference engine, the rule $R = \{R_1, R_2, R_3, \ldots, R_m\}$ is applied to evaluate the aggregated output of the fuzzy logic, where m is the total number of fuzzy rules. Figure 6 shows the composition of the fuzzy rules in the inference engine. The membership function can be the composition of various shapes of membership functions, the fuzzy classes for input (X_i) and output (Y_i) data are expressed in A_{ip} and C_{iq} respectively, where p and q are the total number of fuzzy classes for the input and output data. The mechanism of the inference engine is defined by Mamdani's method (Suthar et al., 2015), which gives the outputs in the form of a fuzzy set rather than a linear mathematical expression. Since the set of input and output parameters has been fuzzified using (3), the value of membership functions can be evaluated according to the antecedent and consequence of given fuzzy rules. By applying m fuzzy rules in the inference engine, the membership function values of the aggregated output can be defined as (4). The OR operator is then applied for combining all membership function values in the consequence part, so that the bounded area in membership function can be established.

$$\mu_{C_i}(Y_i) = \max\{\min_i [\mu_{A_{1j}}(X_1), \mu_{A_{2j}}(X_2), \ldots, \mu_{A_{rj}}(X_r)]\} \quad (4)$$



Sample Rule: IF X_i is A_{i3} and X_j is A_{j1} **THEN** Y_i is C_{i2} and Y_j is C_{j4}

Figure 6. Example of the composition of the fuzzy rule

In the stage of defuzzification, the fuzzy sets are converted back and aggregated to crisp numerical and linguistic values. In practice, there are numeric defuzzification methods, such as bisector and centroid defuzzification, among which the centroid method, also called as center of gravity, is one the most popular methods for obtaining fuzzy output results. Equation (5) shows the mathematical expression for the centroid method of combined output parameters. It is expected that, by using the fuzzy logic approach, the personal occupational safety risk measurements and prediction of cold risks can be achieved.

$$\widehat{Y_i} = \frac{\int_1^n Y_i \cdot \mu_{C_i}(Y_i)\, dY}{\int_1^n \mu_{C_i}(Y_i)\, dY} \quad (5)$$

In order to assess and validate the rules in the proposed fuzzy logic approach, a measure quality Q(R, I)is introduced to classify the performance of the outputs by using the set of input *I* and set of rules *R*. Although the rules and membership functions are formulated by the domain experts who have sufficient field experience and knowledge, the performance may not be applicable to the real-life situations. Firstly, the rule redundancy is assessed by investigating the change of measure quality after counting an addition rule *r*, i.e. Q(R ∪ {*r*}, I) – Q(R, I). If the change of measure quality is less than zero, the additional rule is redundant in the inference engine generates the applicable reasoning. Secondly, the measure quality is also applied to validate the rules and the proposed fuzzy logic approach (Mahalakshmi and Ganesan, 2015). By partitioning the input data-set *I* into *i* equally sized sets I_i, the measure quality is applied individually to investigate the output performance judged by the domain expert, i.e. $q_i = Q(R, I_i)$. The system performance of the proposed system is then calculated by dividing the number of satisfactory results by the total number of subjects considered in the proposed system.

3.4. Module 4: Dynamic Risk Management

Based on the results from the IoT service management and fuzzy occupational safety risk assessment, a dynamic risk management can be established with three major functionalities, namely (i) environment and health status monitoring, (ii) personal occupational safety risk planning, and (iii) mobile/web-based application. Figure 7 shows the output overview of IoTRMS throughout the entire cold chain. Inside the IoT development platform, several logic and threshold values can be embedded in the system design such that environmental and health status can be kept track of in a real-time manner. Once there is any violation of the defined threshold values, a prompt alert and warning can be sent to the operators and on-site supervisors. In addition, the proposed system can generate a specific product monitoring report for the cold chain parties in order to make sure that the previous product handling processes meet the requirements. On the other hand, IoTRMS can generate the personal risk profile for each cold chain party according to their uploaded dynamic and static data in the cloud database. The personal risk profile covers the personal occupational safety risk measurement, i.e. recommended exposure time, IREQ, and recovery time, and prediction of frequency of three types of cold risks, i.e. cold injuries, cold associated illness, and fatality/disability. Table 1 shows the potential effects of above cold risks. By doing so, the supervisor and management level can estimate the effective workforce level and potential medical compensation costs. In order to create a user-friendly application, a mobile/web-based application is developed by integrating the above two functionalities. Web-socket is applied to transmit the real-time dynamic data from back-end to front-end application, while PHP and JavaScript are adopted to embed the fuzzy logic assessment for illustrating the occupational safety risk planning to end users.

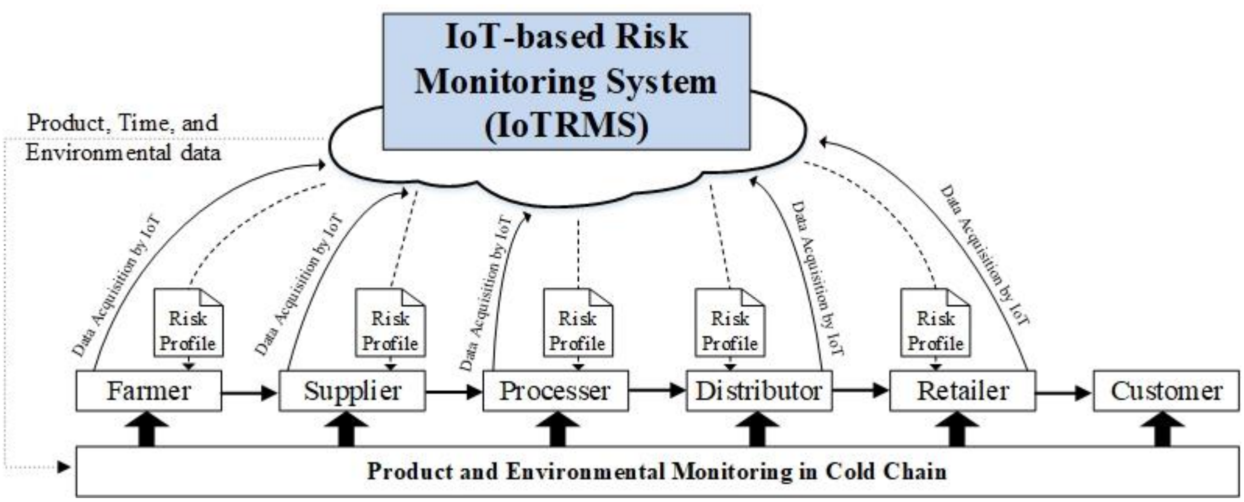


Figure 7. Output overview of IoTRMS

Table 1 Potential effect of cold risks

Types of cold risk	Causes	Potential effects
Cold injuries	Frostbite, hypothermia, trench foot	Temporary disability, lose a few working days
Cold-related illness	Asthma, Chronic Obstructive Pulmonary Disease, cold urticarial	Partial disability, long-term treatment required
Fatality/disability	Serious hypothermia	Death, permanent disability

4. Case Study

In order to validate the feasibility and performance of IoTRMS, a case study was conducted in a cold chain that particularly for handled frozen and fresh food. One of the cold chain parties, as the role of distributor, was selected for illustrating the mechanism of the proposed system. ABC Limited has ambitions for providing customized and one-stop logistics solutions covering the cold chain business. It has strategic and close collaboration with other cold chain parties, with an 18-storey, 28,000 metric tons capacity building for supporting cold chain businesses. The storage facility includes both freezing (-25°C to -18°C) and chilling (0°C to 8°C), while it also owns number of refrigerated trucks for delivery. Figures 8 and 9 show the freezing and chilling sections in the case company. The major logistics operations are performed under such environmental conditions, including put-away, order picking and packing. In order to provide the best cold chain services, the logistics premises comply international standard of ISO9001:2008. Therefore, the operational workflow is standardized so as to deliver high productivity and efficiency in cold chain operations. Since the facility scale is not suitable for adopting automation in logistics operations, the operations presently highly rely on available human resources.

