The following publication Tsang, Y. P., Choy, K. L., Koo, P. S., Ho, G. T. S., Wu, C. H., Lam, H. Y., & Tang, V. (2018). A fuzzy association rule-based knowledge management system for occupational safety and health programs in cold storage facilities. VINE Journal of Information and Knowledge Management Systems, 48(2), 199–216 is published by Emerald and is available at https://doi.org/10.1108/VJIKMS-01-2017-0004.

A Fuzzy-association-rule based Knowledge Management System for Occupational Safety and Health Programs in Cold Storage Facilities

Abstract

Purpose – This paper aims at improving operational efficiency and minimizing accident frequency in cold storage facilities through adopting an effective occupational safety and health program. The hidden knowledge can be extracted from the warehousing operations in order to create the comfortable and safe workplace environment.

Design/methodology/approach – A fuzzy-association-rule based knowledge management system (FARKMS) is developed by integrating fuzzy association rule mining (FARM) and rule-based expert system (RES). FARM is used to extract hidden knowledge from real operations to establish the relationship between safety measurement, personal constitution, and KPI measurement. The extracted knowledge is then stored and adopted in the RES to establish an effective occupational and safety program. Afterwards, a case study is conducted to validate the performance of the proposed system.

Findings – The results indicate that the aforementioned relationship can be built in the form of IF-THEN rules. An appropriate safety and health program can be developed and applied to all workers, so that they can follow instructions to prevent cold induced injuries, and also improve the productivity.

Social implications – Due to the increasing public consciousness of occupational safety and health, it is important for the workers in cold storage facilities where the ambient temperature is at/below 10°C. The proposed system can address the social problem and promote the importance of occupational safety and health in the society.

Originality/value – This study contributes the knowledge management system for improving the occupational safety and operational efficiency in the cold storage facilities.

Keywords Safety and health program, knowledge management system, knowledge discovery, cold storage management

Introduction

Since consumers are quality-driven and health-conscious in the supply chain, especially for food, chemicals and pharmaceutical products, there is a booming demand for cold chain logistics. Compared with products in the generic supply chain, temperature sensitive and perishable products (TSPPs) in a cold chain have certain characteristics, including short shelf life, high perishability, long production throughput time, seasonality, and need for refrigeration in transportation and storage (Aramyan at el., 2007). Particularly for the handling frozen products, warehouses, called cold storage facilities, are specially designed to maintain the product quality and the delivery trucks are also equipped with refrigerators. By using state-of-the-art technologies, the product traceability in cold chain logistics is well-developed by the controlling and monitoring of environmental conditions in transportation and storage (Kuo and Chen, 2010; Lu at el., 2012). It is implied that the temperature and humidity in cold storage environments are extraordinary low, even extreme, which may influence workers' health and safety without effective resource planning.

However, there is limited research on the occupational safety and health (OSH) aspects in cold storage facilities. Since the extreme environmental conditions may affect the productivity and increase the probability of getting cold induced injuries, controlling and monitoring the workers is essential to improve the whole supply chain efficiency. When working at or below 10°C, workers may feel uncomfortable or be prone to cold injuries (Mäkinen and Hassi, 2009). In 2009, two workers died in an American cold storage facility after completing maintenance work (Gazaway, 2009). Due to the lack of appropriate safety and risk management, fifteen workers died and twenty-six workers were injured at a Shanghai cold storage facility due to unexpected ammonia leakage (Laurence, 2013). In order to prevent such unfortunate accidents, certain safety assessments and measurements should be adopted in cold storage environments. The International Organization for Standardization (ISO) introduced a method of determination and interpretation of cold stress, called ISO11079 (Holmer, 2009). This standard provides estimates of the maximum allowed working time and minimum recovery time when working in a cold environment. In current practice, warehouse workers can follow the instructions from ISO 11079, integrated with their experience and judgement, to develop occupational safety and health routines. However, there are two challenges in regard to implementing the comprehensive occupational safety and health program, as illustrated in Fig. 1. The first challenge is that the workers' personal physiques are not included in the ISO11079 estimates. In other words, the existing ISO11079 practice estimates may not fit workers with different BMIs, ages and clothing insulation. However, the existing scheme does not support knowledge discovery from personal physiques and operational efficiency which include both quantitative and qualitative data. Thus, the feasibility and adaptability of current practice is insufficient for most companies in protecting the workers in such labor-intensive operations. Secondly, there is lack of the customized safety and health programs, associated with productivity, seriousness of the safety and health status, and the ISO11079 estimates. Depending on the health status of different workers, the safety and health programs/instructions should be amended in a systematic way. Since data mining (DM) enables knowledge discovery in real-life situations, correlations between various attributes, such as accident frequency rates and ages, can be examined. DM can help the companies discover hidden knowledge that can be integrated into the existing occupational safety and health practice. Therefore, there is a need to improve the deployment of ISO11079 and the establishment of corresponding action plans through DM techniques. In this paper, a fuzzy-association-rule based knowledge management system is proposed to discover the hidden knowledge in the warehousing operations by using the techniques of fuzzy association rule mining (FARM). In addition, through the technique of RES, a customized safety and health program can be formulated based on knowledge discovery.

This paper is organized as follows. Section 2 covers the past literature and research related to cold storage facilities, occupational safety and health, and DM techniques. Section 3 presents the design of the fuzzy-association-rule based knowledge management system (FARKMS). Section 4 includes a case study to validate the proposed FARKMS. Section 5 discusses the results and the effectiveness of FARKMS. Finally, conclusions are drawn in the Section 6.

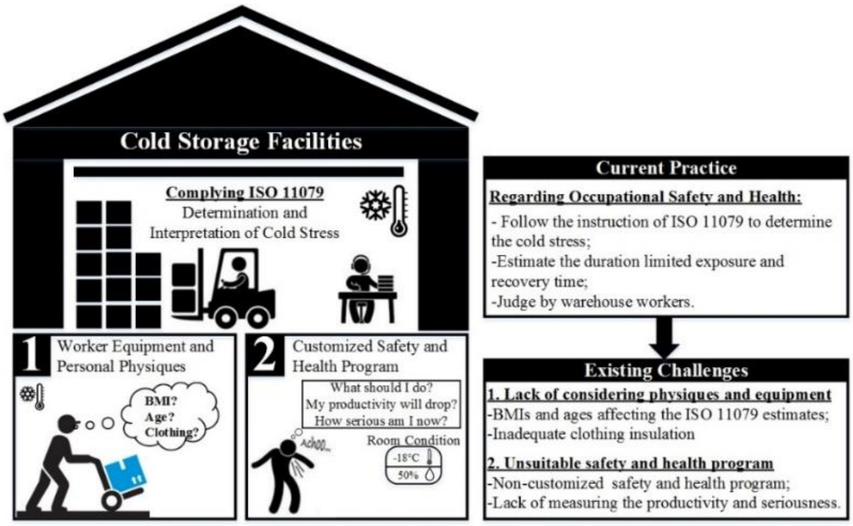

Fig 1. Existing problems in cold storage facilities

Literature Review

Due to the increasingly stringent requirements and concerns on supply chain management, the capacities of cold storage facilities are expected to increase to nearly 20 times of their current capacity over the next decade (International Trade Administration, 2016). The development of cold chain logistics in China is still in its infancy in aspects such as infrastructure, international shipment, competence, tracking and tracing, and timeliness. To better manage cold chain logistics, cold chain management (CCM) was created to improve the effectiveness and efficiency in material, capital, and information flows (Bogataj et al., 2005). The monitoring of environmental conditions, such as temperature and humidity, is important in order to maintain the prescribed product quality before delivery to the end consumers. In other words, the refrigerated transportation and storage are two important areas to prevent deterioration of the product quality (James and James, 2010; Chen et al., 2015). Furthermore, any changes of the microbiological, physiological, biochemical, and physical aspects for products can be reduced. Typically, two refrigerating technologies, i.e. chilling (0-4°C) and freezing (-18°C), are applied in the warehouses. For the typical manual warehouse, the workers are required to handle the inventory in a cold workplace, including unloading, put-away process, picking, packing, and loading. Therefore, occupational safety and health is one of the important measures in maintaining efficiency in the warehousing and transportation operations.

