# Integrating Internet of Things and Multi-temperature Delivery Planning for Perishable Food E-Commerce Logistics: A Model and Application

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## Abstract

With the rapid growth of perishable food e-commerce businesses, there is a definite need for logistics services providers to manage parcel shipments with multi-temperature requirements. E-commerce characteristics, including time-critical delivery, fragmented orders, and high product variety, should be further considered to extend the ontology of multi-temperature joint distribution. However, traditional delivery route planning is insufficient because it merely minimizes the cost of travelling between customer locations. Factors related to food quality and arrival time windows should also be considered. In addition, handling dynamic incident management, such as violations of handling requirements during delivery, is lacking. This leads to the likelihood of food deteriorating before it reaches the consumers, thereby impacting customer satisfaction. This paper proposes an Internet of Things–based multi-temperature delivery planning system (IoT-MTDPS), embedding a two-phase multi-objective genetic algorithm optimizer (2PMGAO). The formulation of delivery routing mainly considers product-dependent multi-temperature characteristics, service level, transportation cost, and number of trucks. Once there are unexpected incidents which are detected by Internet of Things technologies, 2PMGAO can optimize the membership functions of fuzzy logic for re-routing the e-commerce delivery plan. With using IoT-MTDPS, the capability of handling e-commerce orders is enhanced, while customer satisfaction can be maintained at a designated level.

Keywords: Perishable food e-commerce; routing; optimization; Internet of Things; fuzzy logic

## 1. Introduction

Due to the booming e-commerce business in recent years, most Internet users have changed their shopping behaviour, payment methods, and ways to appreciate goods and services to fully engage in e-commerce transactions (Da Costa, 2016). Perishable food, such as frozen meat, chilled seafood, and fresh fruit, is a popular item category for sale on e-commerce platforms all over the world (Zhu et al., 2018). To effectively manage perishable food in the entire supply chain ecosystem, particularly the need to handle the multi-temperature characteristics of perishable food, the concept of multi-temperature joint distribution (MTJD) is introduced to provide an overview of the manner in which temperature-sensitive and perishable products are handled from the suppliers to the end customers (Kuo and Chen, 2010). MTJD was proposed to minimize the cost involved in storage and transportation in the logistics system, while at the same time truck usage and logistics performance can be maximized. The product quality and safe delivery are the top priority in MTJD, ensured by means of various cold chain equipment, such as cold boxes, cold cabins, and eutectic gels. Subsequently, various food requirements can be satisfied to maintain designated levels of customer satisfaction. Compared with the generic food supply chain, handling of perishable food in the e-commerce environment requires not only cold chain equipment, but also efficient and effective e-order fulfilment in order to maintain the desired level of food quality and customer satisfaction. Therefore, this study considers the ontology of MTJD to extend this distribution process to e-commerce logistics by considering the multi-temperature characteristics in managing e-commerce parcel shipments, as shown in Figure 1. Song and Ko (2016) formulated research for the vehicle routing problem of using refrigerated trucks for perishable food products delivery, which was useful for distribution using refrigerated trucks in the supply chain. Also, Hsiao et al. (2018) presented distribution planning for cold chains considering multiple temperature settings in the vehicle storage spaces, and thus delivery using multi-temperature trucks through partitioning of various temperature zones in vehicles. However, there is still a research gap in completing the whole perishable food e-commerce logistics to achieve multi-temperature last-mile delivery planning at a parcel level.

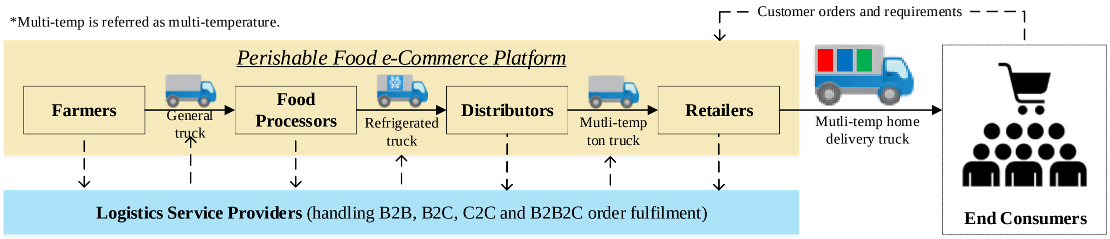


Figure 1. MTJD-based perishable food e-commerce logistics

With regard to last-mile delivery, two research problems are formulated in this study, as illustrated in Figure 2. First, compared with the traditional food supply chain, the significant change in perishable food e-commerce business is the last-mile home delivery because of the need to handle fragmented orders, high variety of stock keeping units (SKUs), and small packages of parcel shipments (Esq and Henry, 2018). Current research studies proved the importance of last-mile delivery in the e-commerce environment, and revealed a number of innovative and efficient delivery solutions for e-commerce businesses (Yu et al., 2017; Mangiaracina et al., 2019). A transportation management system (TMS) is essential to support e-commerce logistics through formulating an effective and efficient fleet management, and data-driven smart TMS is now attracting a number of industrial practitioners and researchers (Zhang et al., 2017). However, the consideration of MTJD characteristics for last-mile home delivery in TMS is limited in the recent research and industrial practice such that product quality and customer satisfaction in the perishable food e-commerce logistics cannot be maintained effectively. Second, sudden incidents from e-commerce systems, including urgent customer order arrival and order cancellation, may change the predetermined delivery schedule. Also, unexpected events during the delivery process, such as serious traffic jams and violation of handling requirements, may cause food deterioration or ripening before reaching the end customers. Particularly for the e-commerce logistics, this could be disastrous if the customers receive spoiled food and the delivery fails to meet the planned schedule, resulting in customer health problems, dissatisfaction, and damage to the company’s reputation (Fikar, 2018; Rothenbächer, 2019). Moreover, perishable food e-commerce distribution has a relatively short planning horizon, where food products are handled by various cold chain equipment to ensure the quality of the food. Therefore, the dynamicity in the delivery process should be considered in a systematic approach. To summarize, two research problems in the perishable food e-commerce logistics are formulated in the following:

a. What is the effective systematic approach to integrate MTJD and perishable food e-commerce logistics for improving product quality and customer satisfaction?
b. How can the delivery planning and systems address the dynamicity due to unexpected incidents during the delivery process?

To address the above research problems, an Internet of Things (IoT)-based multi-temperature delivery planning system (IoT-MTDPS) is proposed for improving delivery planning and scheduling in managing the perishable food e-commerce businesses effectively. To capture real-time information on traffic situations and environmental conditions, IoT technologies are applied to develop a cloud platform for data acquisition and an optimization engine. In the optimization process, a two-phase multi-objective genetic algorithm optimizer (2PMGAO) is developed to search for a set of pareto-optimal solutions by integrating optimization of static and dynamic delivery schedules. For formulating dynamic routing, when unexpected incidents are detected by IoT technologies, 2PMGAO can optimize membership functions in fuzzy logic for assisting removal and reinsertion to formulate dynamic re-routing. With the adoption of IoT-MTDPS, delivery route planning can consider numerous objectives simultaneously, together with dynamic incident management functionality, and therefore customer satisfaction can be improved and company competitiveness can be strengthened in e-commerce logistics.

