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An Intelligent-Internet of Things (IoT) Outbound Logistics Knowledge Management System for Handling Temperature Sensitive Products

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ABSTRACT

A comprehensive outbound logistics strategy of environmentally-sensitive products is essential to facilitate effective resource allocation, reliable quality control, and a high customer satisfaction in a supply chain. In this article, an intelligent knowledge management system, namely the Internet-of-Things (IoT) Outbound Logistics Knowledge Management System (IOLMS) is designed to monitor environmentally-sensitive products, and to predict the quality of goods. The system integrates IoT sensors, case-based reasoning (CBR) and fuzzy logic for real-time environmental and product monitoring, outbound logistics strategy formulation and quality change prediction, respectively. By studying the relationship between environmental factors and the quality of goods, different adjustments or strategies of outbound logistics can be developed in order to maintain high quality of goods. Through a pilot study in a high-quality headset manufacturing company, the results show that the IOLMS helps to increase operation efficiency, reduce the planning time, and enhance customer satisfaction.

KEYWORDS

Artificial Intelligence, Environmentally Sensitive Products, Internet of Things, Knowledge Management System, Outbound Logistics Strategy

1. INTRODUCTION

In today's dynamic and highly competitive manufacturing environment, providing good product quality is essential to maintain competitiveness and achieve customer satisfaction (Choi & Kim, 2013). It is especially important for environmentally sensitive products that can be easily damaged due to unfavorable environmental conditions, such as temperature, humidity, vibration, barometric pressure and light exposure, during the manufacturing and delivery process (Altmann, 2015). Taking electronic products for example, electronic chips and circuit boards may degrade and wear out easily under high temperature. High humidity brings moisture to electronic finished goods, which damages

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internal components and, finally, decreases the service life. In order to ensure that the product quality meets the required standard, it is a usual practice for the manufacturer to establish quality control measures in the production line for testing the functionality of products and identifying product defects (Jozsef & Blaga, 2014). The quality checking at the end of the production process serves as the final stage to ensure that the product is of good quality. The products that pass the quality control process would then be stored in the warehouse until a customer order is received for delivery. However, different types of inventory have their own specific environmental requirements. Improper storage and handling during outbound logistics operations would also have negative effects on the product quality (Maldonado-Siman et al., 2015). Hence, it is essential to develop a total and complete solution in order to monitor the goods as well as to predict the quality of goods during the outbound logistics operations.

To keep monitoring of the workplace environment, industrial thermometers are installed in the fixed areas of the manufacturing plant, such as production areas and warehouses. Records of temperature and humidity are taken regularly, and manually, which are then reviewed by the warehouse manager to ensure the suitable workplace conditions. However, without real-time data capturing technologies on individual products, it is difficult to collect and retrieve data of specific types of products instantly. In addition, the monitoring systems in the current market involve recording raw environmental data, i.e. temperature and humidity, only. Rarely of these used for controlling the environment parameters throughout the storage and transportation process. The items, in fact, would be degraded when transporting from warehouses to customers due to longer delivery route and improper handling methods. Besides, with the data collected in the monitoring system, there is, however, little attention towards further investigation to transform the data to predict the relative quality of the goods. Warehouse managers usually develop outbound logistics strategies based on the past experience and opinions from experts, to estimate the quality of goods during transportation, which is not reliable. The relative loss, in consequence, may be increased due to the high risk of degraded inventory. Therefore, in order to ensure product quality, managing effective outbound logistics operations from the manufacturer to the end customer is a critical activity in a supply chain.

In this paper, an intelligent knowledge management system, namely Internet of Things (IoT) Outbound Logistics Knowledge Management System (IOLMS), is designed, with the objectives (i) to monitor environmentally sensitive products for outbound logistics, as well as (ii) to predict the quality of goods. The IoT concept is adopted for monitoring the product environmental conditions as well as managing outbound logistics operations. The sensing techniques in IoT cover not only temperature and humidity, but also movement, barometric pressure and light exposure. By integrating two artificial intelligence (AI) techniques, case-based reasoning (CBR) and fuzzy logic, an outbound logistics strategy can be formulated and adjusted by the prediction of quality change in the outbound process. The rest of the paper is organized as follows. Section 2 reviews the related literature on logistics operations of environmentally sensitive products, together with IoT and AI techniques in logistics strategy formulation. Section 3 describes the design of the IoT outbound logistics knowledge management system (IOLMS). The system is then implemented in a case company and the implementation flow is presented in Section 4. Section 5 presents the results and discussion, and conclusions are drawn in Section 6.

2. LITERATURE REVIEW

2.1. Logistics Operations of Environmentally Sensitive Products

Due to the special requirement of environmentally sensitive products, managing the logistics operations in a temperature-controlled supply chain is always a challenge in maintaining the product quality. In general, environmentally sensitive products refer to the type of goods that require temperature control and are easily affected by the external environment (Aung & Chang, 2014). Examples of environmentally sensitive products include perishable foods, pharmaceutical products, electronics and fresh products. They have to be stored under certain environmental conditions such as, but not limited to, a specific range of temperature, humidity and light exposure. Lam et al. (2013) mentioned that wine was highly sensitive to storage conditions such as temperature and humidity and hence, real-time controlling and monitoring was critical for providing quick action to prevent the wine quality from deteriorating. Kartoglu and Milsten (2014) suggested that close monitoring of temperature was necessary to ensure the quality of vaccines throughout the temperature-controlled supply chain. Furthermore, handling these types of products require specialized equipment and storage facilities as well as closer monitoring of the product condition. In order to maintain the product quality, research studies have been actively undertaken on the way to handle environmentally sensitive products effectively in logistics operations. Clénet (2018) proposed a kinetic-based modeling approach to predict vaccine stability in different storage conditions and to prevent product damage due to unfavorable storage conditions. Göransson et al. (2018) examined the temperature performance and food shelf-life accuracy in cold food supply chains. From the above literature, it is found that an appropriate environment is critical to ensure the quality of environmental sensitive products. In order to continuously monitor the conditions of goods during logistics operations, the concept of IoT has emerged in recent years to increase information visibility through the supply chain.