Risk management and evaluation of occupational safety and health have always been an active research area so as to prevent the workplace accidents. Occupational accidents/injuries can damage the reputation of a company, decrease the productivity, and result in large losses (Sheu et al., 2000). From the company' perspective, cold induced accidents and injuries should be eliminated as much as possible, in return for better productivity and efficiency. Reinhold and Tint (2009) summarized three safety management processes: people identification, numerical estimation of damage risk, and hazard identification and evaluation. Regarding the workplace in cold chain logistics, the effects of cold exposure results in a decrease of thermal comfort, performance, health, and leads to cold associated injuries (Mäkinen and Hassi, 2009). In addition, the extent of cold exposure is contributed by five dimensions: exposure, physical activity, clothing, individual, and socioeconomic factors. To evaluate the cold hazards, ISO 11079 provides a standardized evaluation method to estimate the maximum allowable working time and the corresponding recovery time. The estimations are based on the required clothing insulation (IREQ) and local cooling effects (Griefahn, 2000; Küpper et al., 2003). However, the ISO11079 estimates are merely indicators, which should be further integrated with knowledge discovery techniques to establish the most suitable safety and health program. Therefore, data mining (DM) techniques are applied to discover more information and the hidden patterns in the operations.

In cold storage facilities, workers can provide information on the ISO 11079 estimates and on individual factors. In addition, their performance can be measured by the key performance index (KPI) by defining useful evaluation criteria. In order to discover the hidden information from the above parameters, fuzzy association rule mining (FARM) is applied in this study. FARM refers to integrating the fuzzy set concepts and data mining to generate meaningful fuzzy association rules (FARs) from quantitative data (Hong et al., 2003). By making use of fuzzy linguistic terms in association rule mining, the parameters can be quantitative. FARM is widely applied in generating the associations in the field of quality management (Lau et al., 2009; Lee et al., 2014), warehouse operations (Ho et al., 2010), and health related decision support (Delgado et al., 2001; Soni and Vyas, 2010).The fuzzy linguistic terms are understandable for human beings such that useful knowledge can be discovered for real-life applications. To establish the appropriate safety and health program, rule-based expert systems

(RESs) were proposed to capture irreplaceable knowledge and expertise, and to develop solutions automatically and systematically by using the core IF-THEN rules (Buchanan and Shortliffe, 1984; Abraham, 2005). The components of RESs include IF-THEN rules, facts, and an inference engine to control the rules and facts. It is a high applicable technique for solving real-life problems based on the previous knowledge and experience. The applications of RES are widely related to occupational safety risk analysis in construction sites (Azadeh et al., 2008; Gürcanli and Müngen, 2009), hazard and operability analysis (Venkatasubramanian, Zhao and Viswanathan, 2000), and healthcare monitoring systems (Seto et al., 2012). In addition, RESs are applicable for integration with other DM techniques to provide better decision support, such as fuzzy association rule mining. However, the integration of FARM and RES in the field of occupational safety and health is rare. This paper aims at filling this research gap in providing appropriate occupational safety and health programs in cold storage facilities.

In summary, based on the above reviewed literature, the refrigeration in cold storage facilities may cause harm to workers, especially in the manual facilities. The estimations from ISO11079 are merely indicators of the maximum allowed working time and recovery time for workers. To establish completed planning, FARM and RES are used to associate the ISO11079 estimates, personal physique and KPI, and hence provide the best occupational safety and health program for workers. With knowledge discovery in the warehousing operations, the developed program can be customized and is suitable for workers to enhance their safety and health in cold storage facilities.

Design of the Fuzzy-association-rule based Knowledge Management System

The system architecture of the proposed fuzzy-association-rule based knowledge management system (FARKMS) is illustrated in Fig. 2. The proposed mining system is divided into three modules, namely the database management module (DMM), the fuzzy association rule module (FARMM), and the knowledge-based decision support module (KDSM).

Module 1 – Database Management Module (DMM)

The database management module is constructed in a cloud-based platform. It collects the ISO11079 estimations, personal physiques, and KPI measurements. Examples of the collected data are listed in Table 1. Regarding database management, ISO11079 estimations, partial personal physiques and KPI measurements can be pre-defined in the database. However, the information on heart beat rates, ambient temperature, and available clothing insulation is collected by using automatic data capturing technologies, namely Bluetooth Low Energy (BLE) integrated with the sensing techniques. In addition, the current occupational safety and health programs are also stored in the database. The information is further used in FARMM and KDSM.

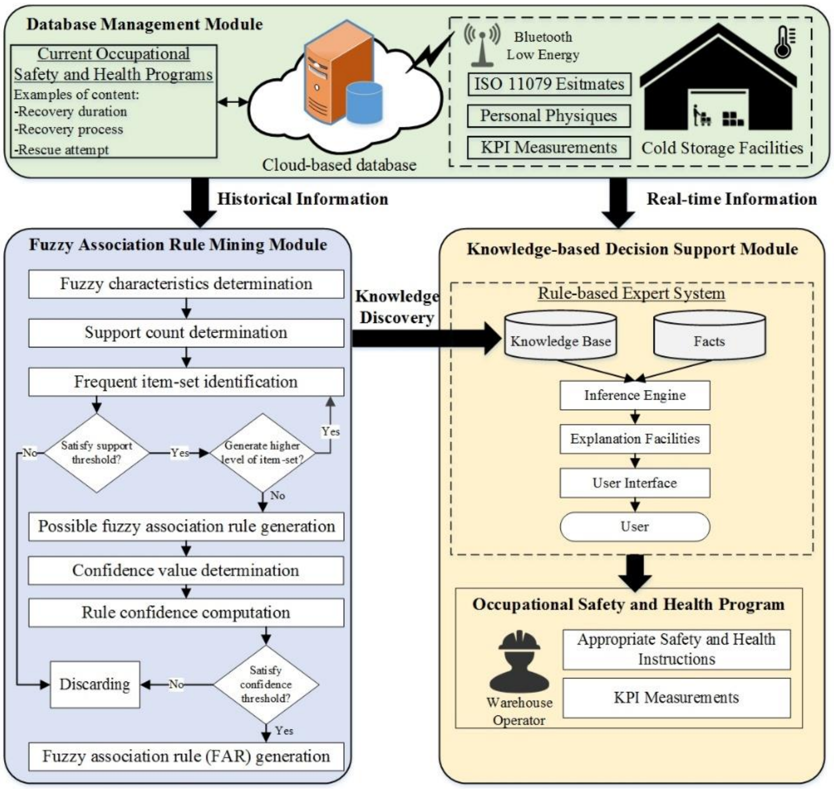

Fig 2. System architecture of FARKMS

Table 1 Data collection in FARKMS

Type of data	Examples
ISO11079 estimations	Duration limited exposure, recovery time
Personal physiques	BMI, ages, heart rates, ambient temperature
KPI Measurements	Productivity, safety and health

