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An Intelligent Model for Assuring Food Quality in Managing a Multi-Temperature Food Distribution Centre

Y.P. Tsang, K.L. Choy, C.H. Wu, G.T.S. Ho, H.Y. Lam, Valerie Tang

Abstract:

In the globalized cold chain network, the effective distribution of perishable food is of utmost importance when transporting multiple types of food with different handling requirements, such as temperature and humidity, for minimizing the food spoilage rate during transportation. Currently, mismanagement of premium fruit and vegetables leads to a huge amount of capital loss such that logistics service providers (LSPs) apply refrigerated trucks to deliver them for the sake of minimizing the food spoilage rate during transportation. Since different types of food have their own different handling requirements, traditional refrigerated distribution management at a fixed environmental condition is insufficient. Without considering such requirements, traditional route planning by merely minimizing the travelling distance is ineffective in maintaining food quality, resulting in an increased likelihood of food deterioration and food chilling injury. In addition, there is a lack of real-time product monitoring to control violations of the required handling requirements in order to prevent delivery of spoilt food to customers. In this paper, an internet of things (IoT)-based route planning system (IRPS) is proposed (i) to design a multi-temperature packaging model, (ii) to develop real-time product monitoring during transportation, and (iii) to optimize routing solutions. Under the IoT framework, the ambient environmental information can be collected automatically by building a wireless sensor network so as to develop total product monitoring during the distribution process. Experiments using the Taguchi method are conducted to examine the most effective packaging model for various products in terms of maximizing duration of optimal environment conditions in tertiary packaging. By integrating the above results and travelling constraints, the optimal delivery routes can be formulated by using genetic algorithms (GAs). With the aid of IRPS, the food spoilage rate during transportation and the time needed in route planning and in the delivery of deteriorated food can be reduced, while customer satisfaction is enhanced.

Keywords: Multi-temperature food distribution, vehicle routing problem, Taguchi method, genetic algorithm, Internet of Things

1. Introduction:

In recent years, multi-temperature food distribution in which the transported food has different recommended handling conditions has drawn significant attention in regard to issues of food quality and safety among the supply chain activities. Almost one-third of produced food is wasted or lost annually due to ineffective management in harvesting, storage and transportation throughout the entire supply chain (Food and Agriculture Organization, 2017). When importing premium fruit and vegetables with similar food spoilage situations, an extraordinary capital loss will be incurred so that the attention of effective food management in distribution should be paid. In order to eliminate the food loss and waste in different supply chain elements, there are several international standards for implementing quality assurance systems to ensure food quality and safety throughout the supply chain process, such as good agricultural practice (GAP), good manufacturing practice (GMP), and hazard analysis of critical control points (HACCP) (Amoa-Awua et al., 2007; González-Rodríguez et al., 2011; Baldera Zubeldia et al., 2016). These practices recommend using certain refrigeration systems in trucks and storage areas, while the shortest possible delivery routes should be taken in handling such temperature-sensitive food. However, logistics companies may face a challenge between cost effectiveness and performance in the adoption of certain refrigerated trucks and facilities, so as to ensure the products are handled within prescribed limits. This is because such refrigerated trucks are only available at a fixed set of environmental conditions, and it is difficult to satisfy all handling requirements, particularly in consolidated shipments. Consequently, the ontology of multi-temperature joint distribution (MTJD) has been proposed, while certain delivery advancements, including cold cabins and eutectic plates, are applied to reduce the operation cost, and to improve product quality and safety (Kuo and Chen, 2010). Therefore, the formulation of an appropriate cold chain packaging model is a critical point in food distribution, and affects the delivery routing. In general, there are three major types of cold chain packaging models, i.e. active, passive and hybrid systems (Ahvenainen, 2003; Kerry et al., 2006; Romero, 2013). An active system mainly applies to refrigeration systems and thermostatic control; A passive system mainly refers phase change materials; A hybrid system refers to phase change materials which are regulated by the refrigeration system. Table 1 shows the comparison of three cold chain packaging models.

Table 1 Comparison of active, passive and hybrid cold chain packaging model

Criteria	Types of cold chain packaging model		
	Active	Passive	Hybrid
Pallet Size availability	Standard	Customized	Standard
Cost	High	Low	Moderate
Thermal flexibility	Fixed	Flexible	Fixed
Reliability	High	High (SOP[a] required)	Moderate
Ease of use	Easy	Difficult	Moderate

[a] SOP stands for standard operating procedures in cold chain packaging model.

In the MTJD network, the passive cold chain packaging model is preferred in managing products with different recommended transport conditions due to its low cost and high flexibility for varying thermal conditions and shipment sizes. Fig. 1 shows a premium fresh food supply chain, and the existing problems in multi-temperature food distribution. The supply chain involves farmers, food processing units, distribution centers, retailers, and consumers. During the entire supply chain, temperature control is essential to ensure food quality and safety until the point of consumption. Traditionally, using passive data collection approaches, such as data loggers, is inefficient in sharing information among various supply chain parties. Thus, the real-time product monitoring under an IoT environment is deemed to be a feasible solution. On the other hand, the food will deteriorate if the ambient environmental conditions are continuously out of specification during transportation. The passive packaging model using phase change materials should be applied for handling multi-temperature food to slow down their own process of deterioration and ripening. However, there is a lack of the in-depth experimental analysis to measure the rate of change of temperature and humidity in the passive packaging model, when selecting the optimal setting for the specific food. Furthermore, the cooling time window established by the optimal packaging settings should be considered in route planning, together with the customers' locations, costs and service time window.

This paper proposes an internet of things (IoT)-based route planning system (IRPS), which integrates Internet of Things, Taguchi experimental design, and genetic algorithms, to formulate the total product monitoring and optimal delivery route planning for multi-temperature food distribution. IoT enhances the information visibility and traceability, particular for the environmental conditions during the whole transportation. The enabling IoT technologies can also provide data for conducting experiments using the Taguchi method so as to determine the optimal number of eutectic plates and cabin volume for specific food, as well as the dominant factors in such a cold chain packaging model. Through integrating the above results, the GA is then adopted to search the optimal delivery routes by minimizing the travelling distance and food spoilage rate, and maximizing the order fulfillment rate. Through the adoption of IRPS, the transported food can be kept under the real-time monitoring and distributed in the desired environmental conditions and optimal settings.

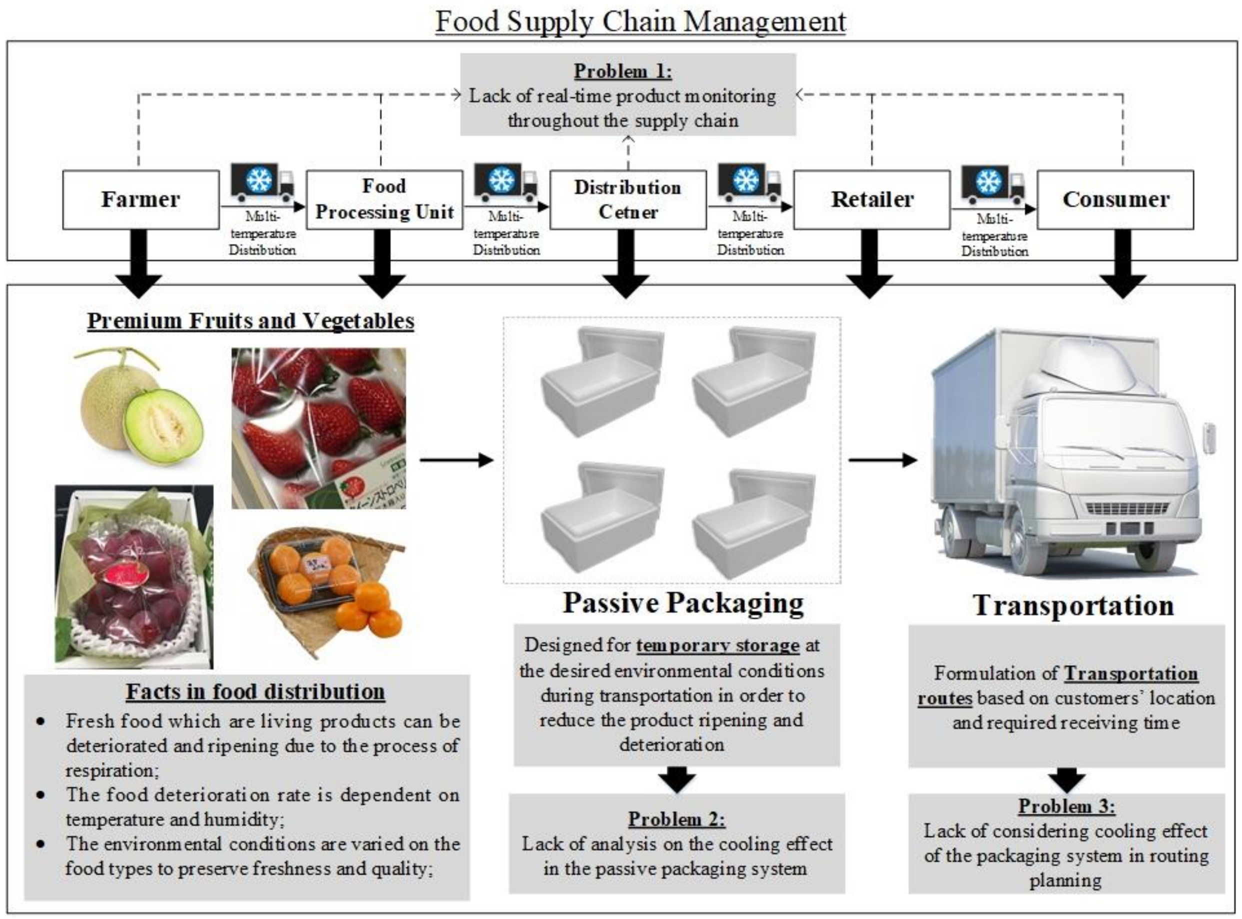


Fig. 1 Existing Challenges in multi-temperature food distribution

This paper is organized as follows. Section 1 is the introduction. In Section 2, the related work and literature in the aspects of cold chains, design of experiments, the IoT framework and developments, and optimization approaches in vehicle routing problem are studied. Section 3 presents the system architecture of IRPS. A case study in implementing the proposed system is illustrated in Section 4. Section 5 gives the results and discussion related to the benefits and limitations of the proposed system. Conclusions are drawn in the Section 6.