Figure 8. Freezing section in ABC Limited

Figure 9. Chilling section in ABC Limited

In order to further consolidate its leading position in cold chain industry and deal with the ever-changing business environment, the company attempts to monitor the goods throughout the cold chain and to improve the ergonomics in such a labor-intensive workplace. However, due to diversified personal health status and lack of real-time environmental data acquisition, the company has difficulty in establishing effective risk management for mitigating product and occupational safety risks. In general, the problems which the company are facing are summarized as follows:

(i) Only checking the product temperature at the point of goods receiving is not reliable;
(ii) The personal constitution and health status of cold chain operators differ, and there is a lack of dynamic occupational safety risk management for assessing the risk level and suggesting the personal planning;
(iii) The prediction of cold risks is lacking in the cold chain so that the workforce stability and performance are very uncertain.

Due to facing these problems, ABC Limited decided to conduct a pilot study on the IoTRMS in the cold storage and distribution center for three months, with the aim of total product monitoring and minimizing occupational safety risks in logistics operations. Consequently, an implementation flow of IoTRMS is proposed with four major phases as shown in Figure 10, namely sensor network deployment, IoT system development, integration with fuzzy logic approach, and establishment of dynamic risk management. Consequently, the IoTRMS was implemented with outputs of real-time product monitoring and personal occupational safety risk planning.

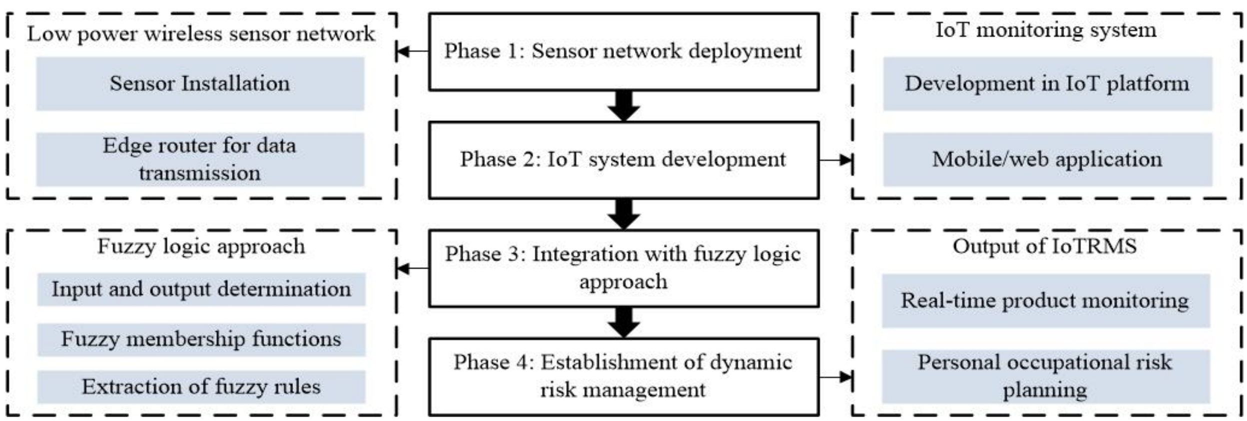


Figure 10. Implementation flow of IoTRMS in ABC Limited

4.1. Phase 1: Sensor network deployment

In this phase, the low power wireless sensor network (LPWSN) is established by the use of SensorTag CC2650 and Microsoft band 2 for collecting environmental data and personal health status. The implementation procedures of the LPWSN can be divided into sensor installation and edge router deployment. In ABC Limited, the sensor nodes of SensorTag CC2650 are installed in cold facility, clothing ensembles, and goods pallets; the sensor nodes of Microsoft band 2 are given to each worker who is required to work inside the cold facility. Figure 11 illustrates the installation of the sensor nodes, including SensorTag and Microsoft band 2, in the case company. The SensorTag is embedded into the collar of the jackets in order to collect the ambient environmental conditions of the workers. For installing the sensor nodes in goods pallets, the SensorTag is attached to the goods for monitoring the temperature, humidity and light intensity. For the cold facility, the sensor nodes are placed in the corners of the facility so that the overall environmental conditions of temperature and humidity can be measured effectively. The average values of temperature and humidity are inputted to the ISO11079 measurement to compute the original recommended exposure duration and recovery time. In order to facilitate the data transmission and synchronization, an edge router is also required for conversion between the sensor network and standard IP header. A smart phone, i.e. iPhone SE, which is set as the master device, is selected for this role by using a Bluetooth connection with the mentioned sensor nodes. By configuring the sensor nodes through the Microsoft Health Cloud API and IBM IoTF registered service in the edge router, the data can be transmitted to the proposed system in a real-time manner. Therefore, the deployment of LPWSN was completed in the case company. By integrating the advantages of IPv6 and IEEE 802.15.4, the 6LoWPAN provides effective internet and internal data exchange so as to support several open IP standards and mesh routing development. Figure 12 shows the transmitted and organized data from both sensor nodes in the JSON format under RFC 4627 standard. It includes sensor data from the SensorTag and Microsoft band 2, namely ambient temperature, object temperature, humidity, lighting level, heart rate summary, and calories burned summary. Due to handling the data from different sensor nodes, the data parsing is required to consistently convert some string data to integer data, such as ambient temperature. With such structured data format, the data can be loaded onto the SQL server for the fuzzy logic approach and monitoring functionality.