Module 2 – Fuzzy Association Rule Mining Module (FARMM)

This module aims at developing the association between ISO11079 estimations, personal physiques, and KPI measurement in a form of the IF-THEN rule. By integrating the concepts of fuzzy sets and the data mining technique, i.e. association rules, the FARMM is proposed to generate the FARs from quantitative data. The workflow of FARMM is shown in Fig. 2, starting from integrating the fuzzy characteristics to the quantitative data, until the generation of FARs. In this algorithm, fuzzy membership functions, threshold support count and confidence values are defined by domain experts in advance, and contribute to the mining process. The process of the creation of fuzzy membership functions is through several interviews, where the domain experts are required to define various fuzzy classes with their specific range of values. The criteria of defining fuzzy membership functions are based on their professional experience and the actual situations in the case company. Moreover, the threshold support count and confidence values are used as the function for the stopping criteria in generating fuzzy association rules. It can affect the reliability and accuracy of the generated fuzzy association rules. In the beginning, for N historical data, where N is a natural number, the quantitative parameters (Q_n) are converted into fuzzy sets based on the defined membership functions, represented as the summation of "occurrence (counts) divided by the fuzzy class", i.e. $f_1/C_1 + f_2/C_2 + \ldots + f_n/C_n$. The support count values can be calculated by the summation of each C_n of Q_n. Since a parameter has specific support count value in the corresponding fuzzy class, the maximum value is sorted out, and 1-itemset can be temporarily defined. Afterwards, if the maximum count value is smaller than the support count threshold, that particular parameter is discarded from the 1-itemset. The algorithm continues to search the k-itemset, where $k \geq 2$, based on the criteria of comparison between the minimum number of counts and the maximum support count threshold. Repeatedly, the search process ends when one of the higher level itemsets is null. Therefore, the possible fuzzy association rules can be generated in a form of IF {X} THEN {Y}. To validate the possible fuzzy association rules, the confidence value is calculated as the number of counts of Y divided by the number of counts of X. By comparing with the predefined confidence threshold (λ), possible FARs are discarded if the calculated confidence values are smaller than the predefined threshold. The remaining FARs are regarded as useful fuzzy association rules, and the recursive mining algorithm ends. The generated FARs are stored in the knowledge base for further applications, where the conditions of antecedents and consequences can be developed, with implications for the management, for example, the "High" and "Low" accident frequency rates in the consequence part. Hence, the antecedents have useful implications in formulating relevant programs and instructions in order to control and monitor the accident frequency rates.

Module 3 – Knowledge-based Decision Support Module (KDSM)

By storing and applying useful FARs, this module aims at generating a customized occupational safety and health program through the rule-based expert system (RES). KDSM consists of two components, namely RES and occupational safety and health program. The RES generally consists of four elements, namely gathering of knowledge bases and facts, inference engine, explanation facilities, and user interface, as illustrated in Fig. 2. The knowledge discovery from FARMM is directly linked to the knowledge base in RES. Thus, the knowledge base stores the IF-THEN rules, represented as IF {antecedent}, and THEN {consequent}. In addition, the rules are able to have multiple conditions, namely AND (conjunction) and OR (disjunction). When the conditions of the rules are satisfied, the rules will be executed in the RES. On the other hand, a set of facts is stored in another database, which refers to actual cases and situations. It is used to match with the antecedent part in the IF-THEN rules. Afterwards, the inference engine executes forward chaining reasoning, which is a data-driven process, to achieve the desired goals. The predefined rules and coming facts can be linked together to find the solutions to the current facts. The explanation facilities are responsible for answering the users' enquiries related to the specific generated solutions. The expert system is capable to explain the reasoning and justify the solutions to the set of facts. To interact between the systems and users, the user interface is a platform to collect information, answer enquiries, and show the particular results to users. Therefore, the occupational safety and health program can be customized according to the actual workers' situations. The KPI measurements are also associated in the programs for the use in decision support such that the occupational safety and health program can be more comprehensive and suitable for real-life situations.

Case Study

In this section, CCS Logistics Limited provided cold storage facilities for conducting a case study. CCS is located in Hong Kong and provides services in cold chain logistics. The FARKMS is applied to guarantee the occupational safety and health of the workers.

Company background

CCS Logistics Limited is a cold chain logistics service provider in Hong Kong that provides sound logistics supports in handling food, pharmaceuticals, and other temperature-sensitive products. The warehouse is 18-storey with a 28,000 metric tons capacity. It is divided into five sections, namely the public bonded warehouse, freezer section, fine wine section, chiller section, and air-conditioned section. In other words, the temperatures of various storage facilities have a large difference, ranging from -20 to 22°C. CCS provides five standard logistics services, including handling incoming shipments, unloading, warehousing, order sorting, repacking, and distribution. Regarding the inventory characteristics, the warehouse facilities are capable of supporting the storage of fresh and frozen food, wine, cigarettes, and other environmentally-sensitive products. In summary, CCS Logistics Limited provides a professional logistics service in handling the inventory in the cold supply chain.

Existing problems in the company

In each floor of the cold storage facility, the assigned warehouse workers are responsible for all warehousing operations, such as receiving, put-away, and sorting. Although the premises have been under the monitoring of round-the-clock CCTV surveillance, it is insufficient to provide real-time and appropriate support of occupational safety and health to the workers. CCTV surveillance provides image capturing and video recording functions, but it lacks any measuring of the workers' health status. In addition, the workers adopt safety and health measures by their own judgement and experience. Therefore, the safety and health measures cannot be customized to the workers' health situation. Secondly, the impact of working performance in the cold storage facilities cannot be easily evaluated with respect to the cold working environment, and affects the expected throughput rate and operational efficiency of the cold storage facilities. To summarize, the company currently lacks the capability to provide customized safety and health programs, and to estimate the impact of productivity of the workers.

Implementation of FARKMS

The implementation of FARKMS is conducted through a pilot study in CCS Logistics Limited. It is divided into three phases referred as the system architecture, i.e. DMM, FARMM, and KDSM, to achieve the goal of establishing appropriate safety and health programs.