2.2. Internet of Things (IoT)

IoT is defined as a world-wide network of interconnected devices and sensors individually addressable, based on standard communication protocols (Kopetz, 2011). According to Atzori et al. (2010), IoT concepts and technologies can be classified into three parts: internet-oriented (middleware), things-oriented (sensors) and semantic-oriented (knowledge). These can be applied through interconnection of sensing and actuating devices, providing the ability to interchange information across platforms through a unified framework, and, developing a common operating picture for enabling innovative applications (Gubbi et al., 2013). In recent years, IoT technologies on real-time data sensing and actuating have become mature. There is a growing popularity of IoT applications in various domains, including manufacturing and supply chains. For many years, temperature and humidity recording was done by using chart recorders which were retrieved upon arrival to detect any temperature difference during transportation. Digital temperature loggers were introduced and replaced the usage of chart recorders later (Kärkkäinen, 2003). The adoption of digital temperature loggers, however, requires physical connection to a computer for downloading data. Therefore, it was impossible to have real-time monitoring during the transit process. With the emergence of IoT, instant remote data capturing becomes viable by connecting a network of physical devices. Chen et al. (2014) integrated semi-passive radio frequency identification tags and sensors to monitor temperature in smart cold chain systems. Tao et al. (2014) proposed an IoT-based cloud manufacturing service system optimal allocation of various manufacturing resources and capabilities. Zhang et al. (2015) mentioned that real-time information visibility and traceability by adopting internet of manufacturing things allows effective decision making in the production shop floor. Cheng et al. (2016) designed a four-layered architecture IoT advanced manufacturing system for manufacturing resource supply and demand matching. Yan (2017) considered to maximize the profit by the application of IoT during manufacturing and logistics processes in a perishable product supply chain. Tu et al. (2018) designed an IoT framework for dynamics system modeling of distributed IoT in order to keep track on the products along a manufacturing supply chain. Wang et al. (2018) integrated multi-sensors to monitor critical ambient parameters including temperature and relative humidity, to order to improve quality control and transparency in honey peach export chains. Although IoT enables data collection and monitoring in real time, there is a need to apply knowledge-based system in order to facilitate decision making in maintaining good product quality.

2.3. Knowledge-based System for Logistics Strategy Formulation

Case-based Reasoning (CBR) is one of the well-known knowledge repository techniques which can solve problems by learning knowledge based on past experience. CBR formulates solutions and acts as a memory of previous cases that could be consulted, resulting in determining similar cases for different problems (Kolodner, 2014). By the use of past relevant solution, CBR has been widely adopted in strategy formulation. Liu et al. (2013) applied CBR to support collaborative strategy making for dynamic lean supply chain management. Mourtzis et al. (2014) formulated the manufacturing strategy for engineered-to-order products by the adoption of CBR to determine the manufacturing lead time. Due to increasing complexity in managing business processes, Müller and Bergmann (2017) proposed the use of process-oriented case-based reasoning for workflow strategy creation. From the above studies, it is found that the learning ability of CBR provides past relevant knowledge as a reference in solution formulation. However, according to Lao et al. (2012), CBR may only be capable of handling the decision-making process at the operations selection level, but it may not be applicable for prediction of product quality. In order to provide decision support in all the parameter level, fuzzy logic is identified as a possible solution.

Fuzzy logic is a kind of multi-valued logic which aims at formalizing the approximate reasoning. It presents a logical model to depict the meaning of unclear concepts and linguistic variables that are imprecise, vague, fuzzy and have no clear underlying measurement. A fuzzy logic system imitates human-reasoning process which is efficient in handling qualitative, uncertain and sophisticated processes (Tahera et al., 2008). Fuzzy control technology is not only based on mathematical theories, but also for practical problems with various uncertainties. Kondratenko and Sidenko (2014) proposed a fuzzy based decision support system to estimate the quality level for cargo delivery. Esmaeili et al. (2015) applied fuzzy logic to assess the service quality and customer satisfaction of a logistics company. Yu (2017) evaluated the service quality when handling e-commerce orders based on fuzzy uncertain linguistic information.

In summary, being able to ensure that the prescribed product quality can be maintained in a temperature-controlled supply chain, as well as to reduce the product damage and related economic loss, a comprehensive outbound logistics knowledge management system is needed. From the above literature review, it is found that IoT is a promising and emerging technology to enable data collection and monitoring in real time. However, it does not provide decision support in logistics strategy formulation, which is critical to maintain the quality of temperature sensitive goods after collecting the real-time product environmental conditions. Hence, this study concerns the design of an intelligent knowledge-based system, integrating IoT, CBR and fuzzy logic, in order to facilitate decision making in maintaining good product quality.

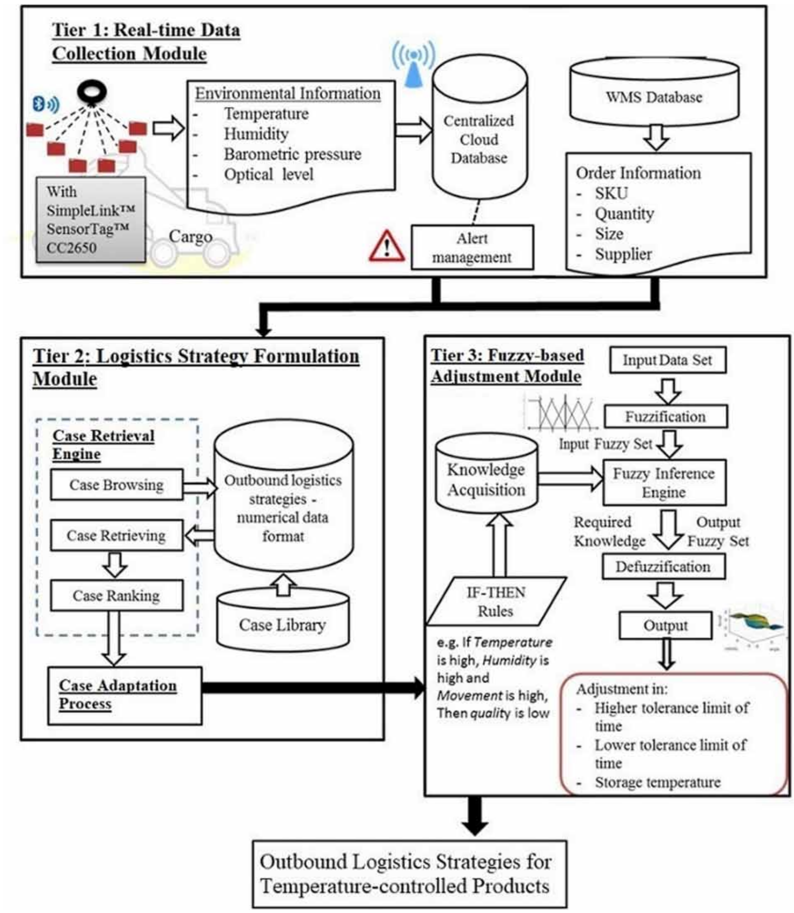
3. DESIGN OF IOT OUTBOUND LOGISTICS KNOWLEDGE MANAGEMENT SYSTEM (IOLMS)