2. Literature Review

In general, supply chain management, which involves various parties, including suppliers, manufacturers, distributors, retailers and customers, is developed to improve the coordination and collaboration among the supply chain parties (Monczka et al., 2015; Christopher, 2016). Regarding the food supply chain, supply chain integrity concerning food safety, food quality and origin fraud is essential such that verified evidence of the prescribed food quality is required to be provided to customers (Aung and Chung, 2014). Compared with traditional supply chain management, the food supply chain is required to pay attention to the impact on social, economic and environmental factors. Incidences of foodborne illness, which may incur additional medical expenses and losses, should be minimized by controlling the environmental factors, such as temperature and humidity, along the whole supply chain (Martin & Ronan, 2000; Logan 2012). Akkerman et al. (2010) also stated that food has limited shelf life, temperature-sensitive characteristics, and an interaction effect with other food, resulting in challenges in effective supply chain management. Due to diversified handling requirements, there are basically three types of the food supply chains, namely frozen (at or below -18°C), chilled (0-15°C), and ambient (22-25°C) (Smith and Sparks, 2007). Products should be handled in suitable environmental conditions for both storage and transportation. Although the desired storage conditions for specific products can be maintained easily, it is difficult to consolidate different types of food while satisfying all the product handling requirements in the single shipment. Since refrigerated trucks are unable to handle food with different handling environmental conditions due to the fixed temperature for each vehicle, MTJD is proposed to improve the flexibility and adaptability in distribution management (Kuo and Chen, 2010). Therefore, the cold chain packaging model has drawn considerable research attention on evaluation of the cooling rate and packaging materials in a cost-effective and resource-efficient manner (Defraeye et al., 2015; Tsironi et al., 2015). However, a standard method to formulate the packaging model is lacking. Design of experiment (DoE) is a feasible approach to investigate the optimal settings in packaging setting for maximizing the duration under optimal environmental conditions for increasing the flexibility in transportation management.

DoE is a systematic process to discover the significant impact between inputs and process outputs through conducting certain experiments (Oehlert, 2010; Montgomery, 2017). Experiments consist of four major components: treatment, units, responses, and specific experimental design, without which the relationship and formula between inputs and outputs are difficult to establish. Since the relationship between responses and independent variables are uncertain, several analytical tools are used in investigating the tendencies and measurement errors, and even validating the results, such as signal-to-noise (S/N) ratios. DoE has been widely applied in many areas, including manufacturing processes and pharmaceutical modeling (Gu and Burgess, 2015; Kanojia et al., 2016). Particularly for a packaging model, Mistriotis et al (2016) designed through experiments the poly-lactic acid based equilibrium modified atmosphere packaging system to build a one-dimensional simulation so as to prolong the product shelf life. Velasco et al. (2014) applied experimental design to explore the relationship between the taste and packaging characteristics, including shapes, typefaces, names, and sounds. However, the classical experimental design needs a huge amount of time, costs, and materials to conduct many experiments. The Taguchi method in DoE, which is robust design for product and production processes, is used to examine the optimal factors in the experiment settings with improved performance, quality and cost (Yang and Tarng, 1998; Aveiro, 2016). This high applicable method has also been widely applied in the logistics and supply chain aspect, including selection of third-party logistics service providers, evaluation of proposed Tabu search-based heuristic method in reverse logistics network, and determination of critical control factors in electronic packaging (Eskandarpour et al., 2014; Sharma and Kumar, 2015; Huang et al., 2016). However, there has been limited experimental research on the passive cold chain packaging model, and thus the formulation of an optimal packaging model would be valuable and beneficial to the vehicle routing for multi-temperature food distribution.

The optimization and determination of delivery routes have always been studied in the area of the vehicle routing problem (VRP) so as to serve a group of customers through arranging a fleet of vehicles (Golden et al., 2008). In general, VRP can be solved by formulating exact and heuristic programming, such as dynamic programming, integer programming, sweep algorithm, and Tabu search algorithm (Laporte, 1992). In addition, modern research has focused on exploring some additional factors in VRP, including time windows and stochastic demand (Marinakis et al., 2013; Lin et al., 2014). In view of MTJD, the models of optimal delivery cycle, time-temperature dependence, shelf life estimation and facilities planning have been formulated (Hsu and Liu, 2011; Hsu et al., 2013; Gogou et al., 2015; Hsiao et al., 2017). The objectives of the above studies are to minimize the daily delivery costs, energy cost, inventory cost and penalty cost with respect to the delivery time window and time-dependent demand, so the food freshness can then be assured. However, consideration of the effects from the cold chain packaging model in multi-temperature joint distribution is neglected, so that there is a possibility that the food will deteriorate due to unexpected incidents, such as broken packaging or electricity failure. Therefore, the existing MTJD model can be further enhanced by considering the cooling time window to prevent food deterioration and ripening during transportation. In addition, for the sake of completely ensuring food quality and safety during the transportation, advanced sensing technologies should be applied to keep monitoring the food, such as IoT.

Along with the rapid growth of IoT, a standard framework from the wireless sensor network to relevant system development was proposed, which is also beneficial in environmental condition monitoring (Gubbi et al., 2013; Kelly et al., 2013). Formulation of IoT applications consists of four major layers, namely device layer, gateway layer, service platform layer, and IoT core network (Rajput and Gour, 2016). Through using the standard protocols in IoT, the performance and security of the proposed applications can be maintained. Hsiao et al. (2016) presented the time-temperature transparency was insufficient as the willingness to share information from food suppliers was low due to bargaining power, business strategy and quality uncertainty. Qi et al. (2014) designed an integrated cold chain shelf life decision support system with a wireless sensor network to support total monitoring, shelf-life visibility and stock management strategy. Xiao et al. (2016) developed a temperature monitoring system with compressed sensing to eliminate the heavy data traffic and achieve cold chain monitoring. There is a room to extend the concept of product monitoring under the IoT environment so as to develop a secure, economic, and applicable system for the logistics industry.

From the above studies, it is summarized that multi-temperature food distribution requires special attention on various desired food handling requirements. The passive cold chain packaging model is deemed to be a feasible solution, particularly in handling consolidation shipments. In order to ensure the food quality and safety, this study explores the most appropriate packaging model for various food products, and the optimal delivery routing can then be formulated. In addition, IoT monitoring application should be deployed to improve the visibility of environmental conditions throughout the entire food chain. Therefore, an Internet of Things (IoT)-based route planning system (IRPS) is proposed in this study.

3. Design of an Internet of Things (IoT)-based Route Planning System (IRPS)

This section presents an Internet of Things (IoT)-based route planning system (IRPS) to design a multi-temperature packaging model, develop real-time product monitoring, and optimize delivery routing for multi-temperature food distribution. Fig. 2 shows the system architecture of IRPS with three modules. Firstly, in the passive packaging modeling module, the optimal packaging setting and dominant factor are determined through the Taguchi method of experiments. Secondly, the cooling time window from the optimal packaging setting is considered in the vehicle routing problem which is then solved by genetic algorithm (GA) together with other factors, such as costs and travelling time. Thirdly, when transporting the food to customers, the ad-hoc product monitoring application is deployed in the IoT monitoring module for ensuring the prescribed environmental conditions.

3.1 Passive packaging modeling module

In this module, experiments are conducted to investigate the cooling rate of the passive packaging model by establishing L_9 (3 × 3 × 3) orthogonal array using the Taguchi method. The materials in the experiments involve three different sizes of polyfoam boxes and three different sizes and numbers of eutectic plates as shown in Table 2. In total, three sets of experiment are conducted repeatedly, to enhance the reliability of results. The experimental set-up for investigating the rate of change of temperature and humidity in the passive packaging model is shown in Fig. 3. A data logger, i.e. Elitech RC-4HC, is used to collect the temperature and humidity for all the experiments, and thus a graph of rate of change of temperature and humidity over time can be plotted. The eutectic plates are set at the bottom of the box, while the food or products are designed to be put on top of the plates. In the Taguchi method of experiments, there are generally six steps to determine the optimal settings and dominant factor, namely objective formulation, factor identification, design of experiment, conducting experiment, data analysis, and validation. Since the food has its own recommended transport condition, the temperature and humidity during the transportation should be maintained within the upper and lower specifications, i.e. $[Temp_{lower}, Temp_{upper}]$ and $[Humi_{lower}, Humi_{upper}]$. Let T(x) and H(x) be two functions for expressing change of temperature and change of humidity over time, and $T^{-1}(x)$ and $H^{-1}(x)$ be the corresponding inverse functions. The objective of this module is to maximize the overlapping data range (φ_i) between $[T^{-1}(Temp_{lower}), T^{-1}(Temp_{upper})]$ and $[H^{-1}(Humi_{lower}), H^{-1}(Humi_{upper})]$, as illustrated in Fig. 4. The required preparation time for a specific packaging model is defined as the time from the beginning to the minimum value in the overlapping data range, i.e. $\min\{\varphi_i\}$. When considering multiple overlapping data ranges simultaneously, the maximum value among all data values is selected as the cooling duration in specific packaging settings, i.e. $\max\{\varphi_i: i \in \mathbb{N}\}$. Three factors in the experiments are identified in Table 2, where all of them have three corresponding levels. In the design of experiments, the full factorial design with the orthogonal array of the Taguchi method L_9 $(3 \times 3 \times 3)$ is established, as shown in Table 3.