DMM is the first step to define data collection for the data mining process in FARMM and KDSM. In the case scenario of CCS Logistics Limited, appropriate input and output parameters are suggested in Table 2, which are related to the recommendations of ISO 11079, personal physiques, and KPI measurements. In total, there are eight parameters, namely duration limited exposure, recovery time, average ambient temperature, body mass index, age, average heart rate, average dock to stock cycle time, and number of accidents and injuries. The workers are given the BLE hand-band integrated with the temperature and bio-signal sensors to collect the ambient temperatures and heart rates. They are used to find the useful fuzzy association rules in the FARMM. The input parameters are the antecedents of the IF part, whereas the output parameters are consequential to the THEN part. In CCS Logistics Limited, there are total 36 warehouse workers performing cold storage operations on 18 different storeys. In order to demonstrate the mechanism of FARMM effectively, six warehouse workers from floors one to three are extracted with the values of defined parameters A to H, as shown in Table 3. They are used as an example to demonstrate the mechanism of FARKMS. Before applying the proposed system, data pre-processing is required for sensor data and ISO11079 estimation. The removal of missing data and the filtering of out-of-expected-range values should be applied when collecting sensor data due to the fluctuation of device connectivity and noise. In the ISO11079 estimation, duration limited exposure and recovery time are generated by using the standard ISO11079 calculation which requires nine inputs, namely metabolic energy production, rate of mechanical work, ambient air temperature, mean radiant temperature, air permeability, walking speed, relative air velocity, relative humidity and available basic clothing insulation. Some of them are collected through the sensing technologies and processed by removal and filtering criteria. Therefore, the quality of data in the proposed system can be ensured and improved. Before generating useful FARs, the minimum support counts, membership functions, and confidence thresholds have to be defined in advance, as shown in Table 4. The confidence threshold (λ) is assumed as 0.75 for rejecting insignificant FARs.

According to the predefined threshold values and membership functions, the first step is to convert the quantitative values into a fuzzy set. For instance, the parameter D_{lim} for staff ID 1 is 1.8 hours, which belongs to the fuzzy classes of "Average" and "Long". The fuzzy set is represented as ($0.2/D_{lim}.A + 0.8/D_{lim}.L$), as shown in Fig. 3. The conversion technique is applied to all parameters for the six staff records, and the results are listed in Table 5. Secondly, the number of occurrences (counts) of each fuzzy class of parameter is calculated and compared with the support count threshold. For example, the number of counts of the fuzzy class "Average" of parameter D_{lim} is (0.2 + 0.4 + 0.9 + 0.8+ 0.8) = 3.1. After computing the number of counts, the maximum number of counts of each parameter is selected. The counts of the three fuzzy classes in parameter D_{lim}, "Short", "Average" and "Long", are 0.2, 3.1, and, 2.7. respectively. Therefore, the fuzzy class "Average" is sorted for representing the parameter D_{lim}. Similarly, the fuzzy classes "Average", "Low", "Overweight", "Old", "Normal", "Relatively Long", and, "High" represent parameters T_r, TEMP, BMI, A, H, T_{dc}, and, N with maximum number of counts of 4.5, 6, 3.3, 4.4, 3.5, 3.3, and 2 respectively. Compared with the minimum support count threshold, the number of counts is removed if it is less than the predefined threshold. Therefore, no parameters are removed from the 1-itemset.

Furthermore, the combinations of the 2-itemset are generated by using the 1-itemset. It is required to calculate the minimum number of counts of each 2-itemsets. Compared with the maximum value of two minimum support thresholds, the possible 2-itemsets are accepted if the number of counts is larger than the new support threshold. For example, {D_{lim}.A, T_r.A} for staff ID 1, since the count values of A.Long and B.Low are 0.2 and 0.5 respectively, the count of {D_{lim}.A, T_r.A} in the first converted fuzzy set is 0.2. Repeating for the 2nd to 6th converted fuzzy sets, the summation of the number of counts of {D_{lim}.A, T_r.A} is (0.2 +0.4 + 0.75 + 0 + 0.8 + 0.75) = 2.9. The new support count threshold is max(2.1, 2.6) = 2.6. The counts and new threshold of the other 2-itemsets are calculated and shown in Table 6, and sixteen 2-itemsets are generated. By repeating the above steps, the feasible i-itemsets with $i \geq 3$ can be investigated. Table 6 also includes the 3rd and 4th itemsets with their number of counts and corresponding new support thresholds. Since only one 4-itemset is generated, i.e. {T_r.A, TEMP.Low, A.O, N.H}, no possible 5-itemsets are available in the mining process. The valid itemsets are classified as the potential FARs. When collecting all potential FARs in the form of IF-THEN rules, the reliability of FARs is calculated so that the count of the antecedent is divided by the count of the consequent, called the confidence value. Therefore, by comparing the confidence threshold (λ) of 0.8, the generated FARs with their confidence values are listed in the Table 7. Only the rules with the output parameters in the "THEN" part are used to compute the confidence values, and extract the KDSM. Hence, based on five historical records, two examples of useful fuzzy association rules are illustrated to support the functions in KDSM in Table 8.

Table 2 Input and output parameters in FARKMS

Parameter			Symbol
Input	ISO 11079 estimation	Duration limited exposure (hour)	D_{lim}
		Recovery time (hour)	T_r

	Personal physique	Average ambient temperature (°C)	TEMP
		Body mass index (kg/m^2)	BMI
		Age (year)	A
		Average Heart rate (bpm)	H
Output	KPI Measurement	Average dock to stock cycle time (min)	T_{dc}
		No. of accidents and injuries (unit)	N

Table 3 Example of staff records for implementing FARKMS

Staff ID	**Floor**	**FARKMS Parameter**							
		D_{lim}	T_r	TEMP	BMI	A	H	T_{dc}	N
1	1/F	1.8	0.5	-17.5	20.5	25	58	36	1
2	1/F	1.6	0.6	-17.5	18.7	36	72	41	3
3	2/F	1.1	0.6	-16	27	47	84	57	7
4	2/F	3	0.6	-16	24.3	52	81	54	7
5	3/F	0.9	0.7	-18.5	23.3	60	76	62	9
6	3/F	1.2	0.8	-18.5	31.1	55	92	58	8

Table 4 Membership function and minimum support counts of parameters

Parameter	**Min. Support Counts**	**Fuzzy Class (short form)**	**Membership Function**	**MF Type**
D_{lim}	2.1	Short (S)	[0, 0, 0.5, 1]	Trapezoid
		Average (A)	[0.5, 1, 2]	Triangle
		Long (L)	[1, 2, 3, 3]	Trapezoid
T_r	2.6	Short (S)	[0, 0, 0.3, 0.7]	Trapezoid
		Average (A)	[0.3, 0.7, 1.1]	Triangle
		Long (L)	[0.7, 1.1, 1.5, 1.5]	Trapezoid
TEMP	3.0	Low (Low)	[-20, -20, -12, -6]	Trapezoid
		Average (A)	[-12, -6, -2, 4]	Trapezoid
		High (H)	[2, 4, 10, 10]	Trapezoid
BMI	3.1	Underweight (UW)	[14, 14, 18.5, 19.5]	Trapezoid
		Normal weight (NW)	[18.5, 19.5, 23, 24]	Trapezoid
		Overweight (OW)	[23, 24, 30, 30]	Trapezoid
A	2.8	Young (Y)	[18, 18, 25, 30]	Trapezoid
		Average (A)	[25, 30, 45]	Triangle
		Old (O)	[30, 45, 65, 65]	Trapezoid
H	3.4	Slow (S)	[40, 40, 50, 60]	Trapezoid
		Normal (N)	[50, 60, 80, 90]	Trapezoid
		Fast (F)	[80, 90, 120, 120]	Trapezoid
T_{dc}	2.7	Low (Low)	[0, 0, 10, 30]	Trapezoid
		Average (A)	[10, 30, 50]	Triangle
		Relatively long (RL)	[30, 50, 70]	Triangle
		Long (L)	[50, 70, 100, 100]	Trapezoid
N	1.9	Low (Low)	[0, 0, 1, 2]	Trapezoid
		Relative low (RLow)	[1, 2, 4]	Triangle
		Average (A)	[2, 4, 6]	Triangle
		Relative high (RH)	[4, 6, 7]	Triangle
		High (H)	[6, 7, 10, 10]	Trapezoid