The IOLMS integrates IoT, CBR and fuzzy logic techniques to assist manufacturers in generating outbound logistics strategies. It results in achieving higher levels of customer satisfaction due to high quality of goods transported. Figure 1 shows the architecture of IOLMS, which consists of three tiers. Tier 1 refers to real-time data collection of goods with the use of sensors and from the warehouse management system (WMS). Tier 2 is a case retrieval engine for retrieving potential cases for formulating the logistics strategies. Tier 3 makes use of fuzzy logic tools to adjust the parameters in the formulated plan, such as tolerance limits of quality.

3.1. Tier 1: Real-Time Data Collection Module (RDCM)

In this tier, both dynamic and static data in the warehouse are collected. The dynamic environmental data, including temperature, humidity, barometric pressure and optical level, is recorded and collected

Figure 1. System architecture of IOLMS



by sensors in real time. SensorTag™CC2650, developed by Texas Instruments, a global semiconductor design and manufacturing company, is selected in this study. It is because SensorTag™CC2650 contains 10 low-power sensors including support for light, humidity, pressure, accelerometer, object temperature, and ambient temperature. In addition, it allows quick and easy prototyping of IoT devices which combines sensor data with cloud connectivity. A variety of technologies with frequency 2.4 GHz are allowed to change and develop directly from the SensorTag™CC2650 app through the cloud. The data collected is transferred to the centralized cloud database through the Bluetooth logical link control and adaptation layer (L2CA). The data collected is stored in JavaScript Object Notation (JSON) format, which is a lightweight data-interchange format. Alerts are provided when any parameters exceed the limit in order to alert users if there is any unusual environmental condition. On the other hand, static data from warehouse management system (WMS) of the company are also collected. The data warehouse stores all data involved in warehouse operations. There are four main tables in the database, namely customer, order, stock and supplier. The data is then transferred to the logistics strategy formulation module.

3.2. Tier 2: Logistics Strategy Formulation Module (LSFM)

Tier 2 composes of three main components: a case retrieval engine, case adaptation process and a case library. The case retrieval engine retrieves past potential cases in order to solve the new problem.

The case adaptation process modifies the retrieved case. The case library stores cases of previous outbound logistics strategies.

3.2.1. Case Retrieval Engine

In this engine, three basic steps, case browsing, case retrieving and case ranking, are performed. The first step, case browsing, refers to the process when the tree structure in the case library is being browsed for the potential cases after inputting specifications by the users. A set of indexed attributes is included in the cases which match the specifications of incoming case. Logistics strategies are then searched by the case retrieval engine through the indexes. The second step is case retrieving, which is intended to retrieve a group of similar past cases by matching the features of the input case. The k-d tree method is adopted in this process. The last step is case ranking, which is the process of prioritizing the retrieved past similar cases by calculating the similarity of the input cases and the retrieved cases. The similarity between the input and retrieved cases is calculated using (1), where w_i represents the weight of feature i, $sim(f_i^I, f_i^R)$ is the similarity value for feature i in the input and retrieved cases, and is calculated using (2). The similarity function $sim(f_i^I, f_i^R)$ ranges from 0 to 1, showing the unweighted similarity between two input values. After calculating the similarity between all retrieved past similar cases with the new input, a set of cases ranked in descending order is presented. The past case with the highest similarity value is selected as a reference for formulating the logistics strategy for the new situation:

$$\mathrm{Similarity}\left(\mathrm{Case_I Case_R}\right) = \frac{\sum_{i=1}^{n} \mathrm{w_i} \times \mathrm{sim}\left(\mathrm{f_i^I}, \mathrm{f_i^R}\right)}{\sum_{i=1}^{n} \mathrm{w_i}} \tag{1}$$

$$\mathrm{sim}\left(\mathrm{f_i^I}, \mathrm{f_i^R}\right) = \frac{\min\left(\left|\mathrm{f_i^I}\right|, \left|\mathrm{f_i^R}\right|\right)}{\max\left(\left|\mathrm{f_i^I}\right|, \left|\mathrm{f_i^R}\right|\right)} \tag{2}$$

3.2.2. Case Adaptation

After retrieving the past case with the highest similarity value, the case adaptation process starts to revise and retain the solution of the new case. Case revising is a process in which the new case is created by editing, combining or adding new suggestions of past retrieved cases. In order to formulate the most appropriate handling method for the product, the system allows some modifications made by the decision maker. Through the case adaptation process, the past relevant case is retrieved to provide a reference for case revision to the new case. Users can review the suggested solution from the retrieved past case, and update solution for the current situation. Generally, there is no generic mechanism for case adaptation and it is common to perform manually. For example, a new outbound logistics strategy is generated by editing the temperature needed for transportation. The revised cases are then stored in the case library in the case retaining step. The cases are considered as references and case assets for future usage.

3.2.3. Case Library

The case library is mainly responsible for the storage of outbound logistics cases in free data format. A set of attributes is involved in a case in the form of text and numbers in order to represent the problem or event. The primary elements of the case library include case number, case indexes and strategy. The case number serves as unique recognition of the case, which is assigned by the system. A case index consists of the attributes of cases which represent the problem or events. It helps in the case-based retrieval engine process.