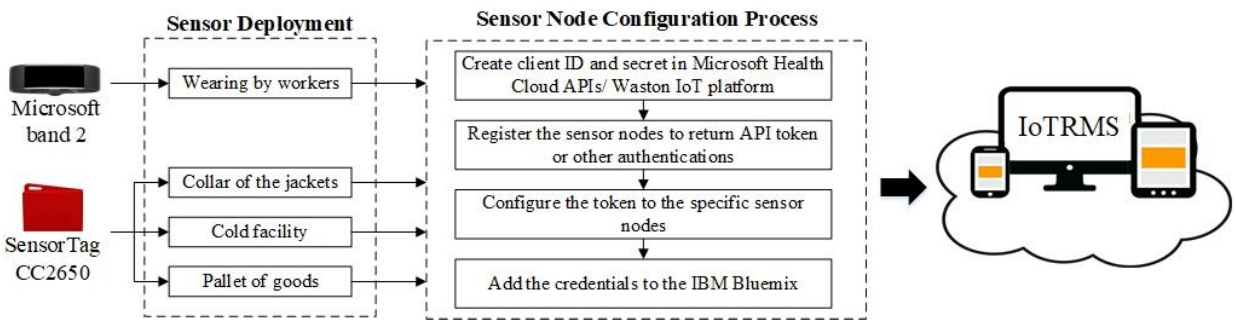


Figure 11. Implementation procedure of IoT technologies

4.2. Phase 2: IoT system development

For the development of IoTRMS, one of the well-known IoT development platform, i.e. IBM Bluemix, is selected to construct the device layer, connectivity layer, as well as IoT cloud layer. The required sensor nodes are registered under its device management tool, i.e. IBM Waston IoT Platform. The simplified gateway communication can be created for real-time data transmission. Inside the Bluemix platform, it supports multiple programming languages for application development with the online library, such as JavaScript and PHP. By integrating the static data stored in MySQL database, the data can be loaded to the mobile or web-based applications by using WebSocket. Therefore, the end users, i.e. operators and managers in the case company, are able to monitor the real-time environmental and health information. The alert function can also be enabled by simply defining the conditions and threshold values of the collected data. In the proposed system, the users, i.e. operators, supervisors, and managers, are able to measure and predict the occupational safety risks for their cold chain facilities. The functionalities of product monitoring and occupational safety risk management are embedded for authorized users in the system.

```
{
  "_id":"00aa268ae1edac411549b2f6d23fe504",
  "_rev":"1-ae2597f6cb4caecafa8b46e1f3180063",
  "d":{
    "myName":"st0001",
    "avgAmbientTemp":"-9.8",
    "avgObjectTemp":"-10.2",
    "avgHumidity":"53.13474",
    "avgLight":"0.16"
  },
  "time":"2017-03-21T13:26:30.896Z",
  "userId":"1560ce1d-0cfb-4ced-9766-4dcfb2166034",
  "startTime":"2017-03-21T09:05:13+00:00",
  "endTime":"2017-03-21T13:26:30+00:00",
  "heartRateSummary":{
    "period":"Daily",
    "averageHeartRate":58,
    "peakHeartRate":109,
    "lowestHeartRate":45
  },
  "stepsTaken":5877,
  "caloriesBurnedSummary":{
    "period":"Daily",
    "totalCalories":2810
  }
}
```


Figure 12. Example of dynamic data in JSON format

Apart from the real-time monitoring, fresh meat is handled in the case company with its supply chain partners. Given that the shelf life of fresh meat will be reduced from 5 to 3 days when temperature increases from -2.8°C to 3°C, following the linear characteristics between quality in term of shelf life and temperature, the shelf life decrease per unit of temperature is 0.35 days/°C. Table 2 shows estimated shelf life and rate of quality degradation for fresh meat in the cold chain. Since the average ambient temperatures among supplier, processer, distributor and retailer are different, the shelf life of the fresh meat is measured to estimate the remaining days for the fresh meat. For example, according to the zero-order degradation nature, the change of shelf life from the supplier side to the processer side is 7 – (-3.8 – (-8.3)) × 0.35 = 5.4 days. Even though the average temperature in the distributor is increased to -6.9°C, the shelf life should be changed by selecting the smallest possible shelf life, i.e. min{5.4, 5.4 – (-6.9 – (-3.8)) × 0.35}. Therefore, the shelf life remains unchanged in order to estimate the shelf life conservatively and maintain a good product quality before reaching the customers. In order to distinguish the rate of quality degradation, a total quality level of 100 is used in this situation. The rate of quality degradation is calculated by considering the linear relationship of zero-order reaction between product quality and shelf life, i.e. the quality is degraded over the time spent in supply chain activities. For example, the rate of quality degradation in supplier is estimated at (100 – 0)/(0 – 7) = -14.3. Therefore, it enables the cold chain parties to estimate the product quality throughout the entire cold chain.

Table 2 Estimation of shelf life and rate of quality degradation for fresh meat

Stage	Supplier (S)	Processer (P)	Distributor (D)	Retailer (R)
Average temperature (°C)	-8.3	-3.8	-6.9	-0.7
Shelf life (days)	7	5.4	5.4	4.3
Rate of quality degradation	-14.3	-18.5	-18.5	-23.26

For the sake of applying fuzzy logic to measure the occupational safety risk in a cold chain facility, the company's database also stores the criteria of membership functions and fuzzy rules. However, in the past, the adoption of the fuzzy logic approach faced challenges related to ineffective membership functions and fuzzy rules so that the fuzzy applications performance fluctuated. In the proposed system, the IoT service platform enables the effective and efficient information exchange across various cold chain partners, while the performance and settings of the fuzzy applications can be shared in real-time. Figure 13 shows the information flow of the occupational safety risks, performance and settings of the fuzzy applications. The wearables and sensors are provided for every operator in each cold chain party, and the data are stored in its own database. Through the cloud service, there is a centralized cloud database for collecting all the information so as to extract the application settings for relatively good performance. Therefore, the domain expert can analyze the information in order to fine-tune the defined fuzzy applications, and the system performance can be maintained at an acceptable level.

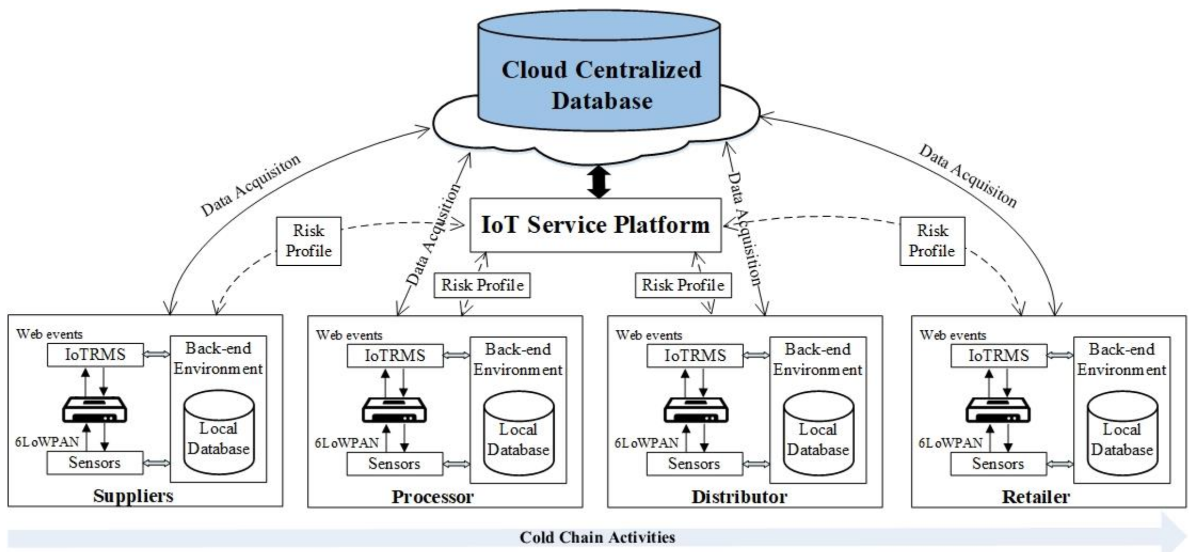


Figure 13. Information flow of IoTRMS in cold chain

4.3. Phase 3: Integration with fuzzy logic approach

According to the defined fuzzy membership functions and fuzzy rules, the fuzzy logic approach can be developed in order to enhance the ISO11079 measurement. Since the ISO11079 measurement has the assumption of fixed personal constitutions, the measurement outputs, i.e. recommended exposure time and recovery time, are insufficient. In addition, the relationship between work experience, constitutions and occupational safety risks is difficult to be formulated in a simple prediction manner. Therefore, the fuzzy logic approach is deemed to be a feasible solution to provide adjustments to ISO11079 and the occupational safety risk. Prior to defining membership functions and fuzzy rules, there are five input parameters, i.e. body mass index (B), age (A), average heart rate (avgHR), average calories burnt (avgCB) and work experience (E), and four output parameters, i.e. percentage change of recommended exposure time (D_{lim}) and recovery time (RT), hazard severity of cold risks (HS) and likelihood of occurrence of cold risks (LO), for the fuzzy logic. Figure 14 shows the structure of fuzzy logic assessment with the above five inputs and four outputs.