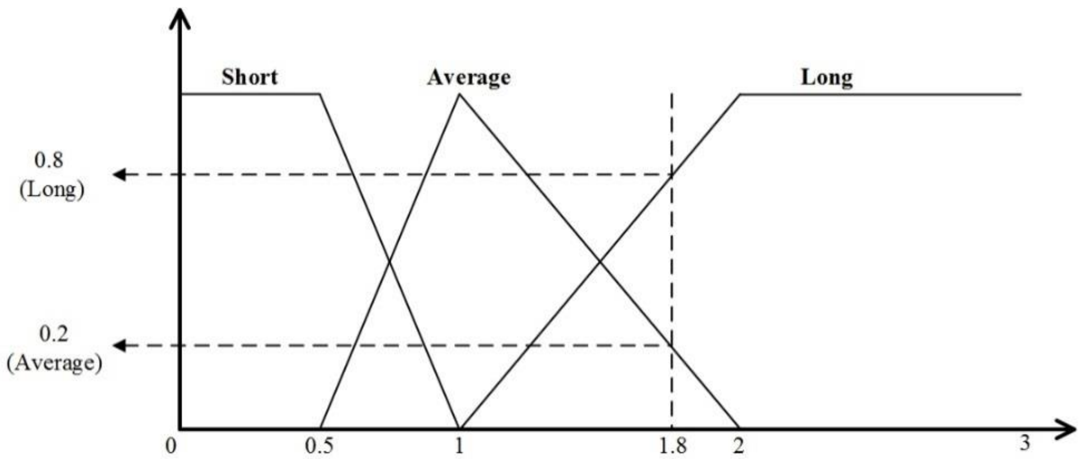

Fig 3. Fuzzy set example of parameter D_{lim} for Staff ID 1

Table 5 Converted fuzzy sets in FARMM

Staff ID	Quantitative values of parameters using fuzzy sets
1	$(\frac{0.2}{D_{lim}.A}+\frac{0.8}{D_{lim}.L})(\frac{0.5}{T_r.S}+\frac{0.5}{T_r.A})(\frac{1}{TEMP.Low})(\frac{1}{BMI.NW})(\frac{1}{A.Y})(\frac{0.2}{H.S}+\frac{0.8}{H.N})(\frac{0.7}{T_{dc}.A}+\frac{0.3}{T_{dc}.RL})(\frac{1}{N.Low})$
2	$(\frac{0.4}{D_{lim}.A}+\frac{0.6}{D_{lim}.L})(\frac{0.25}{T_r.S}+\frac{0.75}{T_r.A})(\frac{1}{TEMP.Low})(\frac{0.8}{BMI.UW}+\frac{0.2}{BMI.NW})(\frac{0.6}{A.A}+\frac{0.4}{A.O})(\frac{1}{H.N})(\frac{0.45}{T_{dc}.A}+\frac{0.55}{T_{dc}.RL})(\frac{0.5}{N.RLow}+\frac{0.5}{N.A})$
3	$(\frac{0.9}{D_{lim}.A}+\frac{0.1}{D_{lim}.L})(\frac{0.25}{T_r.S}+\frac{0.75}{T_r.A})(\frac{1}{TEMP.Low})(\frac{1}{BMI.OW})(\frac{1}{A.O})(\frac{0.6}{H.N}+\frac{0.4}{H.F})(\frac{0.65}{T_{dc}.RL}+\frac{0.35}{T_{dc}.L})(\frac{1}{N.H})$
4	$(\frac{1}{D_{lim}.L})(\frac{0.25}{T_r.S}+\frac{0.75}{T_r.A})(\frac{1}{TEMP.Low})(\frac{1}{BMI.OW})(\frac{1}{A.O})(\frac{0.1}{H.N}+\frac{0.9}{H.F})(\frac{0.8}{T_{dc}.RL}+\frac{0.2}{T_{dc}.L})(\frac{1}{N.H})$
5	$(\frac{0.2}{D_{lim}.S}+\frac{0.8}{D_{lim}.A})(\frac{1}{T_r.A})(\frac{1}{TEMP.Low})(\frac{0.7}{BMI.NW}+\frac{0.3}{BMI.OW})(\frac{1}{A.O})(\frac{1}{H.N})(\frac{0.4}{T_{dc}.RL}+\frac{0.6}{T_{dc}.L})(\frac{1}{N.H})$
6	$(\frac{0.8}{D_{lim}.A}+\frac{0.2}{D_{lim}.L})(\frac{0.75}{T_r.A}+\frac{0.25}{T_r.L})(\frac{1}{TEMP.Low})(\frac{1}{BMI.OW})(\frac{1}{A.O})(\frac{1}{H.F})(\frac{0.6}{T_{dc}.RL}+\frac{0.4}{T_{dc}.L})(\frac{1}{N.H})$

In the KDSM, since the useful fuzzy association rules are stored in the knowledge base, they can show the relationship between the input and output parameters. The extracted knowledge from FARs can be found in order to amend the occupational safety and health program. In view of the RES, the input parameters of FARKMS can be used to adjust the current safety and health program. The past program provides only the standard operating procedures (SOPs) with regard to the protective measurement in the cold storage facilities. The customized safety and health program should consider the parameters of duration limited exposure, recovery time, ambient temperature, BMI, age and average heart rate. When working in a low ambient temperature environment, the company should provide more protective measures to workers with high BMI and/or old age. Moreover, the duration limited exposure is a standardized indicator to show the maximum allowed working time. It can indicate the remaining working time in cold storage facilities to the workers. With the knowledge discovery in the above five historical records, the useful FARs imply that long duration limited exposure may result in relatively high in dock to stock cycle times, and low occurrence of cold accidents and injuries.

Table 6 New support thresholds and fuzzy counts

1-itemset

Parameter	FC	Total count
Dlim	S	0.2
	A	3.1
	L	2.7
Tr	S	1.25
	A	4.5
	L	0.25
TEMP	Low	6
	A	0
	H	0
BMI	UW	0.8
	NW	1.9
	OW	3.3
A	Y	1
	A	0.6
	O	4.4
H	S	0.2
	N	3.5
	F	2.3
Tdc	Low	0
	A	1.15
	RL	3.3
	L	1.55
N	Low	1
	RLow	0.5
	A	0.5
	RH	0
	H	4

2-itemset

Itemset combination			Count	New threshold
Dlim.A	and	Tr.A	2.9	2.6
Dlim.A	and	TEMP.Low	3.1	3
Dlim.A	and	BMI.OW	2	3.1
Dlim.A	and	A.O	2.9	2.8
Dlim.A	and	H.N	2	3.4
Dlim.A	and	Tdc.RL	2.25	2.7
Dlim.A	and	N.H	2.5	2.1
Tr.A	and	TEMP.Low	4.5	3
Tr.A	and	BMI.OW	3.05	31
Tr.A	and	A.O	3.65	2.8
Tr.A	and	H.N	2.95	3.4
Tr.A	and	Tdc.RL	3.25	2.7
Tr.A	and	N.H	3.25	2.6
TEMP.Low	and	BMI.OW	3.3	3.1
TEMP.Low	and	A.O	4.4	3
TEMP.Low	and	H.N	3.5	3.4
TEMP.Low	and	Tdc.RL	3.3	3
TEMP.Low	and	N.H	4	3
BMI.OW	and	A.O	3.3	3.1
BMI.OW	and	H.N	1	3.4
BMI.OW	and	Tdc.RL	2.35	3.1
BMI.OW	and	N.H	3.3	3.1
A.O	and	H.N	2.1	3.4
A.O	and	Tdc.RL	2.85	2.8
A.O	and	N.H	4	2.8
H.N	and	Tdc.RL	1.95	3.4
H.N	and	N.H	1.7	3.4
Tdc.RL	and	N.H	2.45	2.7