3.3. Tier 3: Fuzzy-Based Adjustment Module (FAM)

After the data is processed by LSFM, the results are further processed by the fuzzy-based adjustment module (FAM). A primarily outbound logistics strategy is formulated, such as the types of equipment required during transportation. This module further identifies and predicts the quality of goods under different environment conditions. The tolerance limits of the quality are suggested through the fuzzy inference engine. There are three sub-modules in the fuzzy logic module, fuzzification, fuzzy inference engine and defuzzification. Fuzzification is the process converting crisp input data to fuzzy values by defining the membership function of each fuzzy set. There are four membership functions which are related to the quality of goods: temperature, humidity, barometric pressure and optical level. The fuzzy inference engine converts the input fuzzy set into a fuzzy output set by fuzzy logic. The fuzzy sets undergo "IF-THEN" rules which are generated based on the opinions and findings from experts and professional bodies in the quality prediction areas. A list of rules is formulated, such as the Example Rule: IF temperature is high AND humidity is high AND barometric pressure is high AND optical level is high, THEN quality is Substantially Decreased. Defuzzification is the final step in the fuzzy logic module which translates the fuzzy output set back to a crisp value or linguistic value. The method of center of area (COA) is applied, as calculated using (3), where Y is the output value, w represents the weight, C is center of gravity and A is the area of each individual implication result. The calculation of the COA transfers the fuzzy outputs to crisp values in order to formulate the final outbound logistics strategy:

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} \tag{3}$$

4. CASE STUDY

4.1. Company Background

A case company is used to illustrate the feasibility of applying IOLMS for managing the outbound logistics operations. It is an electronic product manufacturing company, which mainly produces high-quality headsets and other professional acoustic products. The company sets up their own production lines to make the headsets from electronic chips and printed circuit board. After assembling all parts into a headset, quality checking on the appearance and functionality is performed to ensure that the headset meets the required standard. Then, those that passed the quality checking would be moved to the warehouse for storage. After receiving customer orders, the company would then pick the headsets from the warehouse, pack them according to customer requirements, and deliver to their customers. Since the products are made of electronics which are highly sensitive to the storage environment, the company has installed industrial and thermometers in the workplace to monitor the indoor environment.

4.2. Implementation Flow of IOLMS

The implementation of IOLMS is divided into five stages: (i) real-time data collection, (ii) data collection from the warehouse management system, (iii) construction of the logistics strategy formulation module, (iv) construction of the fuzzy-based adjustment module, and, (v) design of the IOLMS user interface.

4.2.1. Real-time Data Collection

Environmental information on the goods, including temperature, humidity, barometric pressure and optical level, are collected by the SensorTag ™ CC2650. The real-time data is transferred to the centralized cloud database. Users are allowed to access the information in real-time by the user-interface of the IOLMS. Users need to register the SensorTag™ CC2650 through IBM Watson IoT Platform by inputting device type, device ID and authentication token before accessing the app. Through the app, users are able to obtain data such as ambient temperature, infrared temperature, humidity, barometer, movement and light sensor, as shown in Figure 2. The real-time environmental information reflects the situation of goods in the warehouse. Managers can access the app, monitor the goods and take corresponding action when abnormal data is obtained. The data collected are then transferred to the cloud database. Figure 3 shows the user-interface for real-time cargo monitoring. The limits of the attributes can be adjusted by staff and depends on the type of SKU. A warning message box is presented when an attribute exceeds the limit set. Staff can then check the air-conditioning in

Figure 2. Data extracting platform of IOLMS

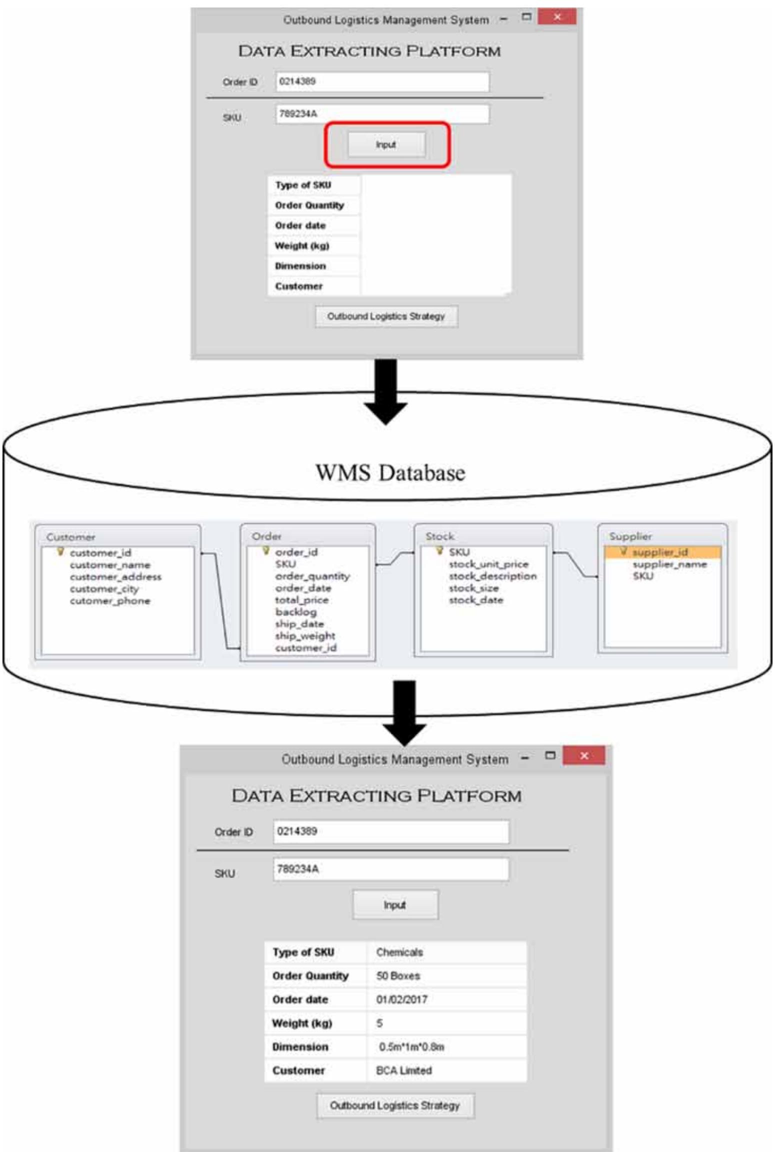
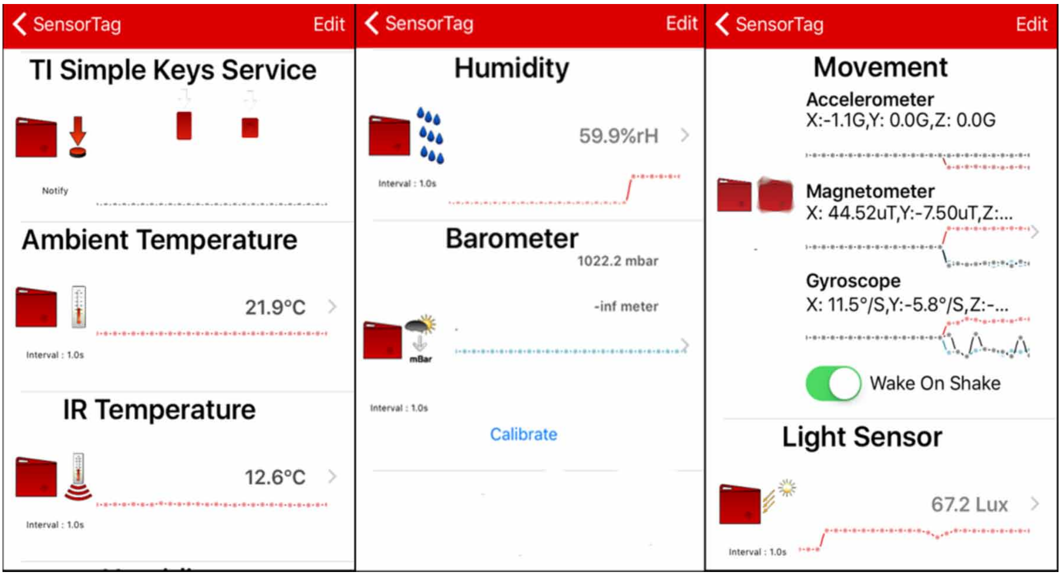