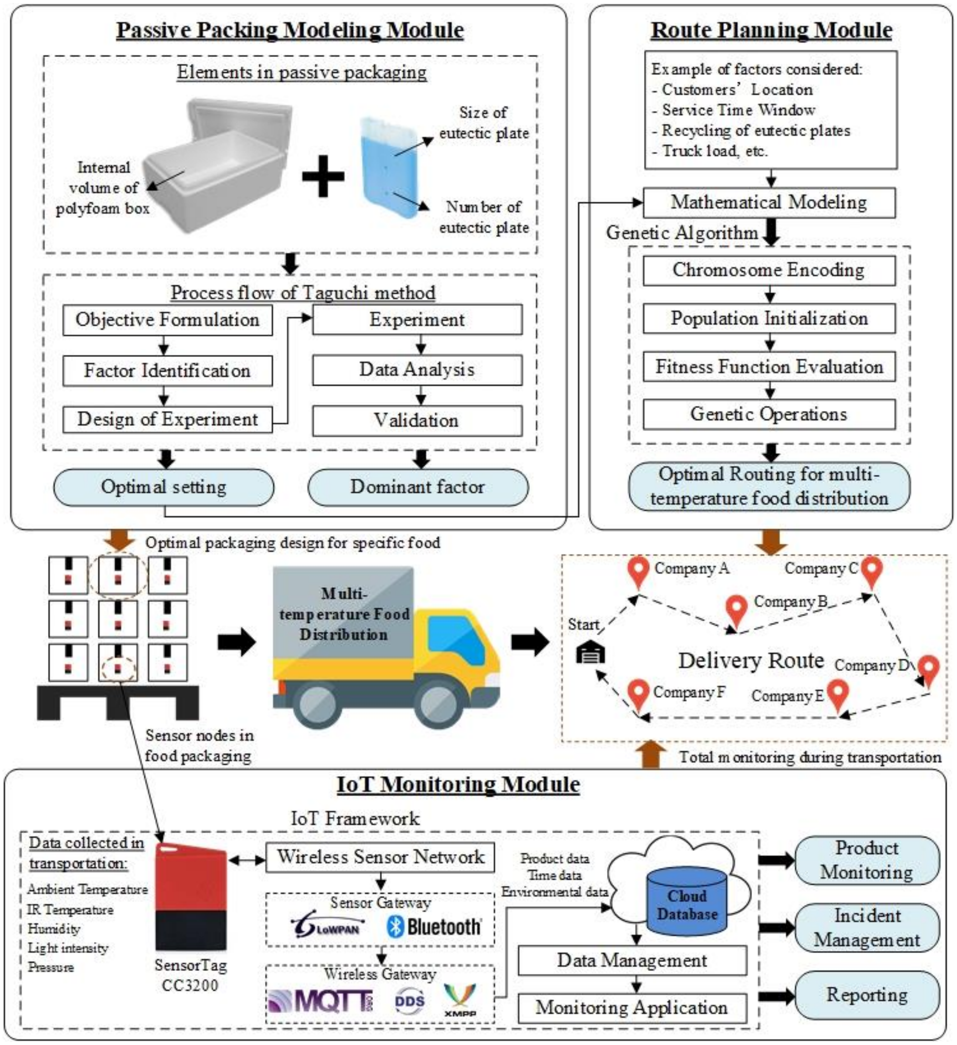


Fig. 2 System architecture of IRPS

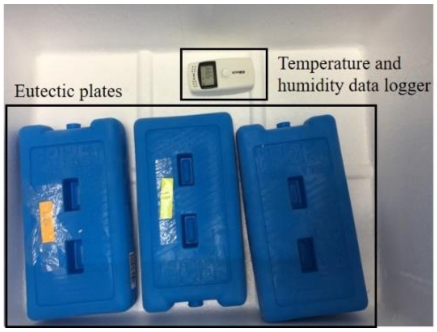


Fig. 3 Example of experimental setup for passive packaging modeling

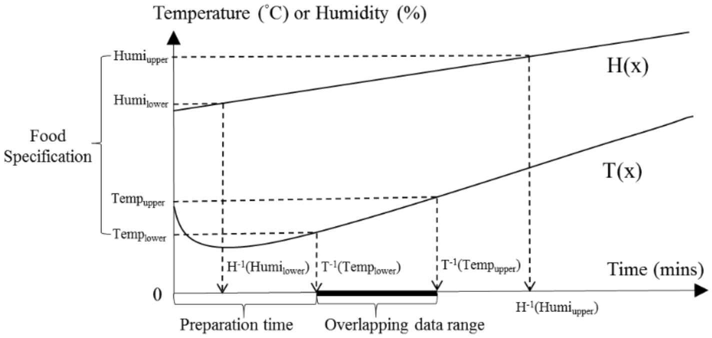


Fig. 4 Rate of change of temperature and humidity over time

Table 2 Properties of polyfoam box and eutectic plate

	Box internal dimension	Eutectic plate volume	Number of eutectic plate
Level 1	53.5 × 39 × 24.5 cm (ESP - 0)	200 ml	1
Level 2	45.5 × 45.5 × 28.5 cm (ESP - 1)	500 ml	2
Level 3	43 × 33 × 23 cm (ESP - 2)	1000 ml	3

Table 3 Full factorial design with orthogonal array of Taguchi L_9 (3^3)

Experiment No.	Factor A	Factor B	Factor C
	Box internal dimension	Eutectic plate volume	Number of eutectic plate
1	ESP - 2	200	1
2	ESP - 2	500	2
3	ESP - 2	1000	3
4	ESP - 1	200	2
5	ESP - 1	500	3
6	ESP - 1	1000	1
7	ESP - 0	200	3
8	ESP - 0	500	1
9	ESP - 0	1000	2

After conducting a set of experiments, the results are then analyzed by a loss function to measure the deviation between the experimental values and the desired values. The loss function is converted into a signal-to-noise (S/N) ratio (η) with three generic quality characteristics, namely the lower-the-better, the higher-the-better, and the nominal-the-better (Gupta et al., 2011). Since the goal of this module is to maximize the time for suitable environmental conditions, the S/N ratio for the higher-the-better quality characteristics is selected, as shown in Equation (1):

$$\frac{\mathrm{S}}{\mathrm{N}}\ \text{ratio}\ (\eta) = -10 \cdot \log \left(\frac{1}{n} \cdot \sum_{i=1}^{n} \frac{1}{{y_i}^2}\right) \tag{1}$$

where n is the number of observations, and y_i is the observed data at the i^{th} experiment. Consequently, the optimal level of the factors, including box dimensions, volume of the eutectic plates, and number of eutectic plates, can be determined by mean of the S/N ratio and the mean of means of the overlapping data range so as to show the best setting in the passive packaging model for specific food. Eventually, the cooling rate of the packaging model for specific food can be converted into a cooling time window for use of optimizing route planning.

3.2 Route planning module

In this module, mathematical closed-loop transportation planning with only one depot is formulated by considering the constraints and factors related to capacity, number of vehicles, customer locations, service time window, recycling of eutectic plates, and cooling time window. Assuming that all vehicles are identical in regard to truck capacity, energy consumption and speed; the speed of all vehicles is constant; customer demands and the required products are known in advance. In addition, the use of trucks requires certain amount of fixed and variable costs, namely installation cost and fuel cost respectively.

In the mathematical modeling, a fleet of vehicles start and finish delivery at the depot, and the requested pallets of food are delivered to the customers. It aims at minimizing the travelling time between various customer nodes conductive to formulate an efficient vehicle routing through using a fleet of vehicles. All the notations used in the model are shown in Table 4, and the objective function and relevant constraints are shown as follows:

Table 4 Notation of route planning module

Notation	**Definition**
Sets:	
D	Set of all delivery locations
D_0	Set of all locations including delivery location and depot, $\mathrm{D_0} = D \cup \{0\}$
M	Set of all products
V	Set of all trucks
Parameters:	
C_f	Fixed cost in using a truck for delivery
C_v	Variable cost for product delivery depended on travelling distance
d_j	Amount of delivery products to customer j, where $\mathrm{j} \in \mathrm{D_0}$
Lij	Travelling distance between location i and j, where $\mathrm{i, j} \in \mathrm{D_0}$ and $\mathrm{i} \neq \mathrm{j}$
n	Number of customer nodes, where $\mathrm{n} = \lvert \mathrm{D_0} \rvert$
p_f	Amount of pick-up from customer f, where $\mathrm{f} \in \mathrm{D_0}$
S	Maximum service hour for the distribution services
t_{ij}	Travelling time between location i and j, where $\mathrm{i, j} \in \mathrm{D_0}$ and $\mathrm{i} \neq \mathrm{j}$
T_b	Maximum transportation duration for product b, where $\mathrm{b} \in \mathrm{M}$
$Wmax$	Maximum truck capacity
Decision variables:	
W_k'	Initial truck load of truck k at the depot, where $\mathrm{k} \in \mathrm{V}$
W_j	Truck load after having served customer j, where $\mathrm{j} \in \mathrm{D}$
x_{ij}^k	Binary variable to decide the truck k travelling location i to j, where $\mathrm{k} \in \mathrm{V}$ and $\mathrm{i, j} \in \mathrm{D_0}$
ω_{bj}	Binary intermediate variable to show the product b received by customer j, where $\mathrm{b} \in \mathrm{M}$ and $\mathrm{j} \in \mathrm{D}$
δ_j	Intermediate variable to prevent the sub-tours

$$\text{Minimize: } \sum_{i\in D_o}\sum_{j\in D_0}\sum_{k\in V}[t_{ij}+(C_v L_{ij}+C_f)]x_{ij}^k \tag{2}$$

Subject to:

$$\sum_{i\in D_0}\sum_{k\in V} x_{ij}^k = 1, \qquad \forall j\in D \tag{3}$$

$$\sum_{i\in D_0} x_{if}^k = \sum_{j\in D_0} x_{fj}^k, \qquad \forall f\in D \text{ and } \forall k\in V \tag{4}$$

$$\left(\sum_{i\in D_0}\sum_{k\in V} t_{ij}x_{ij}^k\right)\cdot \omega_{bj} \le T_b, \qquad \forall b\in M \text{ and } \forall j\in D \tag{5}$$

$$W_k' = \sum_{i\in D_0}\sum_{j\in D_0} d_j x_{ij}^k, \qquad \forall k\in V \tag{6}$$

$$\mathrm{W}_f \ge W_k' - \sum_{b\in M} y_{bf} + p_f - M\left(1-x_{0f}^k\right), \forall f\in D \text{ and } \forall k\in V \tag{7}$$

$$\mathrm{W}_j \ge \mathrm{W}_i - \sum_{b\in M} y_{bj} + p_j - M\left(1-\sum_{k\in V} x_{ij}^k\right), \qquad \forall i\in D, \forall j\in D \text{ and } i\ne j \tag{8}$$

$$W_k', \mathrm{W}_f, \mathrm{W}_j \le W_{max}, \qquad \forall k\in V \text{ and } \forall j,f\in D \tag{9}$$

$$\sum_{i\in D_o}\sum_{j\in D_0} t_{ij}x_{ij}^k \le S, \qquad \forall\, k\in V \tag{10}$$

$$\delta_j \ge \delta_i + 1 - n\left(1-\sum_{k\in V} x_{ij}^k\right), \qquad \forall i\in D, \forall j\in D \text{ and } i\ne j \tag{11}$$

$$\delta_i \ge 0, \qquad \forall i\in D \tag{12}$$

$$x_{ij}^k, y_{bj} \in \{0,1\}, \forall \mathrm{i}, \forall \mathrm{j}\in D_0 \text{ and } \forall k\in V \tag{13}$$

The objective function is to minimize the travelling time and relevant costs stated in equation (2). Ensuring that each customer location is visited exactly once by the same truck through constraints (3) and (4). Constraint (5) shows that the travelling time of each product is strictly limited to the specific cooling duration by the packaging model. Constraint (6) defines the initial truck load by the summating delivery amount. Constraint (7) demonstrates the change of truck load after visiting the first customer, which involves the product delivery and pick-up of the used sensing devices. This change can be extended to the entire routing model in constraint (8). Constraint (9) ensures that the truck load should be less than the maximum truck capacity. Constraint (10) ensures that the total travelling time of each trip does not exceed the service hours defined by the logistics company. Constraints (11) and (12) prevent sub-tours in the routing model formulation and define the non-negativity for the intermediate variable. Constraint (13) shows that binary characteristics of the decision variables.

In order to solve the above mathematical model in an efficient manner, the genetic algorithm (GA) approach is applied to search for the optimal vehicle routing for multi-temperature food distribution, with four major steps, namely (i) chromosome encoding, (ii) population initialization, (iii) fitness function evaluation, and (iv) genetic operations.