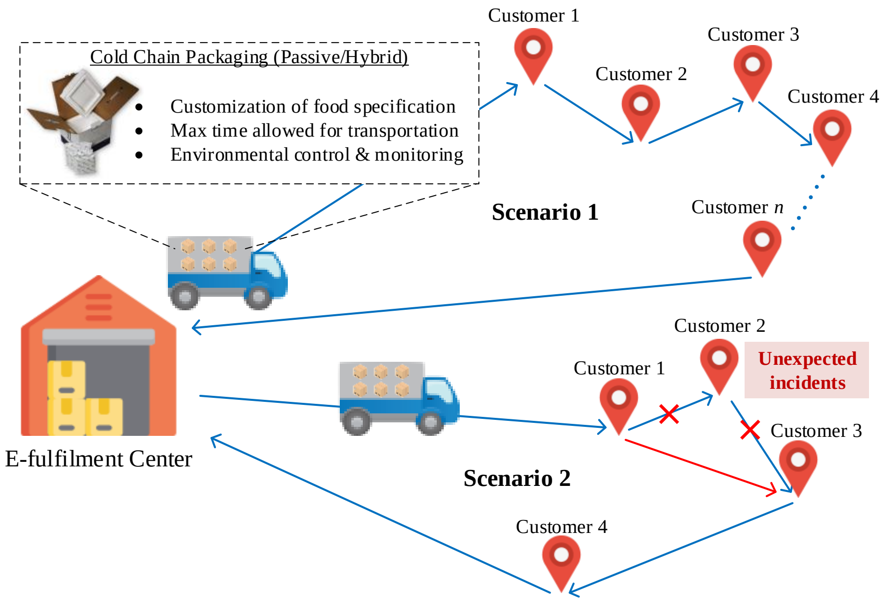


Figure 2. Illustration of two scenarios in perishable food e-commerce logistics

This paper is organized as follows. Section 1 is the introduction. In Section 2, the related work and literature in the aspects of perishable food e-commerce logistics, the vehicle routing problem, and artificial intelligence (AI) techniques are reviewed. Section 3 presents the system architecture of IoT-MTDPS. A case study in implementing the proposed system is illustrated in Section 4. Section 5 gives the results and analysis related to performance and comparison of the proposed system. Discussion and conclusions are presented in Sections 6 and 7, respectively.

## 2. Literature Review

The perishable food supply chain, as a branch of supply chain management, was developed to ensure the desired level of food quality and safety throughout the supply chain (Macheka et al., 2017). Differing from delivering bulk cargo to retailers in the traditional food chain as the final stage, last-mile delivery in the perishable food e-commerce business has become more complicated with regard to the number of customer locations, product sizes, environmental monitoring, and requirements of food quality (Cherrett et al., 2017). Without effective quality assurance during the delivery process, scandals about the food supply may occur, damaging society's trust and the ecosystem of e-commerce businesses. In view of perishable food e-commerce logistics, IoT, which is defined as an interconnection between physical objects and the digital world, plays an important role in facilitation of data acquisition, monitoring product freshness, logistics management, and payment effectiveness (Ruan and Shi, 2016). Also, the demand on perishable food e-commerce and delivery is rapidly growing due to the outbreak of COVID-19 pandemic so that effective delivery planning has drawn considerable attention recently (Singh et al., 2020). Some research studies proposed an IoT-based framework in logistics and supply chain management embedding cloud computing, sensor technologies, and decision-support algorithms as a whole (Zdravković et al., 2018). IoT systems are recently regarded as one of the promising technological aspects for the establishment of Logistics 4.0 on improving the intelligence, adaptability and resilience of the logistics and supply chain management (Winkelhaus and Grosse, 2020). Also, Pournader et al. (2020) reported that IoT could be further integrated with emerging technologies, such as blockchain, to facilitate the trust, trade, traceability and transparency for all supply chain stakeholders. Real-time information provided by IoT can be effectively applied to shorten logistics time, reduce vehicle no-load rate, and control the relevant cost. Also, Wang et al. (2019) indicated that time-precise delivery, elasticity of delivery capability, and cost efficiency were three present challenges in the last-mile parcel delivery, and thus advanced driver-based approaches and unmanned driving by means of IoT should be sought. However, the area of research into integrating IoT and perishable food e-commerce logistics is limited to formulating appropriate delivery planning systems for handling perishable food parcel shipments.

The vehicle routing problem (VRP) has been well defined as an optimization problem for formulating optimal delivery or collection routes from one or multiple depots to several geographically scattered customer locations (Rahmani et al., 2016). The main objectives in the VRP are to minimize the travelling distance and costs involved in the delivery route. Table 1 summarizes the major considerations and factors in VRPs particular to the handling of perishable food. The table shows that the considerations in the VRP formulation for the perishable food supply chain consists of cost, flow conservation, time window, food quality, customer satisfaction, and multi-temperature characteristics. Apart from the essential considerations, most modern VRPs involve integration with additional considerations to enrich the models and improve feasibility and adaptability. However, limited research has been conducted with particular focus on food quality and multi-temperature characteristics, and thus the food quality cannot be fully controlled during last-mile delivery for perishable food e-commerce logistics. Therefore, the consideration of product-dependent multi-temperature characteristics and dynamic routing mechanism is important to enrich the research of perishable food e-commerce logistics. To deal with a number of factors in the optimization model, multi-objective optimization is considered to obtain the best solution, striking the balance between numerous factors, which can be solved to obtain the pareto-solution set (Guo et al., 2017; Chan et al., 2020; Kumar et al., 2020).

Apart from formulating an optimal delivery route before leaving the depot, dynamic and real-time updating of the delivery route, thus accounting for undesired incidents, is essential (Ritzinger et al., 2016). Liu et al. (2019) proposed an approach by integrating

IoT and optimization to provide dynamic routing capability, in which the real-time data, including loading volume, weight, and distance, are considered. However, this research omitted the impacts of the delivery schedule on other customers and the food quality during the transportation process. Fuzzy set theory was proven to be feasible to combine such uncertain information in the VRP, and was widely applied in formulation of the VRP in a number of aspects, such as the fuzzy logic guided genetic algorithm for solving VRPs (Mohammed and Wang, 2017). Beyond that, the fuzzy logic approach should be able to fine tune the factors in the VRP mathematics such that the fuzzy set theory is adopted in the heuristic optimisation methods, such as genetic algorithm, to handle data uncertainty and fuzziness (Xu et al., 2019). Furthermore, the delivery planning can respond to real-time information in the IoT environment to achieve a holistic and practical application system in real-life situations (Ben-Daya et al., 2019). The consideration of food handling requirements and real-time traffic situations, along with the essential factors in VRPs, can then be integrated in the delivery planning system.

To summarize, this study explores the new paradigm of perishable food e-commerce logistics from the basis of MTJD, in which last-mile delivery is deemed to be the most critical and challenging stage among other logistics activities. Subsequently, the multi-temperature characteristics, customer satisfaction, and food quality assurance are considered to formulate an intelligent delivery planning system by means of IoT, fuzzy logic, and multi-objective optimization. As shown in Table 1, the proposed work in this study attempts to include all essential factors for managing perishable food e-commerce logistics, namely cost, flow conservation, time window, food quality, customer satisfaction, and multi-temperature characteristics. Thus, customer satisfaction and food quality can be maintained effectively in the perishable food e-commerce logistics. A systematic approach is therefore developed to address the aforementioned concerns to enrich the area of research into food supply chain and e-commerce logistics.