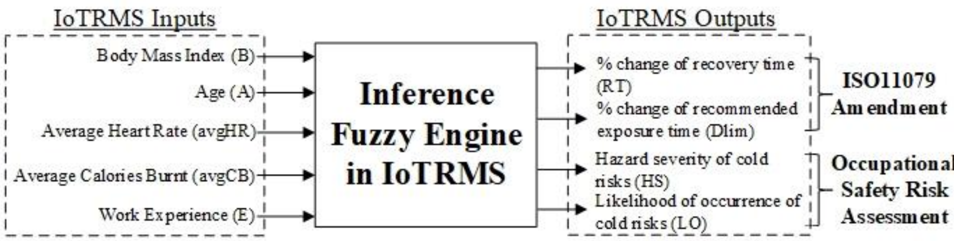


Figure 14. Structure of proposed fuzzy logic assessment

Each parameter is then fuzzified by the membership functions such that number of fuzzy classes and its distribution can be defined for the process in the inference engine and defuzzification. Tables 3 and 4 show the parameters, units, fuzzy classes, membership function regions, and shapes of membership functions for the inputs and outputs respectively.

Table 3 Fuzzification conversion for input parameters

Parameter	Unit	Fuzzy class	Region	Shape
Body Mass Index (B)	kg/m^2	L	[14.5, 14.5, 15.5, 16]	Trapezoid
		RL	[15.5, 16, 16.5]	Triangular
		A	[16, 16.5, 22.5, 23]	Trapezoid
		RH	[22.5, 23, 25]	Triangular
		H	[23, 25, 30, 30]	Trapezoid
Age (A)	years	Y	[18, 18, 25]	Triangular
		RY	[18, 25, 30, 33]	Trapezoid
		A	[30, 33, 45,50]	Trapezoid
		RO	[45, 50, 55]	Triangular
		O	[50, 55, 65, 65]	Trapezoid
Average heart rate (avgHR)	bpm	S	[40, 40, 50]	Triangular
		RS	[40, 50, 60]	Triangular
		A	[50, 60, 70, 80]	Trapezoid
		RF	[70, 80, 90]	Triangular
		F	[80, 90, 120, 120]	Trapezoid
Average calories burnt (avgCB)	kcal	L	[0.6, 0.6, 0.8]	Triangular
		RL	[0.6, 0.8, 1]	Triangular
		A	[0.8, 1, 1.2, 1.4]	Trapezoid
		RH	[1.2, 1.4, 1.6]	Triangular
		H	[1.4, 1.6, 2, 2]	Trapezoid
Work experience (E)	years	L	[0, 0, 1, 3]	Trapezoid
		A	[1, 3, 8, 10]	Trapezoid
		H	[8, 10, 20, 20]	Trapezoid

For the input parameters, the body mass index (B) and average calories burned (avgCB) are defined as {*L*, *RL*, *A*, *RH*, *H*}, where *L* is Low, *RL* is relatively low, *A* is average, *RH* is relatively high, and *H* is high. The age (A) is defined as {*Y, RY, A, RO, O*}, where *Y* is young, *RY* is relatively young, *A* is average, *RO* is relatively old, and *O* is old. The average heart rate (avgHR) is defined as {*S, RS, A, RF, F*}, where *S* is slow, *RS* is relatively slow, *A* is average, *RF* is relatively fast, and *F* is fast. The work experience (E) is defined as {*L, A, H*}, where *L* is low, *A* is average, and *H* is high. For the output parameters, the percentage change of D_{lim} and RT is defined as {*SuD, SiD, SlD, N, SlI, SiI, SuI*}, where *SuD* is substantially decrease, *SiD* is significantly decrease, *SlD* is slightly decrease, *N* is no change, *SlI* is slightly increase, *SiI* is significantly increase, and *SuI* is substantially increase. The hazard severity (HS) is defined by 5-point scale with {*FA, I, DI, PDI, FI*}, where *FA* is first aid attempt, *I* is injury causing time off, *DI* is disabling injury, *PDI* is permanent disabling injury, and *FI* is fatal injury. Similarly, likelihood of occurrence (LO) is defined as {*S, O, L, NC, C*}, where *S* is seldom, *O* is occasional, *L* is likely, *NC* is near certain, and *C* is certain.

Regarding the shapes of the membership functions, the trapezoidal and triangular types are determined intuitively from a group of domain experts in cold chains according to their intelligence, understanding and experience. The intuitive method is capable of considering contextual and semantic knowledge to the system design so that the degree of freedom to formulate the membership functions is sufficiently large. Therefore, in the case company, the trapezoidal and triangular shapes are used to interpret the input and output parameters. On the other hand, there are total 45 fuzzy rules in the format of IF-THEN rules which are obtained from the domain experts as well. All the rules are stored in the knowledge repository and applied in the inference engine.

Table 4 Fuzzification conversion for output parameters

Parameter	Unit	Fuzzy class	Region	Shape
Percentage change of recommended exposure time (D_{lim})	%	SuD	[-1, -0.75, -0.5]	Triangle
		SiD	[-0.75, -0.5, -0.25]	Triangle
		SlD	[-0.5, -0.25, 0]	Triangle
Percentage change of recovery time (RT)		N	[-0.25, 0, 0.25]	Triangle
		SlI	[0, 0.25, 0.5]	Triangle
		SiI	[0.25, 0.5, 0.75]	Triangle
		SuI	[0.5, 0.75, 1]	Triangle
Hazard severity of cold risks (HS)	1-5	FA	[1, 1, 2]	Triangle
		I	[1, 2, 3]	Triangle
		DI	[2, 3, 4]	Triangle
		PDI	[3, 4, 5]	Triangle
		FI	[4, 5, 5]	Triangle
Likelihood of occurrence of cold risks (LO)	1-5	S	[1, 1, 2]	Triangle
		O	[1, 2, 3]	Triangle
		L	[2, 3, 4]	Triangle
		NC	[3, 4, 5]	Triangle
		C	[4, 5, 5]	Triangle

4.4.Phase 4: Establishment of dynamic risk management

In the case company, information on 8 staff is extracted to evaluate their cold risks and suggest corresponding personal risk profiles so as to mitigate the cold risks in the proposed system, as shown in Table 5. They are all working in the staging area which is a chilled environment at around 2°C. In general, the company provides specific insulated jackets to the operators, but the operators are dissatisfied with the current occupational safety risk management associated with cold exposure workplace.

Table 5 Input parameters for fuzzy logic approach

Staff	Input Parameter				
ID	B	A	avgHR	avgCB	E
W0001	24.5	42	82	1.433	5.25
W0002	21.2	25	69	1.687	0.50
W0003	26.0	31	76	1.593	2.00
W0004	20.5	20	65	1.836	1.00
W0005	24.2	49	79	1.413	8.50
W0006	29.0	55	89	1.382	15.0
W0007	27.6	39	75	1.501	6.50
W0008	22.8	24	62	1.567	0.50

In order to illustrate the mechanism of IoTRMS, worker W0001 is used to show the computation of fuzzy logic assessment. Worker W0001 has a BMI of 24.5 kg/m^2, 42 years old, 82 average daily heart rate, 1.433 average calories burned in working hours, and 5.25 years of relevant work experience. Through the fuzzification process, the corresponding membership values can be shown for the five input parameters, as shown in Figure 15.