(i) Chromosome encoding

In the chromosome encoding, the chromosome is defined as a sequence of all the customer nodes and a binary chromosome section, as shown in Fig. 5. According to the defined objective function, the decision variable x_{ij}^{k} implies the arc from node *i* to node *j* with using truck *k*. Therefore, the chromosome can be encoded as follows. The first part shows the selected nodes in this routing model according to the defined constraints, while the second part indicates the starting and ending nodes by using the binary number 1.

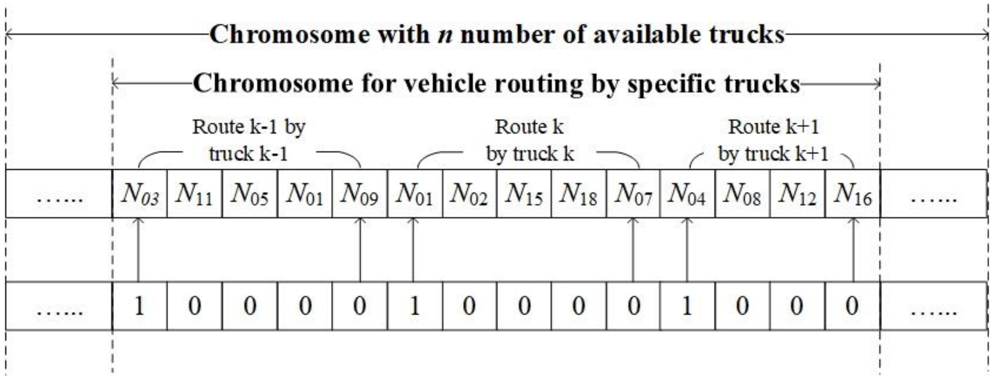


Fig. 5 Example of the encoded chromosome

(ii) Population initialization

The initialization of the proposed model requires population size, crossover rate, mutation rate and maximum number of generations. The population size is used to control the number of chromosomes in the iterations with the random generation of the initial solutions. Moreover, the crossover and mutation rates are user-defined to filter inapplicable chromosomes in the genetic operations.

(iii) Fitness function evaluation

Given the above criteria in the GA, fitness values for all chromosomes can be evaluated to investigate the travelling time and relevant costs in the distribution process. The fitness function in the GA can be referred to the objective function in the above mathematical modelling. It is also required to check any violations of the defined constraints in the model. Once a constraint is violated in the whole chromosome population, the fitness value is then replaced by another extraordinary large value, z_{v}, which affects the weight calculation of each chromosome, by using roulette wheel selection. By doing so, chromosomes with large z_{v} will not be able to continue to the next iteration. The chromosome with the minimal fitness value is the final output searched by the GA.

(iv) Genetic operations

Before reaching the maximum generation in the GA, the chromosomes then continue to the genetic operations, including mating pool formulation, crossover and mutation processes. The mating pool is formulated by randomly selecting the chromosomes from the parent pool of the chromosome population. In the mating pool, a random number between 0 and 1 is assigned to each mated chromosome such that the chromosomes are selected according to the defined crossover rate. The crossover operations are as follows. The specific range of elements is exchanged between the selected chromosomes so as to create a number of offspring chromosomes. In the mutation process, a set of random numbers between 0 and 1 is assigned to the elements of each offspring chromosome, and the elements will be changed when satisfying the mutation criteria. Therefore, a new set of chromosomes is established, while the fitness function is again evaluated to determine a better fitness value in the model. A number of chromosomes with the worst fitness values in the parent pool are then replaced by the better chromosomes in the mating pool. When repeating the above procedures up to maximum number of generations, the optimal solution in the model can be determined. Thus, the vehicle routing planning can be formulated effectively for multi-temperature food distribution.

3.3 IoT monitoring module

During the transportation, environmental conditions, including temperature and humidity, are monitored for each box of food under the IoT environment. In general, the IoT framework consists of three layers: perception layer, network layer, and application layer (Sethi and Sarangi, 2017). Fig. 6 shows the IoT framework for the proposed IRPS. In the perception layer, the sensing technology, i.e. SensorTag CC3200 from Texas Instruments, is applied to gather environmental information, and to identify the cooling box and food. The product specification of the sensor node used in the proposed IoT monitoring application is shown in Table 5. The sensor node is attached to each cooling box along with certain eutectic plates when transporting the food to customers. Under a wireless local area network (WLAN) operating at 2.4GHz, information on the temperature, humidity and product identity can be gathered in the gateway. With the known cloud configuration, such as Message Queuing Telemetry Transport (MQTT) and IBM IoTF registered devices, the information can be transmitted to the Platform as a Service (PaaS) development platform under the 3G/4G/LTE network. In the network layer, the transmitted information can be managed in the cloud database, such as MySQL and Cloudant, and structured in standard data format, such as JSON and XML. Thus, the information can be used in the web and mobile applications through web development programming, such as HTML, CSS and PHP. In the application layer, the proposed system, i.e. IRPS, can be developed on various devices for customers and workers. The functionalities of IRPS include product monitoring, incident management, reporting, and vehicle routing planning. On the one hand, customers are able to check the environmental conditions for the specific food during the entire transportation process, preventing the customers from receiving the deteriorated products, which strengthens their confidence in food quality and logistics services. On the other hand, workers have clear instructions on food packaging for transportation, aiming at prolonging suitable handling conditions, and can be assigned an optimal delivery schedule so as to minimize the travelling distance and corresponding costs.

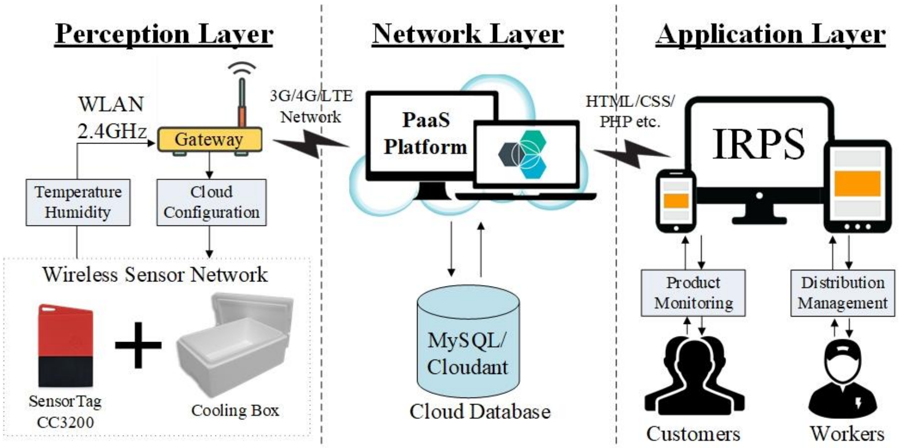
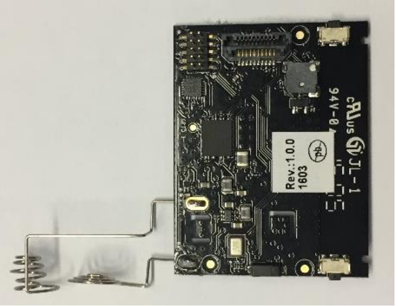


Fig. 6 IoT framework for IRPS

Table 5 Product specification of SensorTag CC3200

Parameter	Value/description
Figure of Sensor node	
Operating frequency	WLAN 2.4Ghz for channel 1 to 11
Reed relay	350MΩ
Sensing devices	3-axis gyroscope, 3-aixs accelerometer, 3-axis magnetometer, thermopile sensor, pressure sensor, humidity sensor, light sensor
Use of battery	Two AAA battery
Serial flash memory	1 MB (on-board)
Accuracy of temperature readings	±1°C (0°C to +60°C) and ±1.5°C (-40°C to +125°C)
Accuracy of humidity readings	±3%

4. Case Study

For the sake of validating the performance of the proposed system, a pilot study was conducted in a third-party logistics service provider in Hong Kong. The company was founded in 2002, and has 18-storey warehousing facilities with a capacity of 28,000 metric tons. It generally is a distributor for managing customers' inventory in cold storage facilities, arranging daily transportation services to numerous customer locations, from the diversified warehouses. One of the core businesses in the company is to handle various kinds of food, such as frozen meat, seafood, fruit and vegetables. Currently, the company relies on refrigerated trucks to deliver the fresh and perishable products to its customers, but it faces the problem of food chilling and freezing injuries as the products are held at the temperature below their recommended conditions, dependent on the product types. Consequently, there is a certain level of food deterioration rate even though the company provides refrigerated trucks. Particularly for importing premium fruit and vegetables, the deterioration rate not only generates huge cost and food wastage, but also influences customers' satisfaction. Besides, the company relies on data loggers to collect information on the temperature and humidity in the transportation process. The truckers can only notice the food deterioration when unloading the products to customers, resulting in a waste of time and transportation costs. Therefore, the effective transportation management of premium fruit and vegetables should pay attention to maintaining product quality and monitoring the environmental conditions in real-time during transportation. The proposed system, IRPS, is therefore implemented in the company to develop effective multi-temperature food distribution and real-time food monitoring for minimizing the food deterioration rate and enhance customer satisfaction.

As shown in Fig. 7, the entire implementation of IRPS is divided into four phases. The experiments on passive packaging modeling have to be conducted as the first priority for determining the optimal packaging settings and maximize the recommended transport duration, depending on the particular type of food. Along with the above information, the vehicle routing for multi-temperature food distribution is then solved by using the GA. When packing the food in the chilling facilities, a low-power sensor is attached to each cooling box for monitoring the ambient environmental conditions during the whole delivery process. Under the IoT environment, the web/mobile application is then established for integrating the routing planning and product monitoring, for both customers and company staff.