Table 1. Comparison of existing models for managing perishable food and e-commerce logistics

| Publications | Model Names | Major factors for VRP formulation in handling perishable food | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cost | Flow conservation | Time window | Food quality | Customer satisfaction | Multi-temperature characteristics |
| Proposed work | IoT-MTDPS | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Hsiao et al. (2018) | VRPTW | ✓ | ✓ | ✓ | ✓ | | ✓, zone-based |
| Padilla et al. (2018) | N/A | ✓ | ✓ | ✓ | ✓ | | |
| Hiassat et al. (2017) | N/A | ✓ | ✓ | ✓ | | | |
| Ma et al. (2017) | COSTDVRPT | ✓ | ✓ | ✓ | ✓ | | |
| Bortolini et al. (2016) | FDP | ✓ | | ✓ | | | |
| Mancini (2016) | MDMPVRPHF | ✓ | ✓ | | | ✓ | |
| Song and Ko (2016) | N/A | ✓ | ✓ | ✓ | | ✓ | ✓, vehicle level |
| Wang et al. (2016) | MO-VRPTW-P | ✓ | | ✓ | ✓ | ✓ | |
| Amorim et al. (2014) | HF-SD-VRPMTW | ✓ | ✓ | ✓ | | ✓ | |
| Govindan et al. (2014) | 2E-LRPTW | ✓ | ✓ | | | | |
| Nahum (2013) | N/A | ✓ | ✓ | ✓ | | ✓ | |

## 3. Design of an Internet of Things–Based Multi-Temperature Delivery Planning System

In this section, an Internet of Things (IoT)-based multi-temperature delivery planning system (IoT-MTDPS) is proposed to (i) formulate a predetermined optimized delivery route, and (ii) provide dynamic incident management functionality. Figure 3 shows the system architecture of the IoT-MTDPS with two separate modules to support the delivery planning process in perishable food e-commerce logistics.