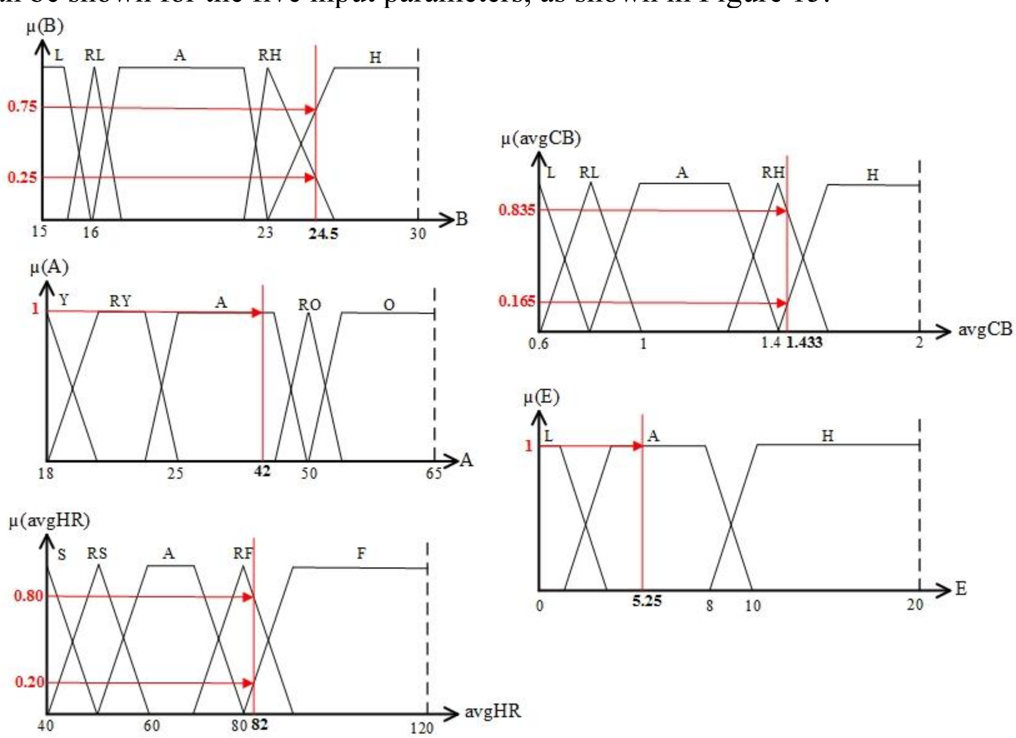


Figure 15. Membership values of input parameters for W0001

In BMI (B), the value 24.5 kg/m^2 cuts the fuzzy classes RH and H at membership values 0.25 and 0.75 respectively. In average heart rate (avgHR), the value 82 bpm cuts the fuzzy classes RF and F at membership values 0.80 and 0.20 respectively. In average calories burned (avgCB), the value 1.433 kcal cuts the fuzzy classes RH and H at membership values 0.835 and 0.165 respectively. In age (A) and work experience (E), the values 42 years and 5.25 years also cut the fuzzy class A in its corresponding membership functions so that their membership values are 1. In the IF-THEN rule-based repository, the successful rules are fired for compositing the membership values in W0001 in order that it can generate the membership values of the output parameters. The six corresponding rules are extracted with their composition result shown in Table 6. Fuzzy set theory is a systematic approach for knowledge conversion in a non-linear mapping mechanism. The smallest membership value of the specific input parameter is obtained as the composition result. Through aggregating with the output membership functions, the fuzzy sets can be turned into crisp values for the decision-making process by using the mentioned centroid method. In this process, the largest membership value of the specific output parameter is extracted to determine the center of gravity in the area of the bounded region. Figure 16 shows the four bounded output membership functions for worker W0001. The percentage change of D_{lim} is -38.1%, percentage change of RT is 41.6%, HS is 2.37, and LO is 3.45. For the sake of establishing the personal occupational safety risk planning for each operator, the knowledge repository is expanded with sufficient rules which are extracted from the IoT environment. The useful rules are then fired and extracted for the fuzzy logic assessment. By repeating the above steps for all the other operators, the crisp output values for all eight operators are summarized in the Table 7. Reasonable and personal ISO11079 measurements can be generated, while the occupational safety risk level associated with cold exposure can be evaluated by multiplying HS and LO.

Table 6 Rule table for fuzzy inference engine

Rule ID	Rule Content	Membership composition	Result
6	**IF** BMI is relatively high, A is average, avgHR is relatively fast, avgCB is relatively high, and E is average, **THEN** D_{lim} is slightly decreased, RT is slightly increased, HS is level of first aid attempt, and LO is level of likely.	min[0.25, 1, 0.8, 0.835, 1]	0.25
7	**IF** BMI is high, A is average, avgHR is relatively fast, avgCB is relatively high, and E is average, **THEN** D_{lim} is slightly decreased, RT is slightly increased, HS is level of first aid attempt, and LO is level of near certain.	min[0.75, 1, 0.8, 0.835, 1]	0.75
8	**IF** BMI is relatively high, A is average, avgHR is fast, avgCB is relatively high, and E is average, **THEN** D_{lim} is significantly decreased, RT is significantly increased, HS is level of injury causing time off, and LO is level of likely.	min[0.25, 1, 0.2, 0.835, 1]	0.2

21	**IF** BMI is high, A is average, avgHR is fast, avgCB is relatively high, and E is average, **THEN** D_{lim} is significantly decreased, RT is significantly increased, HS is level of injury causing time off, and LO is level of near certain.	min[0.75, 1, 0.2, 0.835, 1]	0.2
22	**IF** BMI is relatively high, A is average, avgHR is relatively fast, avgCB is high, and E is average, **THEN** D_{lim} is slightly decreased, RT is no change, HS is level of first aid attempt, and LO is level of occasional.	min[0.25, 1, 0.8, 0.165, 1]	0.165
23	**IF** BMI is high, A is average, avgHR is fast, avgCB is high, and E is average, **THEN** D_{lim} is substantially decreased, RT is substantially increased, HS is level of permanent disabling injury, and LO is level of near certain.	min[0.75, 1, 0.2, 0.165, 1]	0.165