Figure 3. Collection of real-time environmental data by sensors



the warehouse after receiving the alert. Customized reports of the environmental information can be generated so that staff can undertake further analysis, such as the stability of the air-conditioning plant.

4.2.2. Data Collection From Warehouse Management System

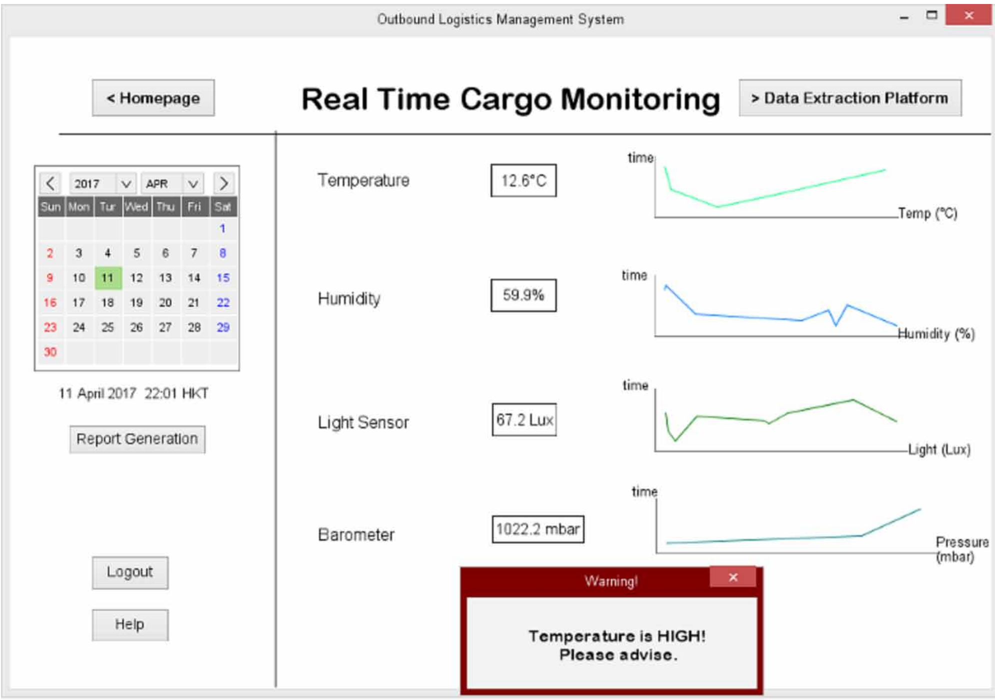
The company applied WMS in order to gain a better management of the inventory. The data including customer information, order details, SKU, supplier information and etc. are stored in the WMS. In this step, data are extracted for the CBR process in the next step. In order to achieve this, a data extracting platform is constructed as shown in Figure 4. Users simply input the order ID and SKU to the data extracting platform. The required data is then searched and extracted from the WMS to the IOLMS platform.

4.2.3. Construction of Logistics Strategy Formulation Module

The data collected from the real-time data collection module and WMS data collection module is processed by the CBR engine. The first step in the CBR engine is the retrieval of cases with high similarity by adopting kd-tree methods, which combine the inductive indexing method and the nearest neighbour method. Figure 5 shows the process of case retrieval. The cases are being browsed and a searching path is generated by matching the types of specification in the tree structure of the case library, as shown in Figure 5. The tree structure consists of six indexing levels: type of SKU, SKU dimension and shape, measuring unit of SKU, unit price of SKU, quality level, and distance to customers. Potential cases are then searched. After obtaining a list of similar cases, the similarity value is computed by the nearest neighbour method. The case with the highest similarity value is the first choice in formulating the outbound logistics strategy. In this example, case number 5 is selected as the first choice, having the highest similarity of score 0.7 among the retrieved cases.