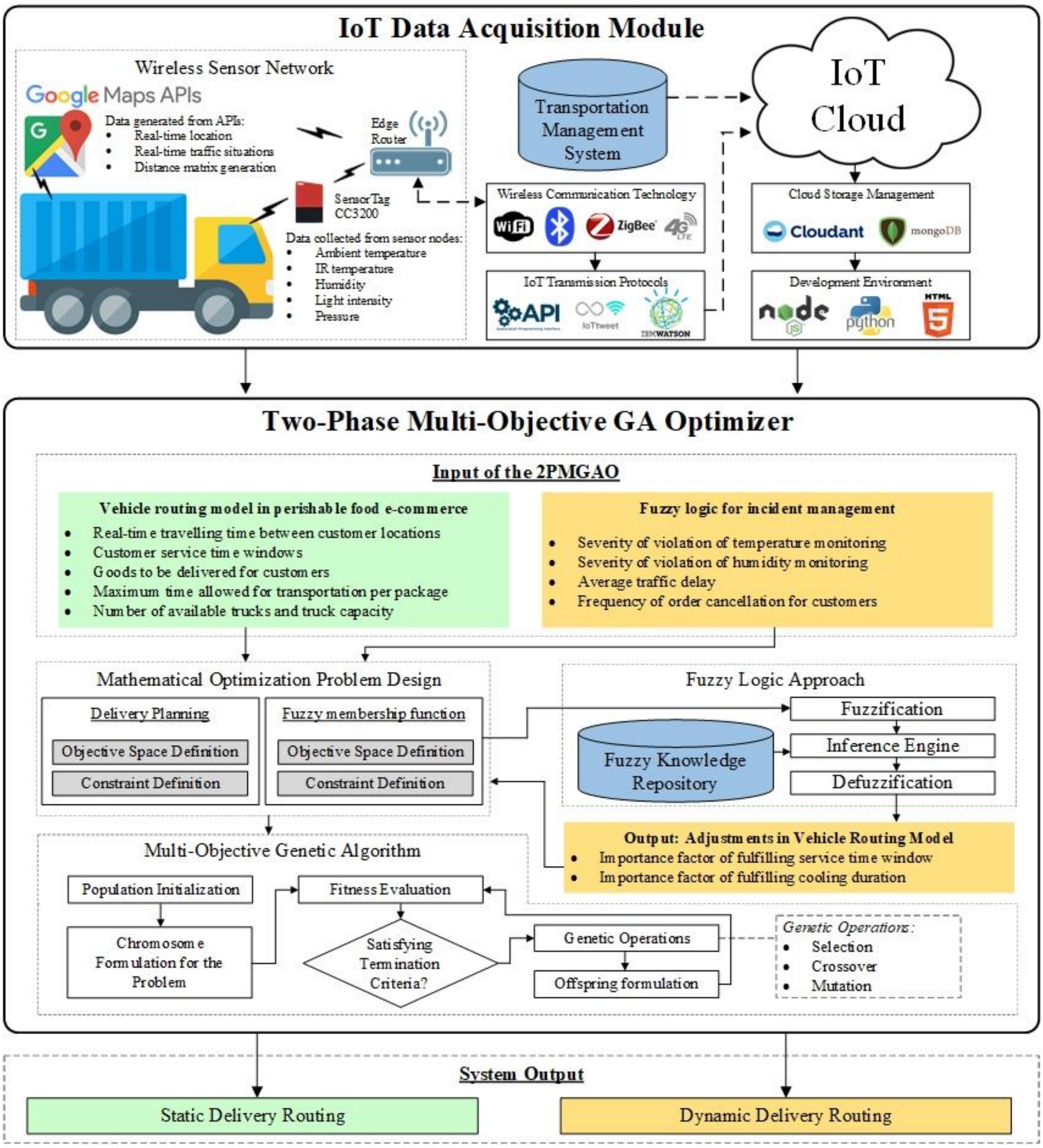


Figure 3. System architecture of IoT-MTDPS

### *3.1 Internet of Things Data Acquisition Module (IDAM)*

This module provides a structural process for IoT data acquisition to facilitate the proposed system. According to the work of Ng et al. (2018), service-oriented architecture (SOA) is an applicable approach in IoT implementation, which provides a significant level of dynamicity and flexibility to IoT middleware. Subsequently, the IoT solutions can be included in a concept of Everything as a Service in the cloud computing environment. In the SOA, a number of layers, including object, network, service, and application, are organized as the bridge between physical objects and the digital world of IoT (Sosa-Reyna et al., 2018). The core concepts and IoT services are included in the following to formulate the SOA for the IoT functionalities in the proposed system. At first, in the device layer, two types of data are collected, namely (i) static data from the TMS, and (ii) real-time data from wireless sensor networks. On one hand, the static data from existing TMS are extracted as an important data source for structuring the customers' locations and the goods to be delivered, which are referred to delivery notes for the customer order fulfilment. It includes but not limited to customer data (e.g., customer names, contact numbers, and delivery addresses), fleet data (e.g., truck capacity, and transportation restrictions), order data (e.g., requested delivery time and list of order goods), and contractor data (e.g., trucker information, and price quote per delivery). On the other hand, two sets of real-time data, namely environmental and traffic conditions, are collected for monitoring delivery processes and achieving incident management. To collect data of environmental conditions, sensing devices (such as Texas Instruments' SensorTag CC3200) are attached in each truck to measure ambient temperature (˚C) and relative humidity (%), conforming to product handling protocols. In the network layer, the entire data payload is then transmitted to designated IoT development platforms (such as IBM Cloud and IoTweet) via the edge router which enables 3G/4G/LTE connection, in which the sensing devices are need to be paired with the edge router in advance by using the wireless communication technologies under 2.4GHz ISM band wireless protocol, for example Bluetooth Low Energy and Wi-Fi. With the defined transmission interval, the data payloads can be sent to the IoT development platforms which are the Platform as a Services (PaaS) solutions for the system development, where the lightweight and publish-subscribe-enabled IoT transmission protocols, such as IBM Watson IoT platform registered services and message queuing telemetry transport (MQTT), are used to transport device data as the role of brokers. The protocols run over TCP/IP to support the end-to-end data transmission for server connection, server disconnection and message publication, which is depended on the network bandwidth. To collect data of traffic conditions, external connection to Google Maps APIs is established so as to enable several web services for supporting transportation management, including the traffic layer in the map, real-time geographic location, and distance matrix among geographic locations. Moreover, the travelling time between two customer locations can be evaluated by considering their locations in a real-time manner, which can be adjusted by the real-time traffic situations to be a partial travelling cost in the vehicle routing problem. In the service layer, the above IoT and external API services are managed as a whole, while the IoT development platform supports the functions of cloud storage management and the system development environment. The collected data can be stored, managed, and queried in the data format of JavaScript Object Notation (JSON). For handling such a large volume of real-time data, NoSQL database services, for example Cloudant, are used so that the data can be stored in a JSON document store without the conversion to SQL tables. It provides a flexible and scalable database schema for managing either structured, semi-structured, or unstructured IoT data. After building the service layer, the designated application for the IoT-MTDPS can be designed and developed. Regarding the system development, front-end web development (HTML5, JavaScript, CSS3), algorithm deployment (Python), and back-end development (PHP) are applied to construct the proposed system. Regarding the novelty of the IDAM, this module provides a structural formulation of the automated data collection for the system development in accordance with the SOA so as to facilitate business-driven solutions, end-to-end automation, integration of operational technology and information technology (Pflaum and Gölzer, 2018; Zhao et al., 2020). Subsequently, it is the essential foundation about the data acquisition to the whole proposed system, without which the contributions from the proposed system in the context of perishable food e-commerce logistics could not be fully realized.

*3.2 Two-Phase Multi-Objective Genetic Algorithm Optimizer (2PMGAO)*

In this section, a two-phase multi-objective GA optimizer (2PMGAO) is described to formulate the static and dynamic routing solutions for handling perishable food e-commerce orders. Since the delivery routing formulation is classified as the NP-hard problem (Amous et al., 2017), the adoption of heuristics algorithms to search for nearly optimal solutions is relatively cost effective and time saving. Among a number of heuristics algorithms, GA is promising as an iterative search, optimization, and adaptive machine learning technique for solving transportation problems in accordance with the principles of natural selection (Panchal and Panchal, 2015). In recent years, a GA-based approach to address the transporting and routing problem are still actively discussed and adopted for solving NP-hard models (Ardjmand et al., 2016; Fazayeli et al., 2018). Consequently, to cope with multiple objectives, GA within multi-objective optimization is selected in this study.

(i) Vehicle routing model in perishable food e-commerce

Referred to Nahum's work (2013), the NP-hard problem is formulated for closed-loop delivery route planning in considering one depot and heuristic optimization under the perishable food e-commerce environment. Since merely considering optimizing a single objective is insufficient in the e-commerce business environment, the proposed model is extended to optimize the travelling time, number of vehicles, and customer satisfaction regarding food quality simultaneously. In addition, the factors of service time window, truck capacity, customer locations, and cooling duration for delivery without affecting the food quality are considered as a number of constraints in the model. Before illustrating the proposed multi-objective vehicle routing model, it is assumed that (i) the truck capacity and energy consumption are known and identical, and (ii) customers' demand is known and confirmed before planning the delivery schedule. In this problem domain, due to integration with the e-commerce business characteristics in the VRP formulation, the service time and cooling duration should be modelled in soft constraints to provide the greatest flexibility in delivery route planning. The proposed vehicle routing problem is modelled in an undirected graph **G** = (**V**, **E**) to fulfil all customer orders through visiting customers' nodes, that is, vertex set **V**, including the depot, by arranging the most efficient edge **E** between two vertices. Each edge from node $i$ to node $j$ is defined by two non-negative properties, that is, travelling distance $d_{ij}$ and travelling time $t_{ij}$. The conversion between travelling distance and travelling time is done by Google Maps API at planning time $\tau$. The customers make the orders on the e-commerce platform to create a total number of delivery orders **N** every day. All the orders are then completed by a fleet of identical trucks **Q** with a certain capacity **P** in the next day. Each customer is assigned a service time window regarding delivery duration in [$ST_{si}$, $ST_{ei}$] with an acceptable tolerance $\varphi$, while soft time windows are considered to prevent the truck arrival, with travelling time cost $c_{ij}^{\tau}$, being earlier than the earliest service time $ST_{sj}$ at node $j$ at time $t$, that is, $\mathrm{TT}_{ij} = \max(c_{ij}^{\tau}, \mathrm{ST}_{sj} - t)$. It is implied that the trucks must wait until the start of the service time window $ST_{si}$ if they arrive earlier than expected. The orders are completed on or before the latest service time window $ST_{ei}$. According to a previous study, perishable food has its own specific handling requirements regarding ambient temperature, and thus the food is packed with appropriate cold chain packaging, which consists of a certain number of eutectic plates in a polyfoam box, before transportation

(Tsang et al., 2018). Thus, a new factor of maximum time allowed for transportation is added in the vehicle routing. Types of environmentally sensitive products **M** are defined with the maximum duration for delivery $CT_m$ and additional acceptable cooling duration for delivery $\theta$, after being packed inside the cold boxes. Appendix A summarizes the notation used in the proposed mathematical model. In real-life situations, it is difficult to guarantee the fulfilment of the expected delivery schedule and the best cooling duration perfectly. Violation of the above parameters constitutes a negative impact on the customer satisfaction level. Therefore, the service time window and cooling duration are modelled as soft constraints by applying fuzzy set theory. As shown in Figure 4, the fuzzy membership functions are used to interpret the customer satisfaction level in the service time window and cooling duration. Depending on the service time and cooling duration, customer satisfaction ranges from 0 to 1, quantified by equations (1) and (2) as the soft constraints on the problem.