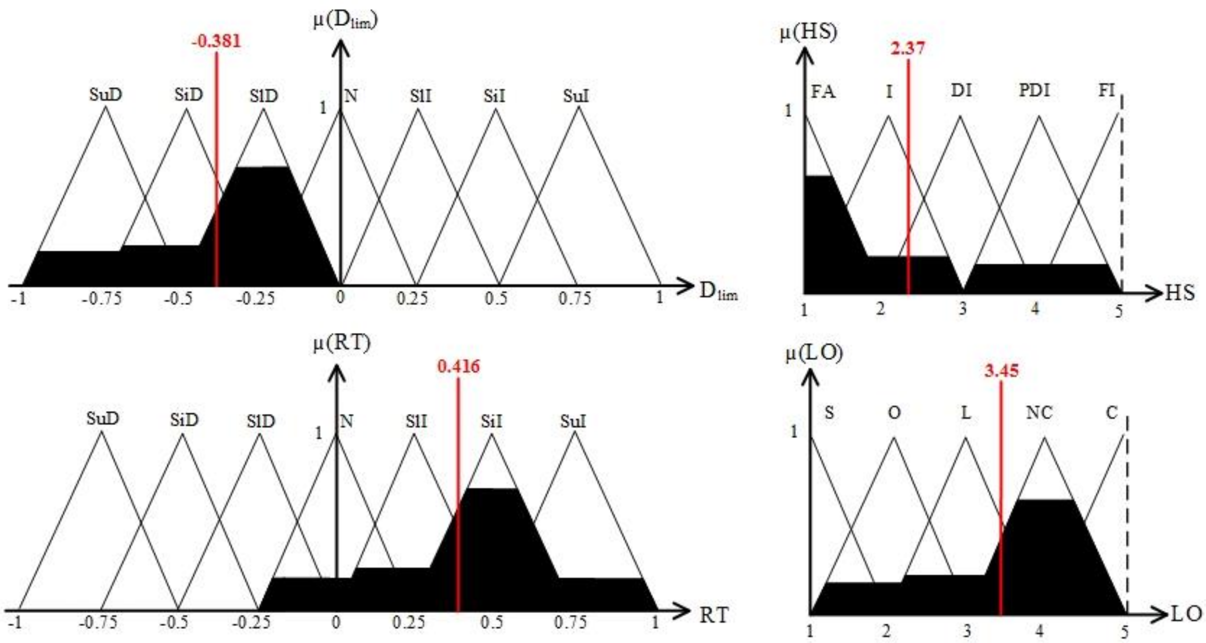


Figure 16. Output of W0001 in fuzzy logic approach

Table 7 Output parameters of the fuzzy logic approach

Staff	Output Parameter							
ID	% of D_{lim}	Personal minimal D_{lim} (hr)	Personal neutral D_{lim} (hr)	% of RT	Personal RT (hr)	HS	LO	Risk level
W0001	-0.381	1.55	0.74	0.416	1.27	2.37	3.45	8.18
W0002	0.25	3.13	1.50	-0.5	0.45	1.32	1.32	1.74
W0003	-0.122	2.20	1.05	0.25	1.13	1.48	2.98	4.41
W0004	0.24	3.10	1.49	-0.169	0.75	1.34	1.72	2.30
W0005	-0.25	1.88	0.90	0.324	1.19	1.44	3.3	4.75
W0006	-0.5	1.25	0.60	0.75	1.58	4	3	12.00
W0007	-0.25	1.88	0.90	0.5	1.35	1.38	4	5.52
W0008	0.351	3.38	1.62	-0.435	0.51	1.4	1.4	1.96

5. Results and discussion

As shown in Table 7, according to the outputs from the fuzzy logic approach, the percentage change of recommended exposure time, recovery time, hazard severity and likelihood of occurrence can be generated. As mentioned above, the workplace temperature is at 2°C so that it is implied that the mean radiant temperature of warehouse workers is almost 2°C. In addition, the humidity for the environment is set at 50% and the available basic clothing insulation is given at 1.5 clo. Regarding the logistics operations, the operators require certain hand work and arm work to handle the goods so that their metabolic energy production is estimated at $100W/m^2$ based on ISO8996. Therefore, a fixed set of ISO11079 measurements including minimal and neutral recommended exposure time and recovery time, is calculated. The selection between two proposed recommended exposure times are based on the level of physiological strain on the operators. On the other hand, by multiplying hazard severity and likelihood of occurrence, the risk level can be estimated for assessing their risks in cold chain operations. Figure 16 shows the occupational safety risk assessment chart for the mentioned eight operators with the corresponding hazard severity, likelihood of occurrence and risk level. There are generally three sections of risk level, in red, orange and green colors, which represent the dangerous, urgent and normal zones. The three risk levels are partitioned by 40% in normal, 20% in urgent, and 40% in dangerous zones, which follow the general practice of risk assessment in the case company. Operators 2, 3, 4, 5, and 8 are classified in the normal zone; operators 1 and 7 are classified in the urgent zone; operator 6 is classified in the dangerous zone. To sum up, it is found that operator 6 is regarded as the highest risk level in the case study, and therefore the prompt action and appropriate care should be taken to mitigate the risks. Moreover, operators 1 and 7 have the second and third highest risk levels in the orange region. The line supervisors and managers should be informed about this issue and take appropriate care actions. Others are measured within the normal risk level and the protection and risk planning are reasonably practicable.

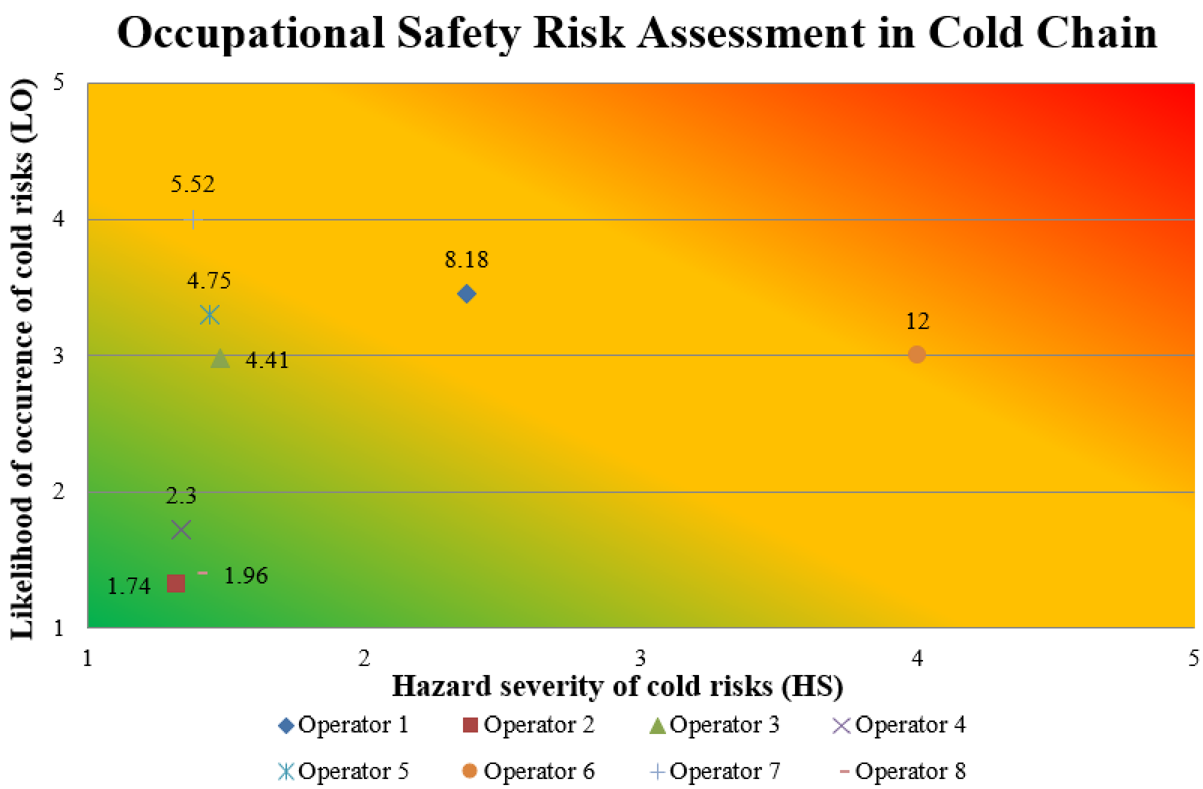


Figure 17. Occupational safety risk assessment chart

Further, the fuzzy occupational safety risk assessment is validated through the assessment and validation procedures stated in module 3 of the proposed system. The classification of the measure quality is divided into three dimensions, i.e. satisfied, moderate, and unsatisfied. Table 8 shows the validation of the results obtained from the IoTRMS. For obtaining the results for each staff in the case company, the corresponding active fuzzy rules are extracted from the knowledge repository. The domain expert who is knowledgeable and experienced in cold chain operations is required to assess the outputs through assigning the appropriate measure quality classification. For the IoTRMS, 7 out of 8 results are classified as satisfied, and the remaining result is classified as moderate. It is concluded that 87.5% of the industrial experts are satisfied with the results so that the proposed system is deemed to be appropriate for real-life applications.