3-itemset

Itemset combination					Count	New threshold
Dlim.A	and	Tr.A	and	TEMP.Low	2.9	3
Dlim.A	and	Tr.A	and	BMI.OW	1.8	3.1
Dlim.A	and	Tr.A	and	A.O	2.7	2.8
Dlim.A	and	Tr.A	and	H.N	2	3.4
Dlim.A	and	Tr.A	and	Tdc.RL	2.25	2.7
Dlim.A	and	Tr.A	and	N.H	2.3	2.6
Dlim.A	and	TEMP.Low	and	BMI.OW	2	3.1
Dlim.A	and	TEMP.Low	and	A.O	2.9	3
Dlim.A	and	TEMP.Low	and	H.N	2	3.4
Dlim.A	and	TEMP.Low	and	Tdc.RL	2.25	3
Dlim.A	and	TEMP.Low	and	N.H	2.5	3
Dlim.A	and	A.O	and	BMI.OW	2	3.1
Dlim.A	and	A.O	and	H.N	1.8	3.4
Dlim.A	and	A.O	and	Tdc.RL	2.05	2.8
Dlim.A	and	A.O	and	N.H	2.5	2.8
Tr.A	and	TEMP.Low	and	BMI.OW	2.605	3.1
Tr.A	and	TEMP.Low	and	A.O	3.65	3
Tr.A	and	TEMP.Low	and	H.N	2.95	3.4
Tr.A	and	TEMP.Low	and	Tdc.RL	3.25	3
Tr.A	and	TEMP.Low	and	N.H	3.25	3
Tr.A	and	A.O	and	BMI.OW	2.55	3.1
Tr.A	and	A.O	and	H.N	2.85	3.4
Tr.A	and	A.O	and	Tdc.RL	2.8	2.8
Tr.A	and	A.O	and	N.H	3.25	2.8
Tr.A	and	Tdc.RL	and	TEMP.Low	3.25	4
Tr.A	and	Tdc.RL	and	BMI.OW	2.3	3.1
Tr.A	and	Tdc.RL	and	H.N	1.95	3.4
Tr.A	and	Tdc.RL	and	N.H	3.25	2.7
TEMP.Low	and	BMI.OW	and	A.O	3.3	3.1
TEMP.Low	and	BMI.OW	and	H.N	1	3.4
TEMP.Low	and	BMI.OW	and	Tdc.RL	2.35	3.1
TEMP.Low	and	BMI.OW	and	N.H	3.3	3.1
TEMP.Low	and	A.O	and	H.N	2.1	3.4
TEMP.Low	and	A.O	and	Tdc.RL	2.85	3
TEMP.Low	and	A.O	and	N.H	4	3
TEMP.Low	and	H.N	and	Tdc.RL	1.95	3.4
TEMP.Low	and	H.N	and	N.H	3.25	3.4
TEMP.Low	and	Tdc.RL	and	N.H	2.4	3
BMI.OW	and	A.O	and	H.N	1	3.4
BMI.OW	and	A.O	and	Tdc.RL	2.45	3.1
BMI.OW	and	A.O	and	N.H	3.3	3.1

4-itemset

Itemset combination							Count	New threshold
Tr.A	and	TEMP.Low	and	A.O	and	Dlim	2.1	3
Tr.A	and	TEMP.Low	and	A.O	and	BMI.OW	2.55	3.1
Tr.A	and	TEMP.Low	and	A.O	and	H.N	2.1	3.4
Tr.A	and	TEMP.Low	and	A.O	and	Tdc.RL	2.8	3
Tr.A	and	TEMP.Low	and	A.O	and	N.H	3.25	3
Tr.A	and	TEMP.Low	and	Tdc.RL	and	Dlim	2.25	3
Tr.A	and	TEMP.Low	and	Tdc.RL	and	BMI.OW	2.3	3.1
Tr.A	and	TEMP.Low	and	Tdc.RL	and	H.N	1.95	3.4
Tr.A	and	TEMP.Low	and	Tdc.RL	and	N.H	2.4	3
Tr.A	and	TEMP.Low	and	N.H	and	BMI.OW	2.55	3.1
Tr.A	and	TEMP.Low	and	N.H	and	H.N	1.7	3.4
Tr.A	and	TEMP.Low	and	N.H	and	Tdc.RL	2.4	3
Tr.A	and	A.O	and	Tdc.RL	and	Dlim	2.05	2.8
Tr.A	and	A.O	and	Tdc.RL	and	BMI.OW	2.3	3.1
Tr.A	and	A.O	and	Tdc.RL	and	H.N	1.5	3.4
Tr.A	and	A.O	and	Tdc.RL	and	N.H	2.4	2.8
Tr.A	and	A.O	and	N.H	and	Dlim	2.35	2.8
Tr.A	and	A.O	and	N.H	and	BMI.OW	2.55	3.1
Tr.A	and	A.O	and	N.H	and	H.N	1.7	3.4
Tr.A	and	Tdc.RL	and	N.H	and	Dlim	2.3	2.7
Tr.A	and	Tdc.RL	and	N.H	and	BMI.OW	2.55	3.1
Tr.A	and	Tdc.RL	and	N.H	and	H.N	1.7	3.4
TEMP.Low	and	BMI.OW	and	A.O	and	Dlim	2	3.1
TEMP.Low	and	BMI.OW	and	A.O	and	H.N	1	3.4
TEMP.Low	and	BMI.OW	and	A.O	and	Tdc.RL	2.35	3.1
TEMP.Low	and	BMI.OW	and	A.O	and	N.H	3.3	3.1
TEMP.Low	and	BMI.OW	and	N.H	and	Dlim	2	3.1
TEMP.Low	and	BMI.OW	and	N.H	and	H.N	1	3.4
TEMP.Low	and	BMI.OW	and	N.H	and	Tdc.RL	2.35	3.1
TEMP.Low	and	A.O	and	N.H	and	Dlim	2.5	3
TEMP.Low	and	A.O	and	N.H	and	H.N	1.7	3.4
TEMP.Low	and	A.O	and	N.H	and	Tdc.RL	2.45	3
BMI.OW	and	A.O	and	N.H	and	Dlim	2	3.1
BMI.OW	and	A.O	and	N.H	and	H.N	1	3.4
BMI.OW	and	A.O	and	N.H	and	Tdc.RL	2.35	3.1

As shown in Table 8, the FAR of "IF {Tr.A} and {TEMP.Low} and {A.O} THEN {N.H}" is that the high likelihood of accidents and injuries is constituted by three antecedents, namely (i) recovery time is average, (ii) ambient temperature in working environment is low, and (iii) the staff is old. On the other hand, the FAR of "IF {BMI.OW} and {A.O} THEN {N.H}" is that the high likelihood of accidents and injuries is constituted the categories of overweight in BMI and old age staff. It is implied that the normal estimation in recovery time is inadequate so that the staff in the "Old" category may need more recovery time after working in a low temperature environment. The "average" number of recovery time is insufficient for them. On the other hand, the staff categorized as "Old" with "high" BMI also have a high probability of getting accidents and injuries so that the management team may change the job specifications from warehousing operations to paperwork, so as to prevent the serious accidents occurred in the cold storage facilities.