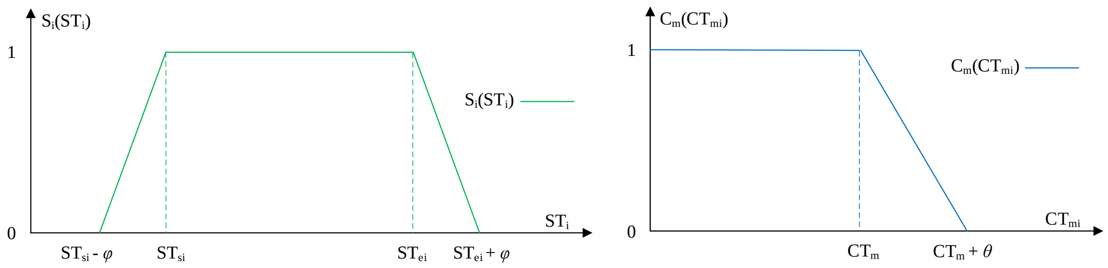

Figure 4. Graphical illustration of fuzzy service time window

$$S_i(ST_i) = \begin{cases} 0, & ST_i < ST_{si} - \varphi \\ \frac{1}{\varphi} \cdot (ST_i - ST_{si} + \varphi), & ST_{si} - \varphi \le ST_i < ST_{si} \\ 1, & ST_{si} \le ST_i \le ST_{ei} \\ \frac{1}{\varphi} \cdot (ST_{ei} - ST_i + \varphi), & ST_{ei} < ST_i \le ST_{ei} + \varphi \\ 0, & ST_i > ST_{ei} + \varphi \end{cases} \tag{1}$$

$$C_m(CT_{mi}) = \begin{cases} 1, & 0 \le CT_{mi} \le CT_m \\ \frac{1}{\theta} \cdot (CT_m - CT_{mi} + \theta), & CT_m < CT_{mi} \le CT_m + \theta \\ 0, & CT_{mi} > CT_m \end{cases} \tag{2}$$

The proposed model aims at optimizing three objectives simultaneously, that is, (i) minimization of travelling time between the nodes, (ii) minimization of the number of vehicles used for the delivery, and (iii) maximization of customer satisfaction, as shown in equations (3), (4) and (5), respectively. First, the transportation cost between the nodes $i$ and $j$ consists of the consideration of $TT_{ij}$, required service time and waiting time in node $j$. Second, the number of trucks used in the delivery is defined as the number of trucks that leave the depot at any time. Third, customer satisfaction has the components of service time window and cooling duration, in which the importance factors $\alpha_i$ and $\beta_i$ are used to convert $S_i(t)$ and $C_m(t)$ into two computable formulas and to compare customer $i$ among all other customers so as to calculate the weighted arithmetic mean of the customer satisfaction level among all customers. In other words, the consideration of multi-temperature characteristics, that is, the cooling duration for each parcel, is designed for the perishable food e-commerce business in a novel manner, as in equation (5). The requirement of multi-temperature characteristics integrates with the service time window

to formulate the objective for customer satisfaction.
Objective functions:

$$\text{Min. } \mathrm{F}_1 = \sum_{i\in V}\sum_{j\in V}\sum_{q\in Q}\sum_{t\in T}\left[\max(c_{ij}^{\tau}, ST_{sj} - t) + ST_j + WT_j\right]x_{ij}^{q\tau} \tag{3}$$

$$\text{Min. } \mathrm{F}_2 = \sum_{j\in V}\sum_{q\in Q}\sum_{t\in T} x_{0j}^{q\tau}\text{, where } j\epsilon V\backslash\{0\} \tag{4}$$

$$\text{Max. } \mathrm{F}_3 = \frac{\sum_{i\in V}\alpha_i S_i\left(\sum_{k\in V}\sum_{q\in Q}\sum_{t\in T}(t + c_{ki}^{\tau})\, x_{ki}^{q\tau}\right)}{\sum_{i\in V}\alpha_i} + \frac{\sum_{i\in V}\beta_i C_m\left(\sum_{k\in V}\sum_{q\in Q}\sum_{t\in T}(t + c_{ki}^{\tau})\, x_{ki}^{q\tau}\right)}{\sum_{i\in V}\beta_i} \tag{5}$$

Subject to:

$$\sum_{i\in V}\sum_{q\in Q} x_{ij}^{q\tau} = 1, \forall j \in V\backslash\{0\}, \forall \tau \in T \tag{6}$$

$$\sum_{i\in V}\sum_{q\in Q}\sum_{t\in T} x_{ij}^{q\tau} - \sum_{i\in V}\sum_{q\in Q}\sum_{t\in T} x_{ji}^{q\tau} = 0, \forall j \in V \tag{7}$$

$$\sum_{i\in V}[(\sum_{j\in V}\sum_{t\in T} x_{ij}^{q\tau}) \cdot W_i] \leq W_p, \forall q \in Q, \forall p \in P \tag{8}$$

$$\sum_{i\in V}[(\sum_{j\in V}\sum_{t\in T} x_{ij}^{q\tau}) \cdot CBM_i] \leq CBM_p, \forall q \in Q, \forall p \in P \tag{9}$$

$$\min\,[S_i^{-1}(\mu_i)] \leq \mathrm{TT}_i + \mathrm{ST}_i + \mathrm{WT}_i \leq \max\,[S_i^{-1}(\mu_i)] \tag{10}$$

$$\min\,[\mathrm{C}_m^{-1}(\mu_i)] \leq \mathrm{TT}_i + \mathrm{ST}_i + \mathrm{WT}_i \leq \max\,[C_m^{-1}(\mu_i)] \tag{11}$$

$$x_{ij}^{q\tau} \in \{0,1\}, \forall i,j \in V, \forall q \in Q, \forall t \in T \tag{12}$$

Regarding the constraints, constraint (6) is set to ensure that exactly one truck must visit each customer to fulfil their orders. Constraint (7) makes sure that the total number of trucks that arrive and depart at the nodes, including the depot and customers' locations, are the same. Constraints (8) and (9) guarantee that the total volume and weights of the customers' orders delivered by a truck do not exceed the truck capacity. Constraints (10) and (11) are to ensure that the sum of the time in reaching the customers, required service time, and waiting time for the customers is limited to the soft service time window and product cooling duration, respectively, according to a customized satisfaction level. The service time window and cooling duration could be more flexible than simply applying standardized restriction on service time and cooling time, such that the proposed model is given a higher flexibility and adaptability. Last, constraint (12) is the binary integrality to the decision variable that expresses whether the truck is required to visit the customer's location at a specific time.

(ii) Fuzzy logic for incident management

Static delivery routes are formulated above, but the formulation lacks the flexibility to handle sudden unexpected incidents during the delivery. A fuzzy logic approach is then proposed to re-optimize the delivery routing model in an efficient manner. According to the IDAM, the environmental and traffic conditions of trucks can be monitored in a real-time manner. To activate the fuzzy logic, there are three conditions: (i) violation of handling conditions, (ii) serious delays in delivery, and (iii) order changes requested by customers. The fuzzy logic approach consists of three major components, that is, fuzzification, inference engine, and defuzzification, in which the computational process can be referred to the previous studies (Castillo et al., 2016; Rustum et al., 2020). During the transportation process, there is a certain likelihood of facing incidents of violation of environmental conditions, road traffic delay, and order cancellation. The fuzzy logic approach gives a flexibility for re-optimizing the delivery schedule. In this proposed approach, the fuzzy relationship is constructed between four inputs, (i) severity of violation of temperature (VT), (ii) severity of violation of humidity (VH), (iii) average traffic delay time (TD), and (iv) frequency of order cancellation for customer $I$ (OC), and two outputs, (i) importance factors $\alpha_i$ and $\beta_i$ of fulfilling service time window (ST) and (ii) importance factor of fulfilling cooling duration (CD).