Then, the retrieved case with the highest similarity is reused and revised to suit the requirement of the new case. As shown in Figure 6, previews of the outbound logistics strategy of retrieved cases are available in the system platform. The content of the retrieved strategies includes the types of vehicle, additional packaging, special handling, report generating. Staff need to review the retrieved strategy and decide whether the strategy can be accepted or not. Upon acceptance of the retrieved

Figure 4. User interface for real-time cargo monitoring



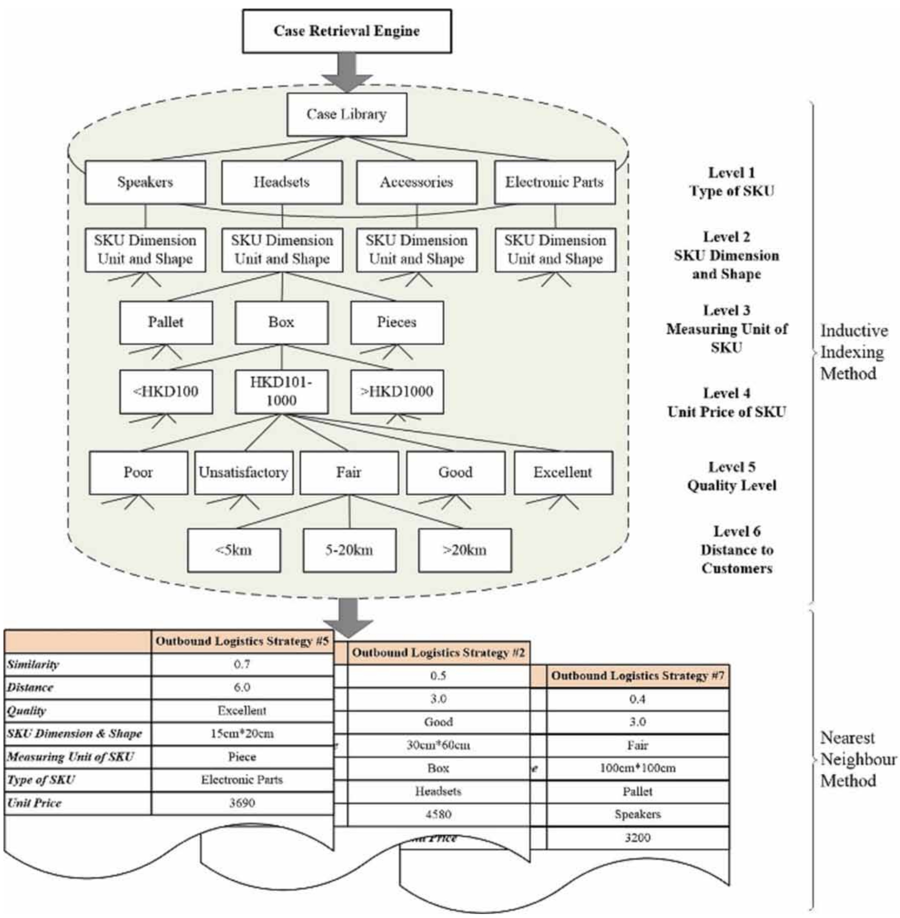
case, the warehouse manager can formulate a new strategy with reference to the retrieved case. The newly formulated strategy is then stored in the case library for retention. A unique case number is assigned to the new case in the case library for future usage.

4.2.4. Construction of Fuzzy-Based Adjustment Module

The primary outbound logistics strategy is formulated from the CBR engine in the previous step. The quality of the goods and optimum storage temperature during transportation, however, cannot be obtained. Thus, a fuzzy-based adjustment module is developed for predicting the tolerance limits of goods and the most suitable storage temperature during transportation. In the past, the quality of goods and relative storage temperature were predicted manually by the senior manager, based on personal knowledge and experience. The manager however may not be familiar with the specifications of various types of environmentally sensitive products. The adjustment of quality tolerance limits and optimum storage temperature can help formulate better outbound logistics plans and lengthen the product shelf life. There are totally four inputs, namely cargo temperature, barometric pressure, humidity and optical level. After inputting to the fuzzy based engine, three outputs, adjustment of upper quality limit, adjustment of lower quality limit and adjustment of storage temperature, are generated using the Fuzzy Logic Toolbox of MATLAB.

Table 1 and Table 2 show the membership functions of each input and output variable. Take "cargo temperature" as an example. The input variable "Cargo Temperature" represents the temperature of the goods, which is one of the most important factors measuring the quality of goods. A five-point scale is adopted to classify different ranges of temperature value: Low (L), Relative Low (RL), Moderate (M), Relative High (RH) and High (H). For the output variables, membership functions are the same for adjustment of the upper quality limit, adjustment of the lower quality limit and adjustment of the storage temperature. It is divided into seven regions, namely Substantially Decrease (SuD),

Figure 5. Process of retrieving cases in CBR engine



Significantly Decrease (SiD), Slightly Decrease (SlD), No Change (NC), Slightly Increase (SlI), Significantly Increase (SiI) and Substantially Increase (SuI).

To analyse the quality and the environmental condition of the goods, a list of rules are generated based on the expert knowledge. The domain experts refer to the decision makers involved in the process of outbound logistics planning. There are two domain experts in the case company, both of them are the senior managers in the operations department and have more than 15 relevant experience in strategy planning. The users can simply input the value of environmental conditions (cargo temperature, pressure, humidity and optical level) and the fuzzy-based adjustment module will suggest adjustment of the tolerance quality limit and storage temperature. As shown in Figure 7, given that input crisp values of cargo temperature, pressure, humidity and optical level are 14°C, 29.21inHg, 54.26% and 250 lux, respectively, the adjustment results generated by the MATLAB Fuzzy Logic Toolbox suggest that the upper tolerance quality limit should be increased by 14.5%, while the lower tolerance quality limit and the storage temperature should be decreased by 4.53% and 1.95% respectively.

4.2.5. Design of IOLMS User Interface

A comprehensive user interface is developed for performing all steps in the formulation of IOLMS. Through the platform, users are first requested to login it by using an assigned username and password. This can ensure the security of the company data and strategies so that they cannot be edited or