Table 8 Validation of the results obtained from the IoTRMS

Staff ID	Active Rules	Measure Quality Classification
W0001	6, 7, 8, 21, 22, 23	Satisfied
W0002	1, 11, 19, 26, 28, 29	Satisfied
W0003	9, 10, 13	Moderate
W0004	1, 11, 13, 19, 27, 28, 29	Satisfied
W0005	32, 35, 36, 41, 43	Satisfied
W0006	26, 29, 30, 36, 38	Satisfied
W0007	31, 32, 37, 42, 43, 44	Satisfied
W0008	15, 18, 32, 36, 37	Satisfied
	System Performance	87.5%

Apart from discussing the mitigation of occupational safety risk, the product quality risk is controlled in the proposed system through the adoptions of (i) IoT monitoring and (ii) the quality degradation model. On the one hand, the environmental sensor, i.e. SensorTag CC2650, which is attached in the goods pallet is able to collect the ambient temperature and humidity in real-time for monitoring the handling condition of the goods. An alarm will be triggered to the relevant cold chain parties if there is a violation of the handling requirements. The transparency when handling the goods in both warehousing and transportation is therefore enhanced. On the other hand, due to the characteristics of the quality degradation mentioned in Section 3, the product quality can be quantified by considering the average handling temperature and the corresponding shelf life. Ideally, the case company, and other cold chain companies, attempt to maintain the stability of the ambient environmental conditions throughout the entire cold chain. However, in the real-life situation, due to different facilities and operation procedures, fluctuation of environmental conditions cannot be avoided. Therefore, the estimated shelf life and rate of quality degradation become known to all the stakeholders in the cold chain.

5.1. Dashboard of IoTRMS

Since the static data is handled in the cloud-based database structured by using SQL, and dynamic data is transmitted by using WebSocket to the proposed system, IoTRMS enables both product monitoring and occupational safety risk assessment functionalities. In view of the IoTRMS dashboard, there are two major sections, namely (i) environmental monitoring and (ii) occupational safety risk management. Figure 18 shows the user interface of the environmental monitoring in the proposed system. After user configuration in the dashboard, there are three functions, i.e. real-time site temperature, environmental conditions in specific intervals and incident management. The real-time temperatures at different sites in the cold chain are displayed, and the data are stored in the cloud database. Users can generate a report in a specific time interval, and then export into Excel or CSV format for recording and reporting. Once there is a violation of the environmental conditions, the details are shown in the Feeds section, helping users realize the key incidents for the entire cold chain activities. Figure 19 shows another user interface of the occupational safety risk assessment in the proposed system. The users are required to connect their pre-stored data from the database by using their own worker ID. The input data can then be extracted for the fuzzy occupational safety risk assessment so as to estimate four outputs, namely (i) recommended exposure time, (ii) recovery time, (iii) hazard severity, and (iv) risk likelihood. The corresponding risk level of W0005 is then shown marked by the triangular shape in the below risk assessment chart.

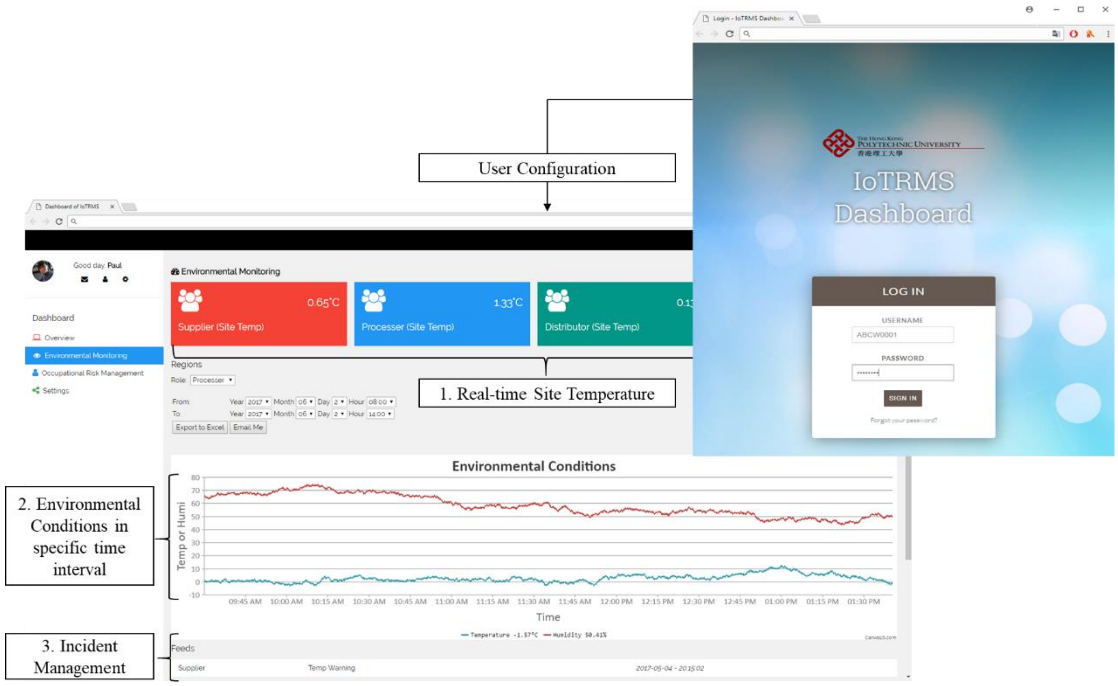


Figure 18. User interface of environmental monitoring in IoTRMS

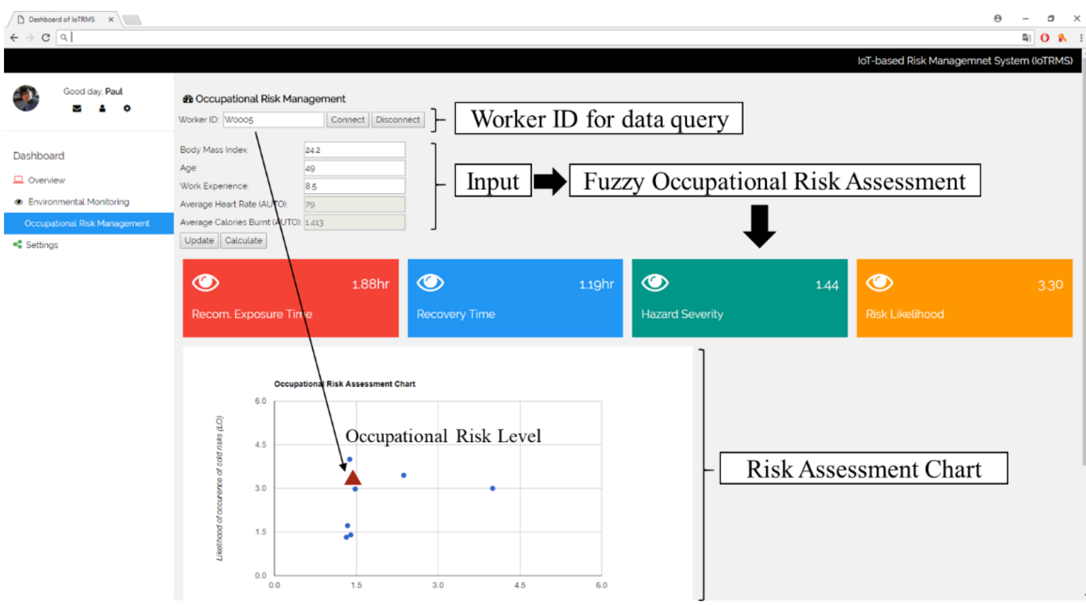


Figure 19. User interface of occupational safety risk management in IoTRMS

5.2. Discussion of IoT-based risk management in cold chain

According to the measured performance of the proposed system in Table 9, the product quality and occupational safety risks can be mitigated so as to improve the ergonomics and provide total product monitoring. Under the IoT environment, the data and related information can be exchanged in real-time, which enables various cold chain parties to formulate tailor-made product quality and occupational safety risk management. In summary, IoTRMS obtains three areas of significant benefit to cold chain parties as follows:

(i) Occupational safety risk mitigation in cold chain premises

The IoTRMS provides personal occupational safety risk planning to each operator in cold chain premises, with suggested recommended exposure time, recovery time and corresponding actions in handling cold accidents and injuries. The proposed system simplifies the effort in ergonomics and comfort design for ease of use, so that the companies are able to adopt the methods in a user-friendly manner. By integrating the foundation of ISO11079 measurement, IoT and fuzzy logic, the occupational safety risk level can be examined in a structured risk assessment chart in return for risk minimization and mitigation. It can greatly reduce the reliance on human judgement and monitoring. In the fuzzy logic assessment on ISO11079 measurement and risk assessment, the proposed cloud services enable the centralized storage and sharing of pre-requisite membership functions and fuzzy rule knowledge so that various cold chain parties can easily establish the most suitable fuzzy inference engine. Hence, the occupational safety risk can be certainly mitigated and minimized.