(iii) Mechanism of 2PMGAO

To effectively solve the above complex and large-scale model, the multi-objective genetic algorithm (MOGA) is selected as an effective method for solving the problem. When handling such a multi-objective optimization problem, the MOGA is able to search for a pareto-optimum set instead of an exact solution. 2PMGAO plays the role of integrating multi-objective optimization in vehicle routing and fuzzy logic approach. Regarding the use of MOGA, the individual representations, i.e. chromosomes, are formulated with two phases for optimizing membership functions in fuzzy logic and the vehicle routing problem, as shown in Figure 5. In phase one, when unexpected incidents are detected, the chromosomes are then activated so as to optimize the membership functions for obtaining better accuracy in the proposed fuzzy logic approach.

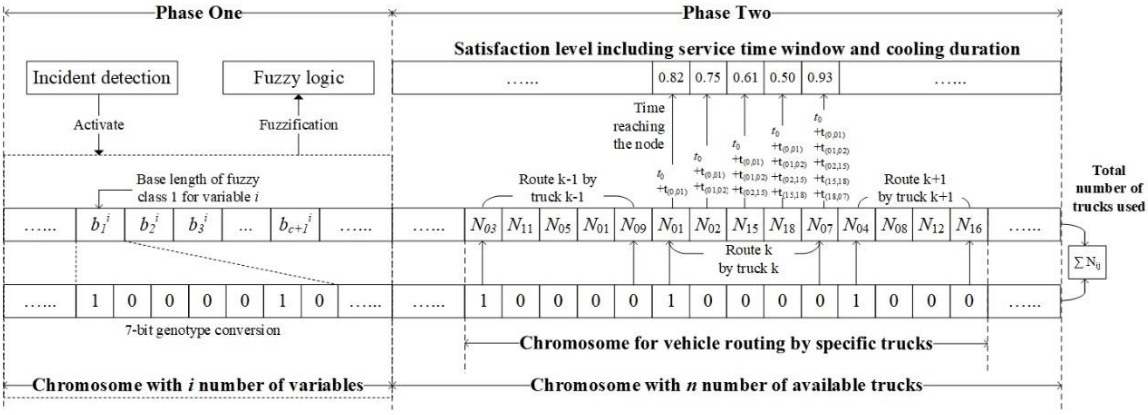

Figure 1. Genotype chromosome of 2PMGAO

It is assumed that triangular membership functions for inputs and outputs are considered in this optimizer. The training data set, including (i) a set of input $X_i$ and desired output $Y_i$ data and (ii) a set of linguistic rules, is required to adjust the base lengths of the triangular membership functions. The ranges of the variables $X_i$ and $Y_i$ are defined as $[X_{(min,i)}, X_{(max,i)}]$ and $[Y_{(min,i)}, Y_{(max,i)}]$, respectively. The objective in the optimization of the membership functions is to minimize the error between the actual output values and the output values obtained by the genetic algorithm, as shown in equation (13). The constraint for this optimization is that the base lengths are limited between the corresponding ranges of the variables. To optimize this objective, the chromosomes are set as 7-bit where the maximum value of each base length is $2^7 - 1 = 127$, while each base length $Z_i$ is encoded in a 7-bit chromosome with using binary numbers for the conversion from phenotype to genotype chromosomes. By making use of equation (14), the decimal values $a$, which are converted from the binary numbers of the genotype chromosomes, are used to calculate the actual base lengths for triangular membership functions. After completing the optimization process, as mentioned previously, the optimal values of the base lengths can be determined by combining with the ranges of inputs and outputs.

$$\text{Min. } F_{MF} = \sum_{i=1}^{n} (Y_i - Y_i^{GA})^2 \tag{13}$$

$$Z_i = Z_{(\min,i)} + \frac{a}{(2^7 - 1)} \cdot [Z_{(\max,i)} - Z_{(\min,i)}] \tag{14}$$

In phase two, there is a sequence of binary numbers assigning a group of customers to the trucks so that the routes can be formulated. In addition, the total number of trucks used in the delivery can be calculated by summing all the values in the binary sequence, where “1” represents that a new truck is considered to handle the customers’ orders. At each customer node, the corresponding average satisfaction level from the service time window and cooling duration can be evaluated by the arrival time. Referred to the MOGA study (Padhi et al., 2016), the aforementioned three objective functions are combined by using the weighted sum method to obtain the optimal solution. A weighting $\omega_i$ is assigned to the objective functions to indicate its own importance among all the functions, where $\omega_i \in [0,1]$ and $\sum_{i=1}^{3} \omega_i = 1$, as shown in equation (15). The genetic operations, including selection, crossover and mutation, have been structured when using MOGA, where the population size, crossover rate, mutation rate, and maximum number of iterations are defined. By repeating the MOGA process until the stopping criteria are reached, the set of pareto-optimal solutions can be obtained. Therefore, the optimal delivery route schedule can be formulated by considering various objectives and constraints in the perishable e-commerce logistics.

$$\text{min. } F_{\text{fitness}} = \omega_1 F_1 + \omega_2 F_2 - \omega_3 F_3 \tag{15}$$

## 4. Case Study

To validate the proposed system, IoT-MTDPS, a pilot study was conducted in ABC Holdings Limited (alias) which is a logistics service provider located in Hong Kong, in which one of the key services is to handle, plan, and deliver e-commerce orders involving perishable food. The company has a 3,000 $m^2$ e-commerce fulfilment centre for processing online orders, with the centre partitioned into three sections, namely, (i) freezing section, (ii) chilling section, and (iii) air-conditioned section, for catering to the storage conditions of various products. The company plays an important role in collecting all the online orders together with the customer information, and in confirming with customers a specific range of delivery time, such as from 10:00 to 14:00, one day in advance. Afterwards, the delivery route can be manually determined by the experience and knowledge of the transportation managers for next-day delivery. However, when handling tens of thousands of orders in a day, it is found that the transportation managers are required to spend a great deal of time on planning the delivery route for a number of trucks, considering both the cost and customer satisfaction simultaneously. Moreover, the truckers, in practice, will follow the planned delivery schedule to distribute the e-commerce orders to customers, but there is a chance of occurrence of violation of handling requirements, serious road traffic jams, and sudden order changes. On the one hand, customer satisfaction can be affected if there is no contingency plan for unexpected incidents, resulting in the company’s reputation being greatly damaged. On the other hand, if the truckers still follow the predetermined delivery route, it wastes time and fuel costs in the whole transportation process. Worse, the quality of the perishable food may be affected, thus generating a certain level of capital loss. Currently, the company has no measures to address the above challenges in the existing transportation management systems. Therefore, the proposed system, IoT-MTDPS, was trialled in the case company for overcoming the above challenges so that the delivery schedule can be automatically determined and dynamically adjusted according to the severity of the unexpected incidents. Thus, the delivery schedule and number of trucks can be optimized, while customer satisfaction can be enhanced. The implementation roadmap of IoT-MTDPS is divided into three phases in the following.

*4.1. Phase One: Setup of IoT Wireless Sensor Network*

In the proposed IoT wireless sensor network, three independent layers, that is, a device layer, connectivity layer, and IoT cloud layer, are used to develop the proposed application following the concept of SOA for IoT implementation, as shown in Figure 6.