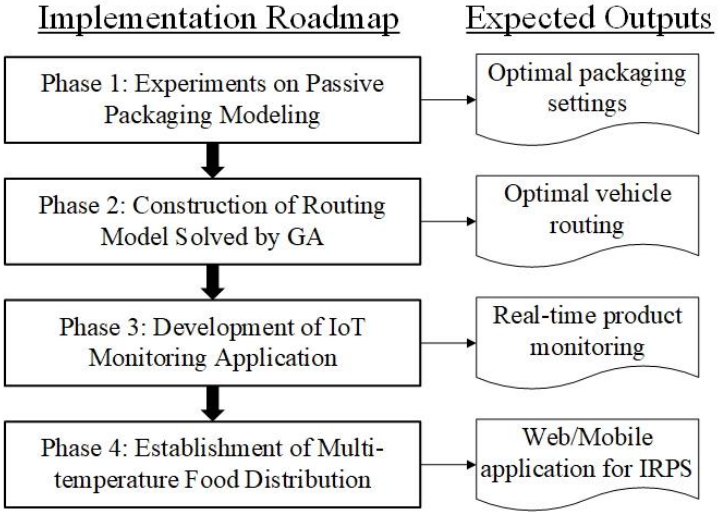


Figure 7 Implementation roadmap for IRPS

4.1 Phase 1: Experiments on passive packaging modeling

In this pilot study, five types of food, namely apples, grapefruit, mango, melons and tomatoes, were selected their own optimal packaging setting and were examined by conducting a set of experiments according to the full factorial design of the Taguchi method (L_9). Each type of food has its own recommended transport conditions in term of temperature (°C) and relative humidity (%). Table 6 shows the specific recommended transport conditions and the corresponding experiment results. In the experiments, each run was conducted for 4 hours to see the rate of change of temperature and humidity, and this experimental duration was matched to a typical delivery schedule of the transportation team in the company. Following the method in the passive packaging modeling module, the cooling durations in minutes are then collected through the experiments, as shown in Table 6. Since there is no guarantee that the internal environmental conditions must fit all the recommended temperature and humidity, the value "zero" in cooling duration will be given to imply that the packaging settings do not fit to the products' handling requirements. However, when applying the higher-the-better approach of S/N ratio in the Taguchi method, the reciprocal value of the square of the cooling durations ($\frac{1}{{y_i}^2}$) stated in equation (1) should exist, and therefore a significantly small numerical value, i.e. 0.001, is used to replace the zero in the cooling duration to maintain the feasibility of the model.

Since the fruits in this study have different recommended transport environmental conditions, the optimal packaging setting by using the eutectic plates and polyfoam boxes can be diversified. Fig. 8 and Fig. 9 present the results of the Taguchi-based experiments in the aspects of the S/N ratios and the means of cooling duration for various packaging settings associated with the five types of fruits. The specific optimal packaging settings are determined through the maximum values of the S/N ratios which are the-higher-the-better type. The highest cooling durations in the packaging model are critical to maintain the desired product quality for transportation. Therefore, the best packaging setting for apples are specified as ESP-0 in box internal dimension (η = -25.86; means = 44.56), 1000ml for eutectic plate volume (η = -25.28; means = 48.45), and three eutectic plates (η = -25.28; means = 47.89), so as to maximize the cooling duration for multi-temperature food distribution. Similar to all other fruits, the best packaging setting for grapefruit is referred to ESP-2 (η = 35.41; means = 138.89), 1000ml of eutectic plate volume (η = 26.61; means = 89.22), and two eutectic plates (η = 35.02; means = 128.33); the best packaging setting for mango is referred to ESP-2 (η = 39.01; means = 123.78), 500ml of eutectic plate volume (η = 38.96; means = 124.89), and two eutectic plates (η = 40.88; means = 128.44); the best packaging setting for melons is referred to ESP-1 (η = 32.09; means = 63.78), 1000ml of eutectic plate volume (η = 28.04; means = 68.67), and two eutectic plates (η = 36.06; means = 91.00); the best packaging setting for tomatoes is referred to ESP-1 (η = 44.78; means = 184.44), 500ml of eutectic plate (η = 44.71; means = 182.44), and two eutectic plates (η = 44.96; means = 182.11). The main effects for S/N ratio and mean value for apples are different to the other fruit as most packaging settings in the experiments do not satisfy the handling requirements of apples in term of temperature and humidity. The negative signal-to-noise ratio, which imply that the noise power is greater than the signal power, is not preferable in the Taguchi method. However, due to limited resources and given environment, the generated packaging setting by using ESP-0, three 1000ml eutectic plates, for the apples is claimed to be optimal.

Table 6 Experiment results for five selected food types

		Apples	Grapefruits	Mango	Melons	Tomatoes
Temperature		-1 to +4 °C	+10 to +15 °C	+9 to +14 °C	+9 to +12 °C	+7 to +15 °C
Humidity		≤ 95%	≤ 90%	≤ 95%	≤ 95%	≤ 90%
Shelf life		2-7 months	1-2 months	2-3 weeks	2-3 weeks	1-4 weeks
No.	Run	Cooling duration (in mins)				
1	(i)	0	0	0	0	0
	(ii)	0	68	5	0	68
	(iii)	0	45	0	0	45
2	(i)	0	97	132	132	181
	(ii)	0	150	165	120	195
	(iii)	0	143	170	134	200
3	(i)	131	13	4	2	6
	(ii)	120	8	3	3	4
	(iii)	150	10	4	4	5
4	(i)	0	200	139	24	200
	(ii)	0	168	92	20	170
	(iii)	0	150	75	20	150
5	(i)	0	0	90	90	150
	(ii)	0	105	150	150	210
	(iii)	30	0	30	30	120
6	(i)	0	270	120	45	270
	(ii)	0	75	120	120	165
	(iii)	0	180	225	75	225
7	(i)	0	120	60	30	120
	(ii)	0	225	210	120	225
	(iii)	0	144	74	0	144
8	(i)	0	136	72	0	136
	(ii)	0	225	90	30	225
	(iii)	0	153	225	80	225
9	(i)	35	5	64	64	140
	(ii)	0	142	184	170	229
	(iii)	0	100	135	135	174

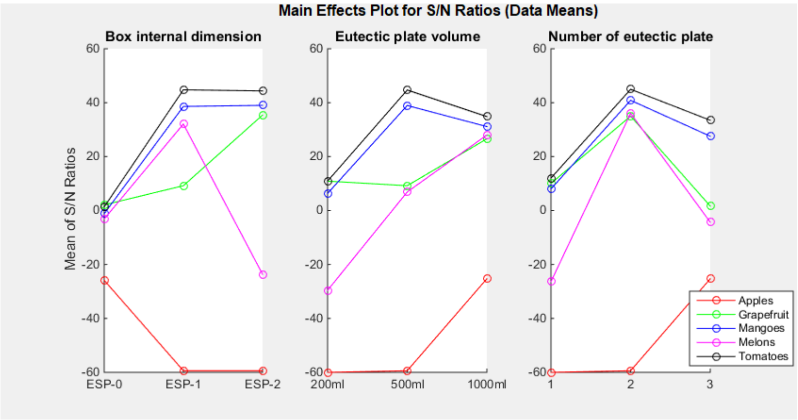


Fig. 8 Main effect plot for S/N ratios for packaging model

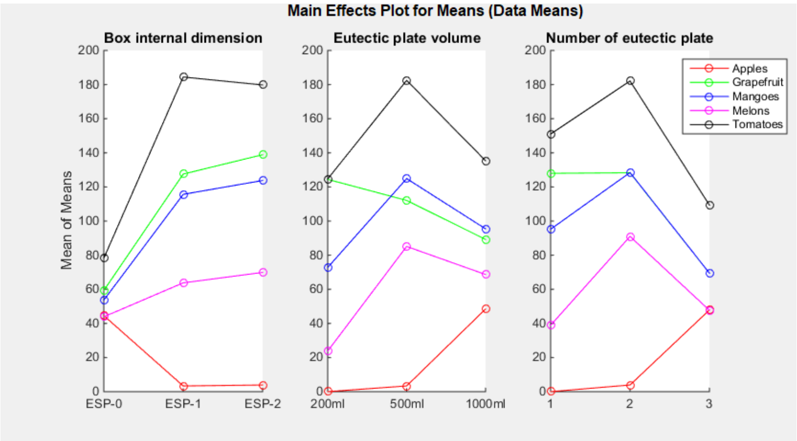


Fig. 9 Main effect plot for means of cooling duration for packaging model

Table 7 summarizes the above optimal packaging settings for the five selected fruits, average cooling duration and required preparation time for the packaging environment. The average cooling duration and required preparation time, which is defined as the shortest time to reach the overlapping data range, are collected in the experiments according to the optimal packaging settings. According to the above results, the cooling durations become the constraint of cooling time window in the route planning model to ensure that the food can be delivered to the customers within the duration of cooling time window. In addition, the insulated box should be prepared in advance according to the required preparation time before the food is picked and packed from the storage section. Therefore, the food is prepared for delivering to the customers, and the effective delivery routes should be constructed for the transportation team.

4.2 Construction of routing model solved by GA

According to the delivery routing model built in the route planning module, the routing results are simulated by using MATLAB® programming to minimize the objective function together with the number of defined constraints. In the case company, the transportation operations are split into morning and afternoon sessions, with 4 hours in each session. Since the company mainly manages the local delivery of premium fruit and vegetables, five 5.5-ton trucks, in which the capacity of each truck is approximately 6-7 pallet spaces, are used to complete the orders. In order to develop the optimal delivery route, 50 customer locations are selected from the customer pool and scattered on a Euclidean plane of 500x500 km^2. For applying the GA in vehicle routing planning, the system parameters are set as follows: number of iterations = 5000; population size = 150; crossover rate = 0.8; mutation rate = 0.05. The termination criteria of this module are either to reach the maximum number of iterations or to have less than 0.01% improvement in the fitness function value in the last 500 iterations. Fig. 10 and Fig. 11 show the results and optimization from the route planning module implemented in the MATLAB® environment. The optimal delivery route is generated at 2764 iteration with 8798.1844km of total distance. Since the speed of the trucks are assumed to be fixed in this study, the conversion between travelling distance and travelling time can be formulated, i.e. speed (v) × travelling time (t) = travelling distance (s). Five trucks are fully utilized in transportation activities, considering the constraints of the service time window, cooling time window, and vehicle capacity.