Figure 6. Review of retrieved potential cases

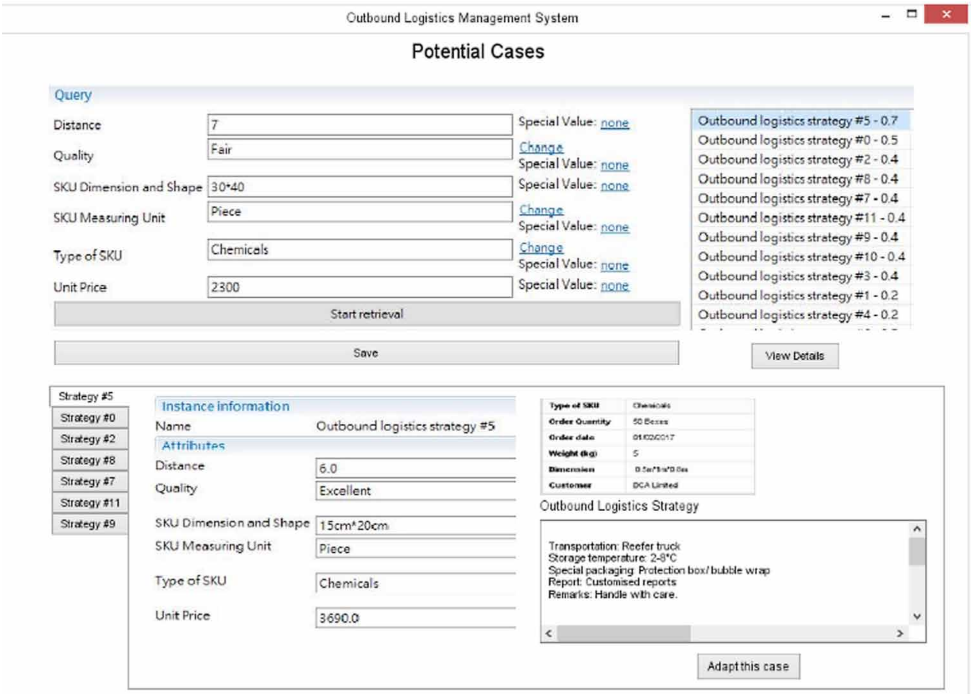


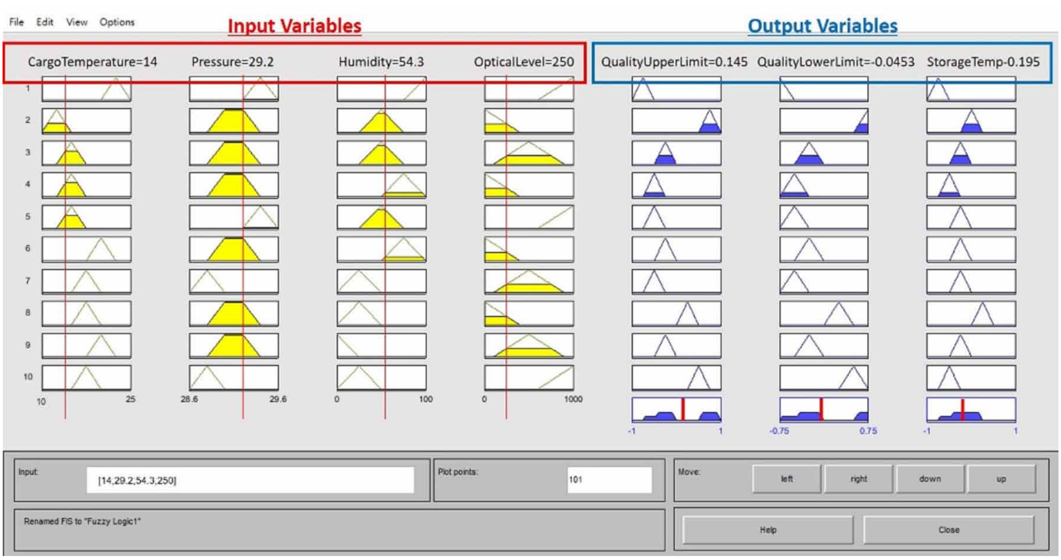
Table 1. Membership function of input variables

Input Variables	Range	Fuzzy Class	Membership Function	Type
Cargo Temperature (°C)	[0 25]	Low (L)	[10 12.5 15]	Triangle
		Relatively Low (RL)	[12.5 15 17.5]	Triangle
		Moderate (M)	[15 17.5 20]	Triangle
		Relatively High (RH)	[17.5 20 22.5]	Triangle
		High (H)	[20 22.5 25]	Triangle
Barometric pressure (inHg)	[28.6 29.6]	Low (L)	[28.6 28.8 29]	Triangle
		Moderate (M)	[28.8 29 29.2 29.4]	Trapezoid
		High (H)	[29.2 29.4 29.6]	Triangle
Humidity (%)	[0 100]	Low (L)	[0 0 25]	Triangle
		Relatively Low (RL)	[0 25 50]	Triangle
		Moderate (M)	[25 50 75]	Triangle
		Relatively High (RH)	[50 75 100]	Triangle
		High (H)	[75 100 100]	Triangle
Optical level (lux)	[0 1000]	Low (L)	[0 0 400]	Triangle
		Moderate (M)	[100 500 900]	Trapezoid
		High (H)	[600 1000 1000]	Triangle

Table 2. Membership function of output variables

Range	Fuzzy Class	Membership Function	Type
[-1 1]	Substantially Decrease (SuD)	[-1 -0.75 -0.5]	Triangle
	Significantly Decrease (SiD)	[-0.75 -0.5 -0.25]	Triangle
	Slightly Decrease (SlD)	[-0.5 -0.25 0]	Triangle
	No Change (NC)	[-0.25 0 0.25]	Triangle
	Slightly Increase (SlI)	[0 0.25 0.5]	Triangle
	Significantly Increase (SiI)	[0.25 0.5 0.75]	Triangle
	Substantially Increase (SuI)	[0.5 0.75 1]	Triangle

Figure 7. Fuzzy rules and crisp outputs of adjustment in quality limits and storage temperature