(ii) Improvement of operational efficiency and employee scheduling

As mentioned above, the implementation of IoTRMS aims at reduction of the accident frequency rate and improvement of the operational efficiency through real-time monitoring and the fuzzy logic approach. Table 9 shows the performance comparison between before and after implementing IoTRMS in the case company. There are five areas for assessing the system performance, namely accident frequency rate, average staff satisfaction, order fulfillment rate, idle time for recovery, and workforce stability. Since the proposed system generates personal occupational safety risk planning for each operator, they can be sufficiently protected by the systematic instructions and monitoring. In view of that, the accident frequency rate recorded an improvement with 60% in the reduction of the number of accidents and injuries. However, the idle time for recovery is slightly increased by 25% as the existing recovery time for the operators is insufficient. For the logistics operations, most of the employees are satisfied with the proposed system which can create a safe and comfortable working atmosphere in the company. As a consequence, it is beneficial to the order fulfillment rate with a 14.1% improvement. In addition, since the hazard severity and likelihood of occurrence can be estimated, it can foresee possible cold accidents and injuries. Apart from providing appropriate care to the operators, the supervisors and managers are also able to assign additional workers for maintaining the normal workforce level. As a result, the workforce stability is improved by 13.1%.

(iii) Enhancement in cold chain monitoring and visibility

Without the adoption of IoTRMS, companies do not have real-time data gathering and transmission regarding the environmental and personal health information. The monitoring is generally done by data loggers which are inefficient for handling tens of thousands of goods at the same time. The IoT application provides the capability for handling real-time events, such as data capturing and data analytics, in return for better visibility in the cold chain. Therefore, various cold chain parties can generate a product monitoring report at the point of goods receiving so that the possibility of product deterioration and contamination can be reduced. It can be seen as evidence for maintaining the right conditions of the products. Besides, the membership function settings and fuzzy rule knowledge are shared among various cold chain parties. They can access the above data and information for establishing their own occupational safety risk management and for viewing the status of the premises and workers. The use of IoTRMS also aids companies to set the specific key performance indexes related to safety and health-related incidents. Consequently, effective warehouse management can be maintained, and hence the decision-making process in occupational safety risk management can be reliable and systematic throughout the cold chain network.

Table 9 Performance of IoTRMS implementation

No.	Area	Measuring unit	Before implementation	After implementation	Percentage of improvement
i	Accident frequency rate	Number/ month	10	4	60%
ii	Average staff satisfaction	Scale (0-10)[a]	6.78	8.13	19.9%
iii	Order fulfillment rate	Order/ Total order	0.78	0.89	14.1%
iv	Idle time for recovery[b]	Minutes/day	60	75	-25%
v	Workforce stability	Available workforce/Total workforce	0.84	0.95	13.1%

Notes: [a]10 is highest comfort in scale, while 1 is the lowest comfort in scale; [b]The idle time mainly refers to the time for recovery after leaving the cold workplace.

5.3. Managerial implications

Food harm scandals, such as food poisoning due to improper storage conditions, and industrial accidents, such as cold accidents due to excessive exposure to cold environments, indicates that product quality and occupational safety are vulnerable in cold chain networks. For the supply chain parties, improper risk monitoring and management for product quality risk and occupational safety risk damages company reputation, gives a weak competitive edge, and high accident frequency rates. Therefore, companies are willing to invest in certain risk assessment tools which follow national or international standards, such as the Health and Safety Executive (HSE) in the UK. In the absence of interconnectivity and interoperability in risk management systems, the risks in cold chains are not fully visible and transparent in minimizing the threats to quality and safety. In the IoT environment, the IoT system is able to connect physical and virtual objects by sensing technologies, cloud computing and artificial intelligence techniques to enhance the visibility and traceability. The cold chain parties can take advantage from the IoT to improve the visibility of products in regard to product information, ambient environmental conditions and expected product quality. On the other hand, the knowledge repository where the knowledge is extracted from the domain expert from one company can be inter-communicated with the others. The deployment of a knowledge repository is changed from a stand-alone task to a shared task. It benefits the companies in establishing an effective knowledge repository for the application of fuzzy logic in occupational safety risk assessment. Some organizations who lack expertise are also able to deploy the knowledge repository as well as the entire decision support system. Therefore, product quality risk and occupational safety risk can be effectively managed in global cold chain networks.

6. Conclusions

With respect to handling environmentally-sensitive products in supply chains, risk management is important in preventing product loss and industrial accidents. On the one hand, there is a probability that the products will either deteriorate or be contaminated at any point in cold chain due to the fluctuation of temperature and humidity. Cold chain parties may bear unnecessary loss if visible product monitoring information is not recorded. On the other hand, most operations and processes are labor-intensive, whereas the operators have to work under demanding environments. Without appropriate risk assessment and management, it may result in cold-associated accidents and injuries, even fatality. In such a sense, the cold chain parties need to develop an automatic system for occupational safety risk management in order to establish better ergonomics and comfort design in the premises. In this paper, an IoT-based risk monitoring system (IoTRMS) is described. Under the IoT environment, the SensorTag CC2650 and Microsoft band 2 as the sensor nodes are applied to collect the real-time environmental and health-related data. The IBM Bluemix is used to build the application for IoTRMS for real-time and automatic monitoring. Based on the collected environmental data, the product shelf life and rate of quality degradation can be estimated. In order to establish the personal occupational safety risk assessment, the fuzzy logic approach is integrated to enhance the ISO11079 measurement and risk level in cold chains. Through the application of IoT, the corresponding data and information can be shared throughout the entire cold chain so as to achieve better cold chain visibility. Unlike typical fuzzy logic-based systems, the proposed IoTRMS takes advantage of the effective data exchange in IoT to investigate the most appropriate membership functions and fuzzy rule knowledge. Therefore, with the aid of IoTRMS for the various cold chain parties, risk management in product quality and occupational safety can be executed effectively and efficiently. Decision makers can adopt appropriate strategies in maintaining desired product quality and reducing the accident frequency rate. This study provides an applicable method for improving product quality risk and occupational safety risk management in cold chains, where it also contributes to the research on cold chain monitoring and industrial safety. Furthermore, other sources of relevant data can be fine-tuned and collected for fulfilling the needs of different industries. The limitations of this study are (i) requirement of full internet coverage for implementing the proposed system, and (ii) reliance of the knowledge collected from the domain expert for the application in fuzzy logic approach. Future work of this study should further enhance the system adaptability through integrating with other AI and data mining techniques, such as genetic algorithms and fuzzy association rule mining.

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