Table 7 Optimal packaging settings for five types of fruit

Food type	Optimal Packaging Setting			Cooling duration (min)	Required preparation time (min)
	Box internal dimension	Eutectic plate volume	Number of eutectic plates		
Apples	ESP-2	1000ml	3	143	18
Grapefruit	ESP-0	1000ml	2	183	20
Mango	ESP-0	500ml	2	176	23
Melons	ESP-1	1000ml	2	232	20
Tomatoes	ESP-1	500ml	2	216	26

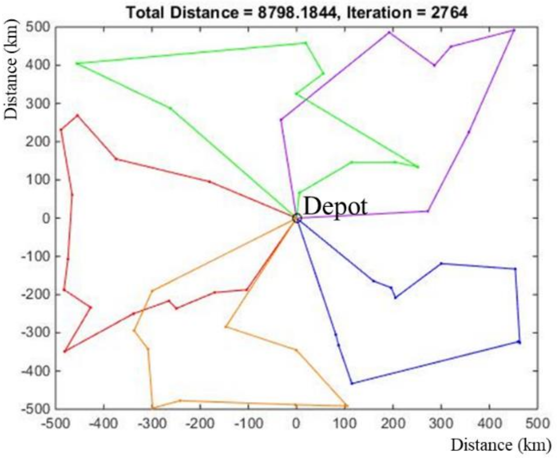


Fig. 10 Generated delivery route for IRPS

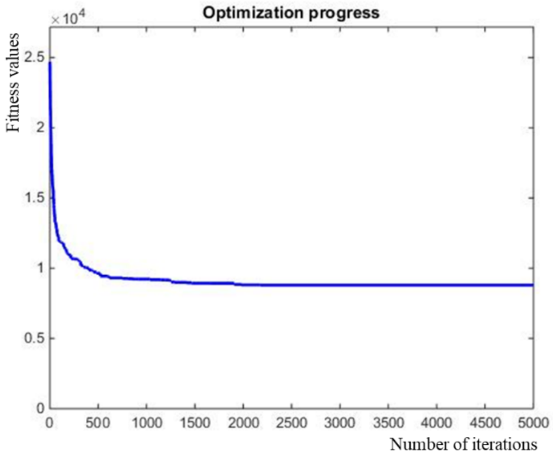


Fig. 11 Optimization progress over 5000 iterations

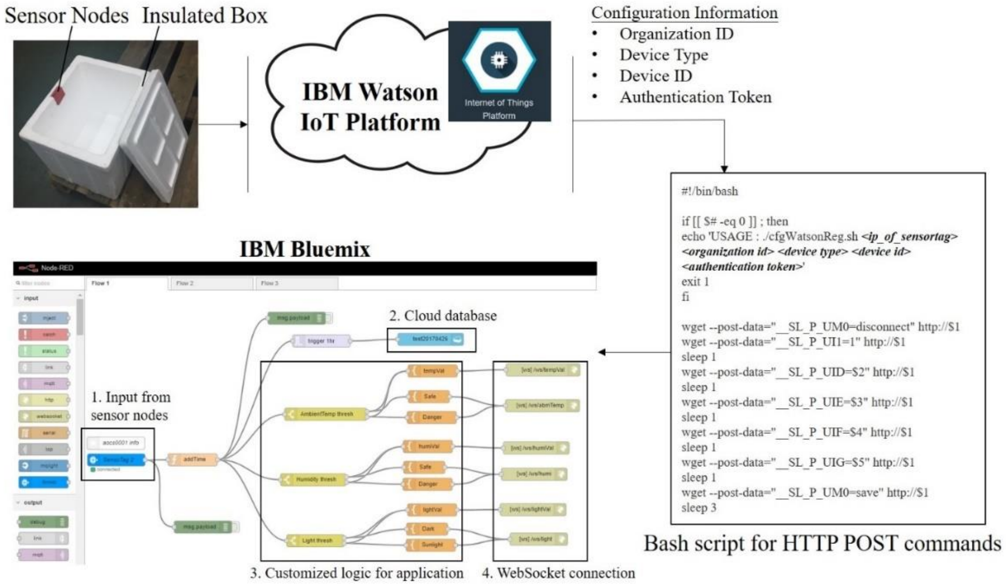
Since the GA is a heuristic algorithm in searching for the optimal solution, multiple trials using the same data set and parameter settings are needed to validate the optimality and reliability of the generated delivery results. Table 8 shows the results of the total distance and iteration in five different trials for the route planning module. The average total distance for the delivery route and iteration for obtaining the results are 8518 km and 3532 respectively. The difference between the maximum and minimum distance value is around 0.06% so that the routing result from the GA is reliable. However, the average iteration for obtaining the optimal result in the route planning is lower than the original number of iterations by almost 30%. In other words, there is a room to reduce the number of iterations so as to shorten the computational time and computer resources.

Table 8 Trials for GA-based route planning module

Number of trials	Total distance (km)	Iterations for obtaining the results
1	8798	2764
2	8540	2880
3	8321	3932
4	8567	3673
5	8364	4411
Average	**8518**	**3532**

4.3 Development of IoT monitoring application

In this section, an IoT monitoring application is developed to collect and show the temperature and humidity during the whole transportation process. Fig. 12 shows the entire setup of the IoT application, from the installation of the sensor nodes to the system development. As mentioned above, the SensorTag CC3200 is installed inside the insulated box as the sensor node so as to formulate a low-power wireless sensor network. Through the Wi-Fi network, the sensor nodes are configured in IBM Watson IoT Platform by the setup information, including device type, device ID, organization ID and authentication token. These credentials are required to configure into the sensor nodes for connecting to the IoT development platform, namely IBM Bluemix, in this study. In furtherance of issuing the customized HTTP POST commands, bash script is used to transfer all the credentials together with the specific IP address to the SensorTag CC3200. Consequently, the sensing information can be smoothly and securely transmitted to the Bluemix platform. In the Bluemix platform, it has a great flexibility for developing the application, for example in compatibility with various databases, i.e. SQL, cloudant, mongodb, dashDB, as well as support of different kinds of programming languages for web and mobile development, such as HTML, PHP, JavaScript and Python. On the one hand, the real-time environmental data from the sensor nodes are transferred to the front-end web application by using WebSocket and JavaScript. Through setting the functions of onmessage, onopen and onclose, the values of temperature and humidity can be updated in real-time in the web and mobile applications. On the other hand, the data can be simply stored into Cloudant which is a managed NoSQL JSON database service. By querying the cloud database, the IoT application can support the functions of reporting and incident management. In other words, a report on environmental conditions during transportation can be generated in the format of Excel or CSV according to the specific time duration. In addition, the ad-hoc logic can be customized in the Bluemix platform to detect any violations of temperature and humidity before reaching the customers. This automatic data acquisition should be integrated with the packaging setting and routing solutions to establish effective multi-temperature food distribution.



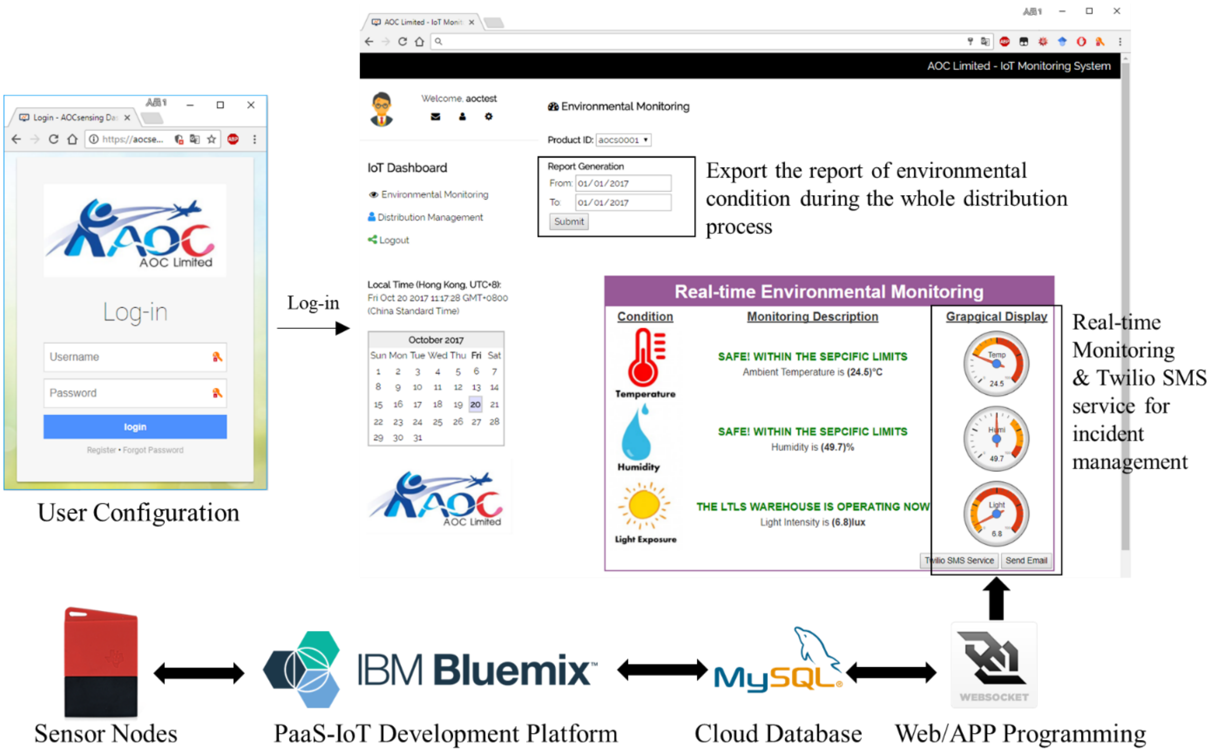
```
#!/bin/bash

if [[ $# -eq 0 ]] ; then
echo 'USAGE : ./cfgWatsonReg.sh <ip_of_sensortag>
<organization id> <device type> <device id>
<authentication token>'
exit 1
fi

wget --post-data="__SL_P_UM0=disconnect" http://$1
wget --post-data="__SL_P_UI1=1" http://$1
sleep 1
wget --post-data="__SL_P_UID=$2" http://$1
sleep 1
wget --post-data="__SL_P_UIE=$3" http://$1
sleep 1
wget --post-data="__SL_P_UIF=$4" http://$1
sleep 1
wget --post-data="__SL_P_UIG=$5" http://$1
sleep 1
wget --post-data="__SL_P_UM0=save" http://$1
sleep 3
```

Fig. 12 Setup of IoT monitoring application

4.4 Establishment of multi-temperature food distribution

The proposed system, i.e. IRPS, is mainly designed and developed for transportation staff and customers to enhance the distribution efficiency and effectiveness, as well as customer satisfaction. In the front-end development, these two groups of users are classified in the page of user configuration so as to direct them to the relevant pages in the proposed system. Fig.13 and Fig. 14 show the user interface of IRPS for aiding the transportation process and in product monitoring. After configuring the user information, the users can view a real-time graphical display for temperature, humidity and lighting intensity of the specific cooling box. This real-time data transmission is completed from the sensor nodes, the PaaS-IoT development platform, cloud database, and Web/APP programming. If there are any unexpected incidents, such as violation of handling requirements over a long period of time, the Twilio SMS service will be triggered to inform the corresponding parties. Finally, a report of the environmental information during the whole distribution process can be exported through specifying the time intervals.

For the transportation team, the delivery notes and schedule are shown under "Distribution Management". The information for truckers and customers are pre-processed and loaded into the cloud database and PaaS-IoT development platform for the route planning module. After optimizing the vehicle routing solutions, the locations and routes will be shown on the map. It is user-friendly for the staff to check the delivery route and product information at any time. By making use of Google Maps API, the shortest path and traffic situation between the customers' locations can be visualized. It is convenient for the truckers to understand the driving routes and real-time traffic situations. Therefore, for both customers and transportation staff, the proposed system can support the daily operations and enhance food traceability and monitoring.