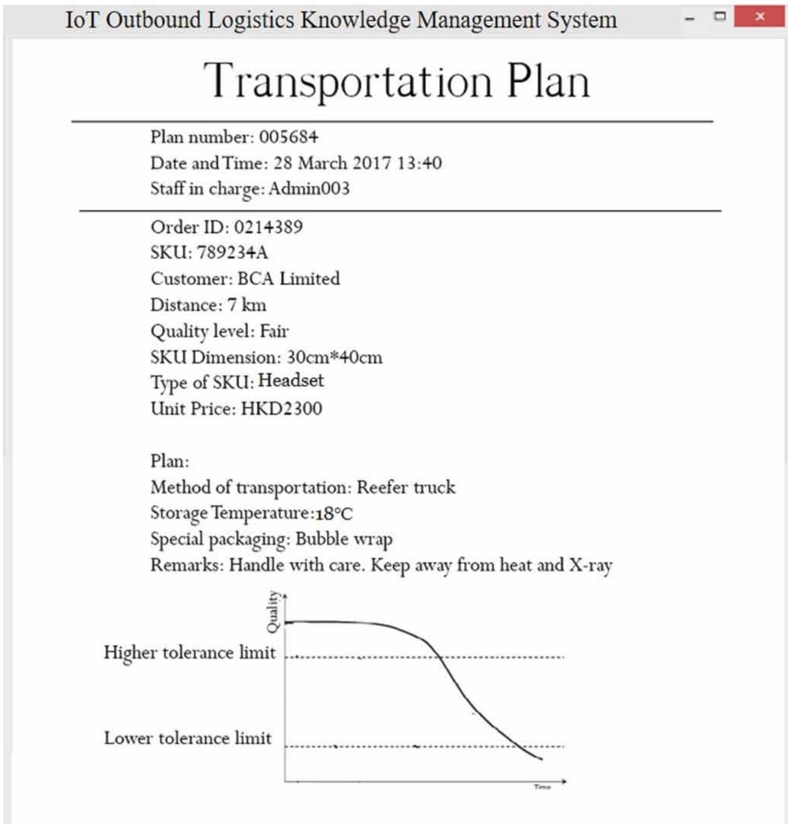


viewed by an unauthorised person. After that, the user is able to access the three major parts, i.e. real time cargo monitoring, formulation of outbound logistics strategy and fuzzy-based adjustment, for monitoring and decision making. Figure 8 shows the generated plan, which is generated for staff in the outbound area and drivers to pack and deliver the goods more effectively. A unique number is assigned to each transportation plan in order to facilitate the storage of documents for further usage if necessary. The generation time and responsible staff name are included in the beginning of the plan which allows easy contact with the relative staff-in-charge for a certain transportation plan. The details of the order such as SKU, dimensions and customer name, are indicated in the plan so that staff can distinguish the transportation plan and relative orders easily. In the transportation plan, basic items include the method of transportation, packaging method, storage temperature and quality – time graph.

5. RESULTS AND DISCUSSION

After implementing IOLMS in the case company for three months, it is found that the performance of the outbound logistics operations improved in terms of quality control, operation efficiency, and

Figure 8. Generated transportation plan



customer satisfaction. Performance comparison before and after the implementation of IOLMS is summarized in Table 3.

5.1. Improvement on Quality Control

As illustrated in the case study, tolerance limits of quality are predicted and are indicators of the quality change under the warehouse environment. It improves the quality of goods since the goods are delivered to the customers before the quality drops to a lower tolerance limit. Staff can adjust the optimum storage temperature of the reefer trucks in order to maintain the quality of goods throughout

Table 3. Performance comparison after implementation of IOLMS

Category	Key Performance Index	Manual Approach	Approach with IOLMS	% of Improvement
Quality control	• % of defective goods • Financial loss	17% 9%	8% 5%	53% 44%
Operation efficiency	• Average time for outbound process	80 mins/order	45 mins/order	44%
Customer Satisfaction	• Customer complaints due to poor quality	15 complaints/ month	6 complaints/ month	60%

the transportation process. Staff can undertake the guidelines suggested by the system directly. Before the system is implemented, manual approaches were adopted in which errors and inconsistent decisions occurred. The IOLMS helps monitor the goods and predict quality change under different environment conditions. To measure the quality control level, the percentage of defective goods is an appropriate assessment factor by calculating the ratio of number of defective goods to the total goods. The result shows that the values before and after implementing the IOLMS are 17% and 8% respectively. In addition, the poor-quality control also brings financial loss to the company. Since an effective approach has been applied to reduce the defective goods, an improvement of 44% is resulted after the implementation of the proposed system.

5.2. Improvement on Operation Efficiency

Before the implementation of IOLMS, strategies were formulated manually by human-based data collection and analysis. Information on the goods was collected by manual searching and extraction from the company database. It took more than 10 minutes for extracting the guidelines and relative documents. Extra time was needed if new SKUs were received. Related outbound logistics strategies such as the type of transportation vehicles were then formulated based on the experience and knowledge of the managers. Table 4 shows the time reduction in the operation process. On average, around 80 minutes is required to finish the strategy formulation and the whole outbound process of an order. After the implementation of the IOLMS, the manager is able to develop strategies with reference to past similar cases. The formulation time is therefore significantly reduced. The whole outbound logistics process requires 45 minutes, which is an improvement of 44%.

5.3. Enhancement on Customer Satisfaction

The outbound logistics strategies formulated by the system are user-friendly and assist staff to monitor the quality of goods according to the customer requirements. The success in fulfilling the customer requirement leads to customer satisfaction. Customer satisfaction is an important indicator of repurchase intentions and loyalty. When the company provides services that satisfy the needs of the customers, customer lifetime values can be increased. One major factor in measuring customer satisfaction is the number of customer complaints per month. Before the implementation of the system, the number of customer complaints was 15 per month. The majority of complaints were quality degradation and defective goods. Since there are comprehensive strategies suggested by the system, the number of customer complaints per month is dropped to 6.

6. CONCLUSION

Temperature controlled logistics has received growing interest from both industry and academia. In this paper, an intelligent knowledge management system, IOLMS, is introduced with real-time cargo

Table 4. Time reduction in operation process

Time (mins)	Manual Approach	Approach with IOLMS	% of Improvement
Data extraction	10	1	90
Strategies formulation			
- Operation involved	8	3	63
- Corrective actions	5	1	80
Outbound operations	60	40	33
Total	83	45	45.8

monitoring function, and decision support function in determining product quality prediction and optimum storage temperature. By the use of sensors in collecting instant dynamic environmental data, such as temperature, humidity, barometric pressure and optical level, IoT enables a faster response rate under an abnormal situation, for example, an unusual temperature drop. In addition, with the assistance of technologies such as CBR and fuzzy logic, manufacturers can formulate an outbound logistics strategy in an effective way based on past similar records. After a pilot study in an electronic product manufacturing company, it is found that the system can provide better quality control, higher operation efficiency, improved customer satisfaction and lower planning cost. The proposed system which provides real-time cargo monitoring and back-end decision support function can significantly upgrade the service standard of manufacturing industry. On the other hand, there is limitation in this paper. By using CBR engine, similar cases are retrieved by calculating the similarity value of each attribute. The engine, however, cannot retrieve reliable cases if the case library is poorly organized. The strategies formulated will not be reliable and may need excessive time for revising the strategies. Further research will focus on the design of an effective taxonomy for knowledge storage.

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