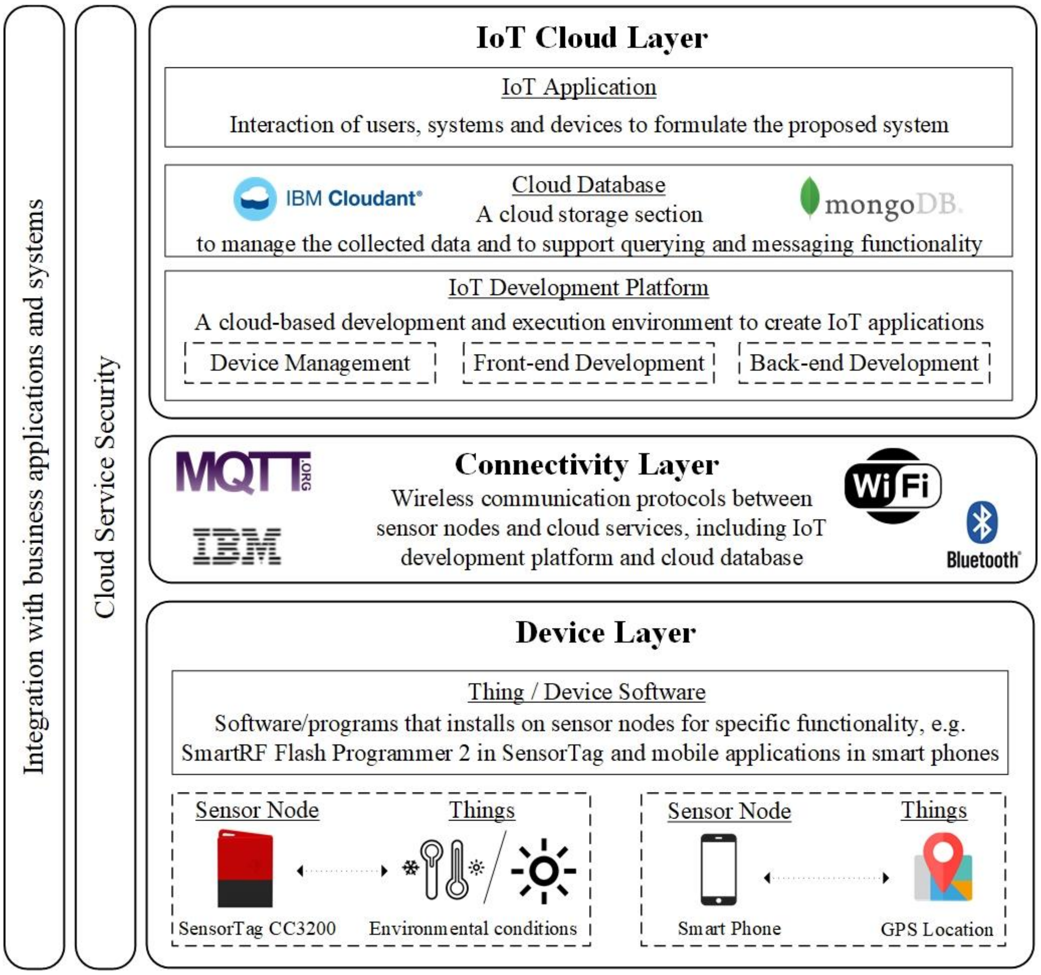


Figure 6. IoT application framework of IoT-MTDPS

At the device layer, the sensor nodes, that is, the SensorTag CC3200, are installed in the container area of the trucks to collect data on the ambient temperature (°C) and relative humidity (%). The sensor nodes are then connected to an edge router, i.e. TP-Link M7310 – 4G/LTE Mobile Wi-Fi, via the 4G connection for recording the real-time data for the trucks and uploading the data to the designated IBM Cloud in this case study. The IBM device registered services are used to connect the sensor nodes to the IBM Watson IoT Dashboard, where organization ID, device type, device ID, and authentication token should be configured into the sensor nodes. On the other hand, the GPS location data from the smart device is also collected regarding the real-time outdoor locations of the trucks. Together with the delivery notes, the Google Maps API is adopted to build a distance matrix with the most updated travelling time between customer locations. All the sensor and API data are managed in the centralized IoT dashboard for supporting the functionalities of the proposed system. Before reaching the IoT cloud layer, the connectivity layer is required to standardize the data and to connect to the IoT development platform. The SensorTag CC3200 is registered by IBM Bluemix IoTF services, while the GPS data is directly streamed into the cloud database, that is, Cloudant, via a 4G/LTE network. All the collected data are stored in the JSON format under the NoSQL environment, and therefore the data can be effectively accessed to measure the situation of the delivery processes. Concurrently, the data related to the orders and customer information are imported from an external database for supporting optimization. In the IoT development platform, that is, IBM Cloud, the data payload from the sensor nodes is collected for developing front-end and back-end applications of the proposed system. The algorithms and computations can be deployed in the back-end development to obtain the static delivery schedule and to achieve incident management during the delivery process.

*4.2. Phase Two: Formulation of Static Delivery Schedule*

In phase two, the next day, or n + 1, delivery schedule is determined for confirmed delivery orders from the e-commerce platform. The customer service team in the company is responsible for confirming the delivery time and creating a table containing all the next-day delivery orders, and a summary of the delivery orders is then passed to the transportation team for arranging the delivery schedule. Figure 7 shows the mechanism of converting the delivery address into the travelling distance and time between customer locations for further optimization. The summary contains the data on the shipment order ID (SO), customer ID (CID), delivery address, expected delivery time interval, and ordered items. By making use of Google Maps Geocoding API and Directions API, the delivery locations can be converted to a set of geo-coordinates, and the cost matrix can be established to show the travelling time between the delivery locations at this stage. The expected delivery time interval can be used to define the constraints of the service time window, with a tolerance of ±15 mins. The information on ordered items can determine the maximum delivery time interval for the products, and thus the customer satisfaction can be quantified.

As shown in figure 7, there are 14 customers with different delivery locations, delivery times, and ordered items in the pilot study, and two cargo vans are assigned to complete the delivery orders. To formulate the optimal predetermined delivery schedule, the proposed 2PMGAO is developed in the Python programming environment, using the module DEAP 1.2.2 to formulate the multi-objective optimization. Appendix B shows the pseudo-code of the multi-objective optimization solved using the MOGA. As mentioned in Section 3, several parameters are required in the multi-objective optimization and genetic algorithm, such that population size is 500, crossover rate is 0.6, mutation rate is 0.1, and number of chromosome replacements is 5. In addition, the three fitness functions conform to equations (3), (4), and (5), while the combined fitness value is evaluated using the weighted sum method, with $w_1$ = 0.05; $w_2$ = 0.05; $w_3$ = 0.9. Before reaching the stopping criteria, that is, 5,000 iterations and a percentage change of the best combined fitness value less than 0.01, the genetic operations are conducted to create off-spring chromosomes and to formulate the improved near-optimal solutions. Consequently, the optimal chromosome can be obtained to formulate the optimal static delivery schedule by using two cargo vans, as shown in figure 8.