Therefore, the design of the safety and health program can include the above hidden information from FARs. To communicate the information to the workers, a user interface prototype is developed to display the customized safety and health program by entering the input parameters, as shown in Fig. 4. The outputs from FARKMS are verified by conducting a comparison between the before and after implementation of the proposed system. During the implementation period, another three separate cold storage rooms are also required to conduct control experiments in order to investigate the actual changes from FARKMS. Hence, the occupational safety and health can be guaranteed and improved.

Table 7 Generated fuzzy association rules with confidence values

Potential FAR	Confidence value	$\geq \lambda$?
IF {D_{lim}.A} THEN {N.H}	3.1/4 = 0.775	No
IF {T_r.A} THEN {T_{dc}.RL}	4.5/3.3 = 1.364	Yes
IF {T_r.A} THEN {N.H}	4.5/4 = 1.125	Yes
IF {TEMP.Low} THEN {T_{dc}.RL}	6/3.3 = 1.818	Yes
IF {TEMP.Low} THEN {N.H}	6/4 = 1.5	Yes
IF {BMI.OW} THEN {N.H}	3.3/4 = 0.825	Yes
IF {A.O} THEN {N.H}	4.4/4 = 1.1	Yes
IF {T_r.A} and {TEMP.Low} THEN {T_{dc}.RL}	4.5/3.3 = 1.364	Yes
IF {T_r.A} and {TEMP.Low} THEN {N.H}	4.5/4 = 1.125	Yes
IF {T_r.A} and {A.O} THEN {T_{dc}.RL}	3.65/3.3 = 1.106	Yes
IF {T_r.A} and {A.O} THEN {N.H}	3.65/4 = 0.913	Yes
IF {T_r.A} THEN { T_{dc}.RL } and {N.H}	4.5/2.45 = 1.837	Yes
IF {TEMP.Low} and {A.O} THEN {N.H}	4.4/4 = 1.1	Yes
IF {BMI.OW} and {A.O} THEN {N.H}	3.3/4 = 0.825	Yes
IF {T_r.A} and {TEMP.Low} and {A.O} THEN {N.H}	3.65/4 = 0.913	Yes

Table 8 Example of useful fuzzy association rules

FAR	**IF** {T_r.A} and {TEMP.Low} and {A.O} **THEN** {N.H}	**IF** {BMI.OW} and {A.O} **THEN** {N.H}
Explanation	**IF** recovery time is average **and** average ambient temperature is low **and** age of the staff is old, **THEN** number of accidents and injuries is high.	**IF** body mass index is overweight **and** age of the staff is old, **THEN** number of accidents and injuries is high.

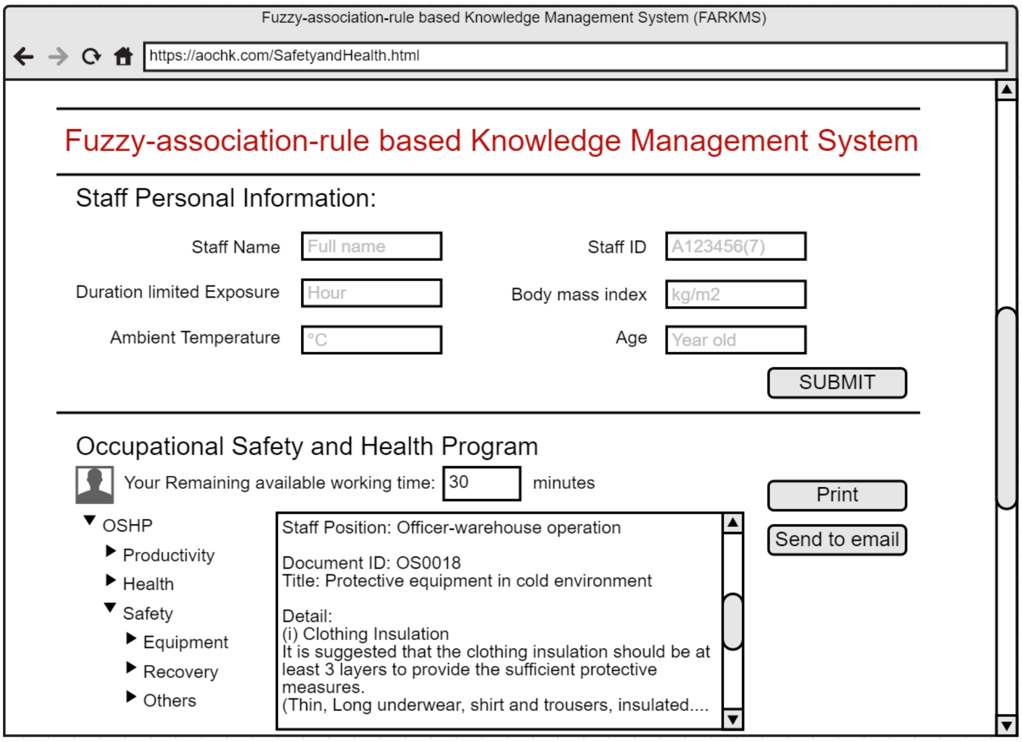

Fig 4. User interface prototype of FARKMS

Results and Discussion

In order to guarantee and improve the occupational safety and health in cold storage facilities, this paper presents the FARKMS approach to extract useful information from FARM to support the mechanism of RES for establishing customized and appropriate safety and health programs. The historical records of workers' performance are important in generating the FARs, which are then stored in the knowledge base for further decision support. The customized safety and health program can be established according to the criteria of the workers. The workers can follow the instructions in the user interface generated by FARKMS to support their daily operations. The customized programs create a safe and healthy working atmosphere such that it is more systematic and efficient in guaranteeing their safety and health. In addition, this cloud-based application is user-friendly with good Wi-Fi coverage in the cold storage. They can conveniently check the instructions and guidelines on their own smart devices. The case study in CCS Logistics Limited provides a real case validation for the proposed system. In its cold storage facility, 3 storeys followed the existing OSH policy unchanged, and another 3 storeys used the new FARKMS approach to update the OSH instructions/programs. This implementation of FARKMS lasted for a month and the FARKMS was activated in every working day, and the accident frequency rates were recorded for validating the effectiveness of the proposed system. By the use of FARKMS, the case company have recorded an improvement in reduction of injuries and accidents from 12 times/week to 5 times/week, which is equal to 58.3% accident reduction. The relevant workers feel more secure and comfortable when working in the cold storage facilities. Through the use of the proposed mining system, two significant advantages are achieved as summarized below.

(i) Improving the operational efficiency

Since the productivity measurement can be linked with the proposed mining system, the effect of the input parameters on operational efficiency can be defined systematically. With inputting a sufficiently large historical record to FARMM, more useful and precise FARs can be generated to define the relationship between the operational efficiency and other parameters.

This allows the company to adjust the workforce or working patterns to achieve the optimal operational efficiency.