Local Time (Hong Kong, UTC+8): Fri Oct 20 2017 11:17:28 GMT+0800 (China Standard Time)

SAFE! WITHIN THE SEPCIFIC LIMITS
Ambient Temperature is (24.5)°C

SAFE! WITHIN THE SEPCIFIC LIMITS
Humidity is (49.7)%

THE LTLS WAREHOUSE IS OPERATING NOW
Light Intensity is (6.8)lux

Export the report of environmental condition during the whole distribution process

Real-time Monitoring & Twilio SMS service for incident management

Log-in

User Configuration

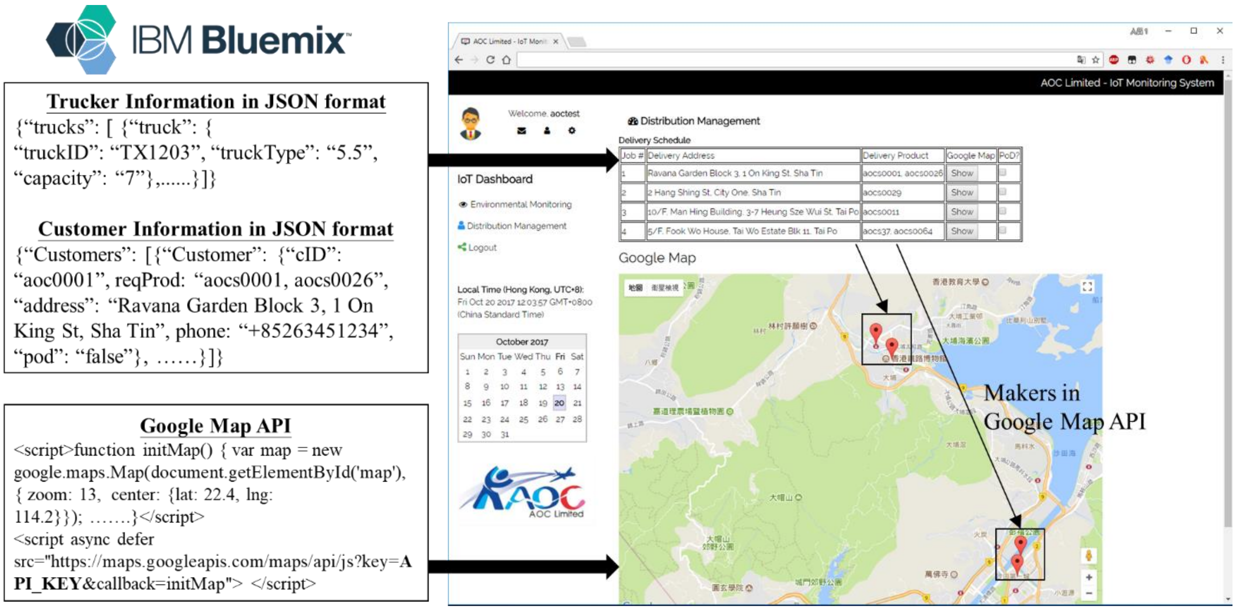
Sensor Nodes

PaaS-IoT Development Platform

Cloud Database

Web/APP Programming

Fig. 13 Prototype of the proposed system in environmental monitoring



Trucker Information in JSON format

{“trucks”: [{“truck”: { “truckID”: “TX1203”, “truckType”: “5.5”, “capacity”: “7”},......}]}

Customer Information in JSON format

{“Customers”: [{“Customer”: {“cID”: “aoc0001”, reqProd: “aocs0001, aocs0026”, “address”: “Ravana Garden Block 3, 1 On King St, Sha Tin”, phone: “+85263451234”, “pod”: “false”}, ……}]}

Google Map API

```
<script>function initMap() { var map = new google.maps.Map(document.getElementById('map'), { zoom: 13, center: {lat: 22.4, lng: 114.2}}); …….}</script>
<script async defer src="https://maps.googleapis.com/maps/api/js?key=API_KEY&callback=initMap"> </script>
```

Local Time (Hong Kong, UTC+8): Fri Oct 20 2017 12:03:57 GMT+0800 (China Standard Time)

Delivery Schedule

Job #	Delivery Address	Delivery Product	Google Map	PoD?
1	Ravana Garden Block 3, 1 On King St, Sha Tin	aocs0001, aocs0026	Show	☐
2	2 Hang Shing St, City One, Sha Tin	aocs0029	Show	☐
3	10/F, Man Hing Building, 3-7 Heung Sze Wui St, Tai Po	aocs0011	Show	☐
4	5/F, Fook Wo House, Tai Wo Estate Blk 11, Tai Po	aocs37, aocs0064	Show	☐

Makers in Google Map API

Fig. 14 Prototype of the proposed system in distribution management

5. Results and discussion

Concerning to verify the proposed system, i.e. IRPS, the prototype of the proposed system has been developed for the case company for aiding its distribution management of multi-temperature food. It took one month in system implementation to measure the performance and impact. The functions of IRPS integrate (i) optimization of packaging settings with given packaging materials and resources, (ii) optimization of vehicle routing for order delivery, and (iii) real-time product monitoring under IoT environment. Therefore, it is beneficial for both staff in transportation team as well as the customers through the systematic operational procedures and high visibility of the whole distribution process.

5.1 Advantages of IRPS

With the aid of IRPS, it is found that the food spoilage rate during transportation is reduced, and customer satisfaction and operational efficiency are enhanced.

(i) Reduction of food spoilage

Since the optimal packaging model and delivery routing are established under given resources and constraints, the product quality for multi-temperature food should be maintained in the distribution. Therefore, the food spoilage and deterioration rates should be reduced after implementing the proposed system. The implementation of IRPS took one month to investigate its impact and effect, and the key performance indicator is the food spoilage rate which is calculated by the amount of spoilage food divided by the total number of orders from customers. The records in the case company show that the food spoilage rate which is presented as the percentage value out of monthly total orders is decreased from 22.6% to 7.9%, a reduction of 65%. Traditionally, the original food spoilage rate is still acceptable for the normal fresh fruits and vegetables whose costs and selling prices are economical. However, when handling the premium fruits and vegetables, such as imported food from Japan, such a high food spoilage rate will accumulate a huge loss in monetary values for the logistics companies. In addition, the proposed system makes use of the existing resources to maximize the cooling duration in the insulated box during transportation, rather than investing on packaging materials and equipment. Consequently, the implementation of proposed system is cost-effective and user-friendly in most logistics companies.

(ii) Enhancement of customer satisfaction and operational efficiency

The adoption of IRPS has positive influences on customer satisfaction and operation efficiency. Table 9 shows the numerical improvements in customer satisfaction and operational efficiency after implementing the proposed system. Since the IRPS provides efficient delivery routes and appropriate packaging settings for the products, customer complaints recorded a greatly reduction from 8 to 3 times, a decrease of 62.5%. In addition, the overall customer satisfaction is increased from 6.5 to 8.3 points, a 27.7% increase. Therefore, the overall delivery service after applying the IRPS can further satisfy the customers’ needs and expectations. For the operational efficiency, the on-time performance on the fulfillment of orders increased from 56.8% to 86.1%, an increase of 51.6%. The transportation team benefits from the generated optimal delivery routes as well as the functions in Google map. Furthermore, the average time for picking and packing operations and the average number of return deliveries are changed from 8min to 10min, and 11 to 4 orders respectively. Since the proposed system provides detailed instructions on the packaging settings, the workers are required to spend additional time on the packing process. Thus, the average time for picking and packing operations is slightly increased. Thanks to such appropriate packaging settings, the number of return deliveries due to food spoilage and cargo discrepancy was greatly reduced by 63.6%.

Table 9 Improvement in customer satisfaction and operational efficiency

Area	Before	After (with IRPS)	Percentage change
Customer related:			
-Customer complaint	8.0	3.0	-62.5%
-Customer satisfaction	6.5	8.3	27.7%
Operation related:			
-On-time performance on fulfillment orders	56.8%	86.1%	51.6%
-Average time for picking and packing operations	8 min	10 min	25.0%
-Average number of return deliveries	11.0	4.0	-63.6%

5.2 Discussion on the system investment

Since logistics companies use refrigerated trucks for distributing the multi-temperature food, a certain level of food loss and capital loss can be estimated by their experience and practices. The companies will have less motivation if the system investment of the proposed system cannot cover the loss and create more business opportunities. As mentioned above, the original percentage of average food loss is about one-fifth in the total transactions. For handling premium imported food, the capital loss caused by the food spoilage and contamination is estimated to be huge such that the motivation for implementing the IRPS should be increased. For investigating the motivation, a cost analysis was carried out to examine the cost-effectiveness of the proposed system. At the beginning, the implementation cost of IRPS includes the set-up and equipment costs, which refers to the purchasing of sensor nodes and 4G/LET mobile routers, as well as system installation. The performance of the system implementation is then measured by the average capital loss for food spoilage, average penalty, and annual compensation to customers. Table 10 shows the costs associated with the system deployment, and cost performance indicators before and after the implementation. Based on the above information, the total cost saved per year is:

HK\${[(*average capital loss for food spoilage per month before implementation – average capital loss for food spoilage per month after implementation*) + (a*verage penalty per month before implementation – average penalty per month after implementation)*] × 12 + (*annual compensation spent to customers before implementation – annual compensation spent to customers after implementation*) – *annual system maintenance cost* }

= HK\${[(75,000 – 35,000) + (10,000 – 5,500)] × 12 + (63,000 – 28,000) – 15,000}

= HK\$554,000

Therefore, the expected break-even point can be calculated as follows:

System investment ÷ total cost saved

= 380,000 ÷ 554,000 = 0.69 years = 8.2 months

From the above analysis, the company is expected to invest HK\$380,000 at the beginning for system development and installation. Since the performance of IRPS in maintaining the food quality and optimizing the vehicle routing during transportation has been verified, a continuous improvement in cost saving related to food spoilage and transportation penalty can also be expected. In addition, the company only requires 8.2 months to get back the money invested. This break-even duration is acceptable for the case company, striking a balance between the costs and benefits in maintaining the prescribed food quality and in efficient route planning.