(ii) Providing good practice of occupational safety and health

The core concept of the proposed mining system is to provide comprehensive occupational safety and health programs to the workers. The traditional SOPs and manual judgement are insufficient to guarantee the safety and health for every worker. Hence, five input parameters are used to amend the program, and integrate with the FARs in order to link the ISO11079 estimations and personal physiques to the safety and health measurement. Knowledge discovery can support the establishment of the complete program to improve and ensure occupational safety and health.

Conclusions

Due to the increasing demand for cold chain logistics to handle environmental-sensitive products, workers handle more products in the cold storage facilities. In order to maintain high operational efficiency, occupational safety and health is an important measure. This paper presents a fuzzy-association rule based knowledge management system with a focus on occupational safety and health in cold storage facilities. Traditionally, occupational safety and health are guaranteed by SOPs and personal experience. The safety and health programs are difficult to fit all workers' needs and requirements, and, in addition, there are no insights related to the operational efficiency. Through implementing FARKMS, the recursive mining process algorithm generates useful FARs to enhance the intelligence of the RES. RES can suggest various occupational safety and health programs based on the input criteria. In addition, it can be linked to the operational efficiency such that the workers/managers can further understand productivity in the cold storage facilities. This is a significant contribution to knowledge discovery by a fuzzy-association rule based expert system in providing appropriate and customized safety and health programs. In conclusion, the proposed mining system not only satisfies the needs of occupational safety and health, but also extracts the hidden information from the historical data to support decision making. This paper significantly contributes to the research field of knowledge acquisition and management in cold storage facilities. It helps in developing complete occupational safety and health programs for working inside cold storage facilities. It is recommended to collect more historical records so as to generate more accurate FARs to enhance the knowledge base. Therefore, the design of the program, and the safety and health of workers can be further improved and guaranteed. In future, researchers can utilize the methodology to protect the human beings in other extreme working environments.

Acknowledgements

The authors would like to thank the Research Office of the Hong Kong Polytechnic University and AOC Limited for supporting the project. (Project Code: RUDV)

References

Abraham, A. (2005). Rule-Based Expert Systems. *Handbook of measuring system design*. Stillwater, Oklahoma: John Wiley & Sons, Ltd.

Azadeh, A., Fam, I. M., Khoshnoud, M., & Nikafrouz, M. (2008). Design and implementation of a fuzzy expert system for performance assessment of an integrated health, safety, environment (HSE) and ergonomics system: The case of a gas refinery. *Information Sciences*, *178*(22), 4280-4300.

Aramyan, L. H., Oude Lansink, A. G., Van Der Vorst, J. G., & Van Kooten, O. (2007). Performance measurement in agri-food supply chains: a case study. *Supply Chain Management: An International Journal*, *12*(4), 304-315.

Bogataj, M., Bogataj, L., & Vodopivec, R. (2005). Stability of perishable goods in cold logistic chains. *International Journal of Production Economics*, *93*, 345-356.
Buchanan, B. G., & Shortliffe, E. H. (Eds.). (1984). *Rule-based expert systems*(Vol. 3). Reading, MA: Addison-Wesley.
Chen, H., Li, Y., Mu, Y., Wang, L., & Zhang, X. (2015). A Quality Research Analysis of Logistics Distribution Process of Fresh Meat Cold Chain in Beijing. In *LISS 2013* (pp. 697-703). Springer Berlin Heidelberg.
Delgado, M., SáNchez, D., MartıN-Bautista, M. J., & Vila, M. A. (2001). Mining association rules with improved semantics in medical databases. *Artificial Intelligence in Medicine*, *21*(1), 241-245.
Gazaway, C. (2009). Workers killed in industrial accident. *Wave 3 News*, p.1. Retrieved from http://www.wave3.com/story/10358890/workers-killed-in-industrial-accident
Griefahn, B. (2000). Limits of and possibilities to improve the IREQ cold stress model (ISO/TR 11079). A validation study in the field. *Applied ergonomics*,*31*(4), 423-431.
Gürcanli, G. E., & Müngen, U. (2009). An occupational safety risk analysis method at construction sites using fuzzy sets. *International Journal of Industrial Ergonomics*, *39*(2), 371-387.
Holmer, I. (2009). Evaluation of cold workplaces: an overview of standards for assessment of cold stress. *Industrial Health*, *47*(3), 228-234.
Ho, G. T. S., Choy, K. L., & Poon, T. C. (2010, October). Providing decision support functionality in warehouse management using the RFID-based fuzzy association rule mining approach. In *Supply Chain Management and Information Systems (SCMIS), 2010 8th International Conference on* (pp. 1-7). IEEE.
Hong, T. P., Lin, K. Y., & Wang, S. L. (2003). Fuzzy data mining for interesting generalized association rules. *Fuzzy sets and systems*, *138*(2), 255-269.
International Trade Administration. 2016. 2016 Top Markets Report Cold Supply Chain. United State: Department of Commerce.
James, S. J., & James, C. (2010). The food cold-chain and climate change.*Food Research International*, *43*(7), 1944-1956.
Kuo, J. C., & Chen, M. C. (2010). Developing an advanced multi-temperature joint distribution system for the food cold chain. *Food Control*, *21*(4), 559-566.
Küpper, T., Steffgen, J., & Jansing, P. (2003). Cold exposure during helicopter rescue operations in the Western Alps. *Annals of occupational hygiene*, *47*(1), 7-16.
Lau, H. C., Ho, G. T., Chu, K. F., Ho, W., & Lee, C. K. (2009). Development of an intelligent quality management system using fuzzy association rules. *Expert Systems with Applications*, *36*(2), 1801-1815.
Laurence, J. (2013). Ammonia leak at Shanghai refrigeration plant kills 15, injures 26. *REUTERS*, p.1. Retrieved from http://www.reuters.com/article/us-china-accident-ammonia-idUSBRE97U04420130831
Lee, C. K. H., Ho, G. T. S., Choy, K. L., & Pang, G. K. H. (2014). A RFID-based recursive process mining system for quality assurance in the garment industry. *International Journal of Production Research*, *52*(14), 4216-4238.
Lu, L., Zheng, W., Lv, Z., & Tang, Y. (2013). Development and application of time–temperature indicators used on food during the cold chain logistics. *Packaging Technology and Science*, *26*(S1), 80-90.
Mäkinen, T. M., & Hassi, J. (2009). Health problems in cold work. *Industrial health*, *47*(3), 207-220.
Seto, E., Leonard, K. J., Cafazzo, J. A., Barnsley, J., Masino, C., & Ross, H. J. (2012). Developing healthcare rule-based expert systems: case study of a heart failure telemonitoring system. *International journal of medical informatics*, *81*(8), 556-565.

Sheu, J. J., Hwang, J. S., & Wang, J. D. (2000). Diagnosis and monetary quantification of occupational injuries by indices related to human capital loss: analysis of a steel company as an illustration. *Accident Analysis & Prevention*,*32*(3), 435-443.

Soni, S., & Vyas, O. P. (2010). Using associative classifiers for predictive analysis in health care data mining. *International Journal of Computer Applications*, *4*(5), 33-37.

Venkatasubramanian, V., Zhao, J., & Viswanathan, S. (2000). Intelligent systems for HAZOP analysis of complex process plants. *Computers & Chemical Engineering*, *24*(9), 2291-2302.