Table 10 Cost analysis of the IRPS

	Implementation cost (in HK\$)	Before implementation (in HK\$)	After implementation (in HK\$)
System set-up cost	80,000	/	/
IoT equipment including sensor nodes, routers and system development	300,000	/	/
Annual system maintenance cost	/	/	15,000
Average capital loss for food spoilage per month	/	75,000	35,000
Average penalty per month[a]	/	10,000	5,500
Annual compensation spent to customers	/	63,000	28,000

[a] Penalty incurred by late delivery and waste of transportation costs

6. Conclusions

The business of selling premium fruit and vegetables has become popular in recent years due to the change of life style, growth of e-Commerce platforms, and the expansion of international freight networks. Traditional distribution management, which uses either general or refrigerated trucks, is ineffective and inefficient in maintaining the desired quality for multi-temperature food and in monitoring real-time environmental conditions. Consequently, the MTJD ontology has been developed for the multi-temperature products for satisfying all the handling requirements in the distribution. Without such an approach, the food ripening and contamination processes may be hastened, resulting in a huge amount of food loss. Most distributors and 3PLs are facing challenges in improving the existing packaging methods, optimizing the delivery schedule, and monitoring the food during the distribution. This paper proposes a IoT-based route planning system (IRPS) which integrates Internet of Things (IoT) technologies, the Taguchi method for packaging settings, and vehicle routing problem in order to establish the comprehensive packing instructions, automated delivery schedules, and real-time product tracking for the transportation team and end customers. Based on the existing packaging resources in companies, the packaging model is optimized by the handling requirements of multi-temperature food, and the maximum cooling time window is then generated. By defining the cooling time window constraint, the route planning is applicable for multi-temperature food distribution, optimized by using the GA. During the distribution, the real-time product and environmental information are collected and processed by IoT sensors, i.e. SensorTag CC3200, so that the staff and customers can track and trace the status of the products, including product information, temperature and humidity, in real-time. By conducting a case study, the proposed system was validated in reducing the food spoilage rate, and improving customer satisfaction, as well as operational efficiency. The proposed system is limited to the use of existing packaging materials, and reactive incident management through IoT technologies. Future work may be conducted in regard to two aspects:

(i) The packaging model should not only focus on eutectic plates, but also other kinds of phase change materials (PCMs), such as dry ice and contact icing. Other types of unit load device (ULD) in the food industry can also be applied to the proposed model, catering for different distribution purposes. In addition, the application of the proposed system can spread to other environmentally-sensitive products, such as pharmaceuticals and agricultural products;

(ii) Integrating more data mining and artificial techniques, such as fuzzy logic and decision tree analysis, will enable dynamic flexibility in the vehicle routing problem when formulating a proactive approach for incident management. The decision-making processes in the multi-temperature food distribution can be therefore supported.

Acknowledgements:

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Appendix:

Appendix A Term glossary of this article

Full Name	Acronyms
Application Programming Interface	API
Design of Experiment	DoE
eXtensible Markup Language	XML
Genetic algorithm	GA
Good agricultural practice	GAP
Good manufacturing practice	GMP
Hazard analysis of critical control points	HACCP
Internet of Things	IoT
Internet of things (IoT)-based route planning system	IRPS
JavaScript Object Notation	JSON
Logistics service providers	LSPs
Message Queuing Telemetry Transport	MQTT
multi-temperature joint distribution	MTJD
phase change materials	PCMs
Platform As a Service	PaaS
Signal-to-noise ratio	S/N
Standard operating procedures	SOP
Unit load device	ULD
Wireless local area network	WLAN

References:

Ahvenainen, R. (Ed.). (2003). *Novel food packaging techniques*. Elsevier.

Akkerman, R., Farahani, P., & Grunow, M. (2010). Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. *Or Spectrum*, 32(4), 863-904.

Amoa-Awua, W. K., Ngunjiri, P., Anlobe, J., Kpodo, K., Halm, M., Hayford, A. E., & Jakobsen, M. (2007). The effect of applying GMP and HACCP to traditional food processing at a semi-commercial kenkey production plant in Ghana. *Food Control*, *18*(11), 1449-1457.

Aung, M. M., & Chang, Y. S. (2014). Traceability in a food supply chain: Safety and quality perspectives. *Food Control*, *39*, 172-184.

Aveiro, P. (2016). *Design of experiments in production engineering*. J. P. Davim (Ed.). Switzerland: Springer International Publishing.

Baldera Zubeldia, B., Nieto Jiménez, M., Valenzuela Claros, M. T., Mariscal Andrés, J. L., & Martin-Olmedo, P. (2016). Effectiveness of the cold chain control procedure in the retail sector in Southern Spain. *Food Control*, *59*, 614-618.

Christopher, M. (2016). *Logistics & supply chain management*. Pearson UK.

Defraeye, T., Cronje, P., Berry, T., Opara, U. L., East, A., Hertog, M., Verboven, P., & Nicolai, B. (2015). Towards integrated performance evaluation of future packaging for fresh produce in the cold chain. *Trends in Food Science & Technology*, 44(2), 201-225.

Eskandarpour, M., Masehian, E., Soltani, R., & Khosrojerdi, A. (2014). A reverse logistics network for recovery systems and a robust metaheuristic solution approach. *The International Journal of Advanced Manufacturing Technology*, *74*(9-12), 1393-1406.

Food and Agriculture Organization. (2017). FAO's role in food losses and waste. Retrieved from http://www.fao.org/food-loss-and-food-waste/en/

Gogou, E., Katsaros, G., Derens, E., Alvarez, G., & Taoukis, P. S. (2015). Cold chain database development and application as a tool for the cold chain management and food quality evaluation. *International Journal of Refrigeration*, *52*, 109-121.

Golden, B. L., Raghavan, S., & Wasil, E. A. (Eds.). (2008). *The vehicle routing problem: latest advances and new challenges* (Vol. 43). Springer Science & Business Media.

González-Rodríguez, R. M., Noguerol-Pato, R., González-Barreiro, C., Cancho-Grande, B., & Simal-Gándara, J. (2011). Application of new fungicides under good agricultural practices and their effects on the volatile profile of white wines. *Food Research International*, *44*(1), 397-403.

Gu, B., & Burgess, D. J. (2015). Prediction of dexamethasone release from PLGA microspheres prepared with polymer blends using a design of experiment approach. *International journal of pharmaceutics*, *495*(1), 393-403.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future generation computer systems*, *29*(7), 1645-1660.

Gupta, A., Singh, H., & Aggarwal, A. (2011). Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel. *Expert Systems with Applications*, *38*(6), 6822-6828.

Hsu, C. I., Chen, W. T., & Wu, W. J. (2013). Optimal delivery cycles for joint distribution of multi-temperature food. *Food Control*, *34*(1), 106-114.

Hsu, C. I., & Liu, K. P. (2011). A model for facilities planning for multi-temperature joint distribution system. *Food Control*, *22*(12), 1873-1882.

Hsiao, H. I., & Huang, K. L. (2016). Time-temperature transparency in the cold chain. *Food Control*, *64*, 181-188.

Hsiao, Y. H., Chen, M. C., & Chin, C. L. (2017). Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure. *Trends in Food Science & Technology*, 61, 80-93.

Huang, D. S., Tu, W. B., Zhang, X. M., Tsai, L. T., Wu, T. Y., & Lin, M. T. (2016). Using Taguchi method to obtain the optimal design of heat dissipation mechanism for electronic component packaging. *Microelectronics Reliability*, *65*, 131-141.

Kanojia, G., Willems, G. J., Frijlink, H. W., Kersten, G. F., Soema, P. C., & Amorij, J. P. (2016). A Design of Experiment approach to predict product and process parameters for a spray dried influenza vaccine. *International journal of pharmaceutics*, *511*(2), 1098-1111.

Kelly, S. D. T., Suryadevara, N. K., & Mukhopadhyay, S. C. (2013). Towards the implementation of IoT for environmental condition monitoring in homes. *IEEE Sensors Journal*, *13*(10), 3846-3853.

Kerry, J. P., O'grady, M. N., & Hogan, S. A. (2006). Past, current and potential utilisation of active and intelligent packaging systems for meat and muscle-based products: A review. *Meat science*, *74*(1), 113-130.

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.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European journal of operational research*, *59*(3), 345-358.

Lin, C., Choy, K. L., Ho, G. T., Lam, H. Y., Pang, G. K., & Chin, K. S. (2014). A decision support system for optimizing dynamic courier routing operations. *Expert Systems with Applications*, *41*(15), 6917-6933.

Logan, N. A. (2012). Bacillus and relatives in foodborne illness. *Journal of applied microbiology*, *112*(3), 417-429.

Marinakis, Y., Iordanidou, G. R., & Marinaki, M. (2013). Particle swarm optimization for the vehicle routing problem with stochastic demands. *Applied Soft Computing*, *13*(4), 1693-1704.

Martin, G., & Ronan, G. (2000). Managing the cold chain for quality and safety. Europe, Retrieved from http://www.teagasc.ie/ashtown/research/preparedfoods/managing_the_cold_chain.pdf

Mistriotis, A., Briassoulis, D., Giannoulis, A., & D'Aquino, S. (2016). Design of biodegradable bio-based equilibrium modified atmosphere packaging (EMAP) for fresh fruits and vegetables by using micro-perforated poly-lactic acid (PLA) films. *Postharvest Biology and technology*, *111*, 380-389.

Monczka, R. M., Handfield, R. B., Giunipero, L. C., & Patterson, J. L. (2015). *Purchasing and supply chain management*. Cengage Learning.

Montgomery, D. C. (2017). *Design and analysis of experiments*. John Wiley & Sons.

Oehlert, G. W. (2010). *A first course in design and analysis of experiments*.

Qi, L., Xu, M., Fu, Z., Mira, T., & Zhang, X. (2014). C 2 SLDS: a WSN-based perishable food shelf-life prediction and LSFO strategy decision support system in cold chain logistics. *Food Control*, *38*, 19-29.

Rajput, D. S., & Gour, R. (2016). An IoT Framework for healthcare monitoring systems. *International Journal of Computer Science and Information Security*, *14*(5), 451.

Romero, B. (2013). Cold Chain Packaging Systems: Comparison of Active, Passive and Hybrid Thermal Systems. Retrieved from https://www.pharmalogisticsiq.com/packaging-shipping-systems/articles/cold-chain-packaging-systems-comparison-of-active

Sethi, P., & Sarangi, S. R. (2017). Internet of Things: Architectures, Protocols, and Applications. *Journal of Electrical and Computer Engineering*, *2017*, Article ID 9324035, 25 pages. https://doi.org/10.1155/2017/9324035

Sharma, S. K., & Kumar, V. (2015). Optimal selection of third-party logistics service providers using quality function deployment and Taguchi loss function. *Benchmarking: An International Journal*, *22*(7), 1281-1300.

Smith, D., & Sparks, L. (2007). Temperature controlled supply chains. *Food supply chain management*, *179*.

Tsironi, T., Giannoglou, M., Platakou, E., & Taoukis, P. (2015). Training of SMEs for frozen food shelf life testing and novel smart packaging application for cold chain monitoring. *International Journal of Food Studies*, *4*(2).

Velasco, C., Salgado-Montejo, A., Marmolejo-Ramos, F., & Spence, C. (2014). Predictive packaging design: Tasting shapes, typefaces, names, and sounds. *Food Quality and Preference*, *34*, 88-95.

Xiao, X., He, Q., Fu, Z., Xu, M., & Zhang, X. (2016). Applying CS and WSN methods for improving efficiency of frozen and chilled aquatic products monitoring system in cold chain logistics. *Food Control*, *60*, 656-666.

Yang, W. P., & Tarng, Y. S. (1998). Design optimization of cutting parameters for turning operations based on the Taguchi method. *Journal of materials processing technology*, *84*(1), 122-129.