*4.3. Phase Three: Activation of Fuzzy Logic for Dynamic Routing*

During the delivery, there is a certain likelihood that the truckers will receive information that may affect the delivery routing, such as violation of environmental requirements, suddenly serious traffic jams, and customer order changes. Sometimes, the truckers have to modify the predetermined delivery schedule by their own experience and knowledge, which is time consuming and dangerous when driving, and ensuring the efficiency of such modifications is dangerous. Therefore, the fuzzy logic approach is used to address the difficulties and challenges faced by the truckers. Before using this approach, a supervised learning process is conducted to train the membership functions in 2PMGAO with the given set of training data. It is collected by the company from 10 active customers out of 210 customers by conducting a survey of customers regarding their perspectives on changes in the importance factors and the effect on their satisfaction level due to the occurrence of the unexpected incidents. Table 2 shows the example of training data for tuning the membership functions in the fuzzy logic approach. Thus, the base lengths of membership functions are optimized in 2PMGAO. To bound the solutions of the above optimization, the fuzzy classes and ranges of the four input and two output parameters are also defined: VT = {Low, Medium, High} with [0, 1], VH = {Low, Medium, High} with [0, 1], TD = {Short, Medium, Long} with [0, 120], OC = {Infrequent, Slightly frequent, Frequent} with [0, 20], ST/CD = {Significantly decreased, Slightly decreased, No change, Slightly increased, Significantly increased} with [-1, 1].

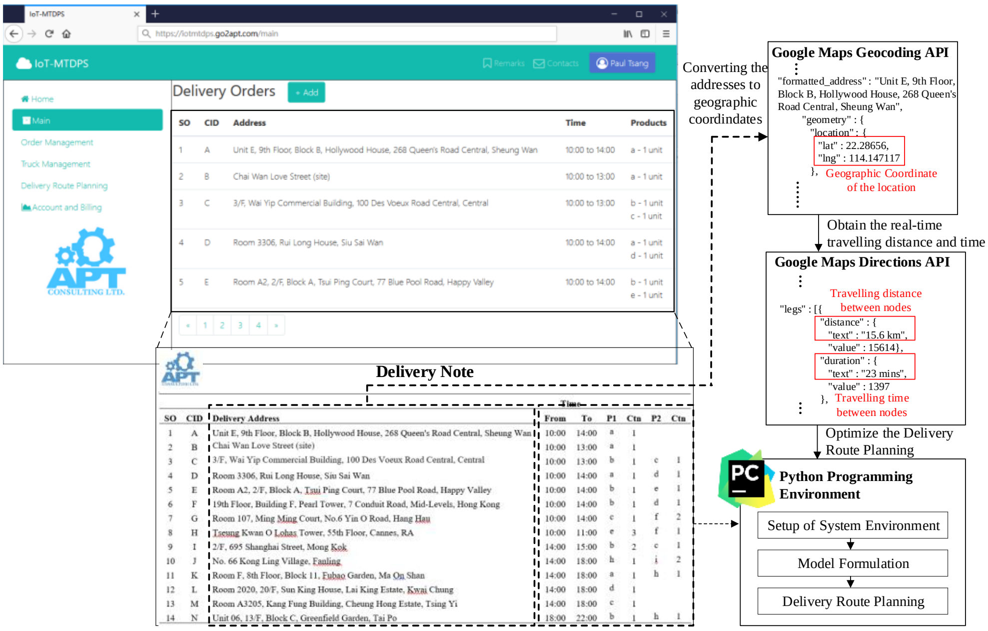


Figure 7. Mechanism of obtaining travelling distance and time between nodes

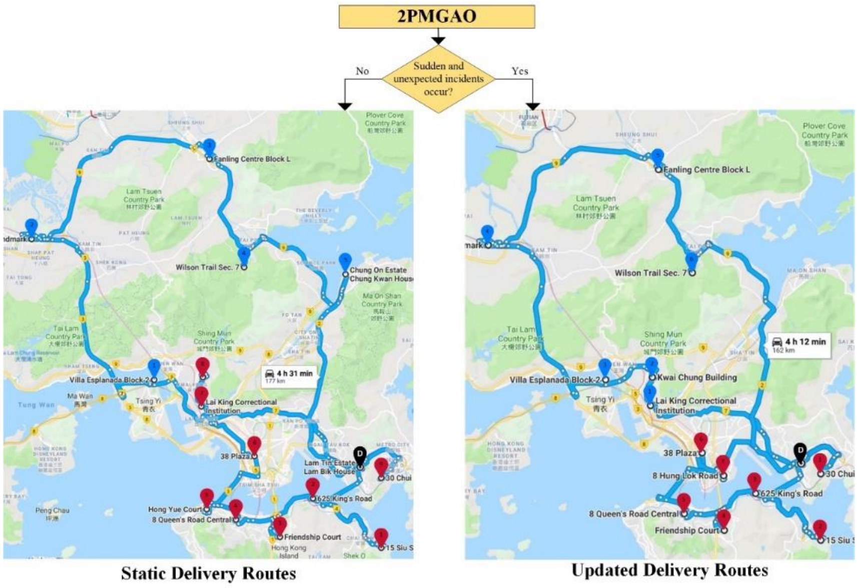


Figure. 8. Delivery planning using 2PMGAO

Table 2. Example of training data set for fine tuning membership functions

| | Input Parameter | | | | Output Parameter | |
|---|---|---|---|---|---|---|
| No. | VT | VH | TD | OC | ST | CD |
| 1 | 0.50 | 0.50 | 5 | 0 | -0.10 | 0.52 |
| 2 | 0.10 | 0 | 10 | 1 | 0.1 | 0 |
| 3 | 0.25 | 0.15 | 30 | 0 | 0.51 | 0.13 |
| 4 | 0.05 | 0.13 | 5 | 8 | -0.24 | 0.05 |
| 5 | 0.18 | 0.22 | 45 | 10 | -0.38 | -0.42 |
| 6 | 0.32 | 0.10 | 15 | 2 | 0.15 | 0.26 |
| 7 | 0.69 | 0.23 | 0 | 1 | 0.38 | 0.62 |
| 8 | 0.16 | 0.05 | 60 | 4 | 0.38 | 0.06 |
| 9 | 0.11 | 0.15 | 10 | 15 | 0.06 | 0 |
| 10 | 0.21 | 0.09 | 5 | 3 | 0.03 | 0.14 |

Once the membership functions are optimized, the fuzzy logic approach can be applied to adjust the two importance factors, that is, $\alpha_i$ and $\beta_i$, for re-optimizing the delivery routes. To computerize the process of the fuzzy logic approach, skfuzzy 0.2, a fuzzy logic library in the Python programming environment, is used to customise the proposed fuzzy logic application, covering fuzzification, Mamdani's inference engine, and defuzzification. After aggregating the above elements, the fuzzy logic approach can generate the two output values by analysing the inputs, which are measured in real time during the delivery. Appendix C shows the pseudo code of the fuzzy logic approach for processing the real-time information. The optimal result with the finalized chromosome is then partitioned and decoded from genotype to phenotype, according to the predefined fuzzy classes and range of input and output parameters. Each triangular membership function can be defined as $[x_1, x_2, x_3]$, the three vertexes of the triangular function, that is, fuzz.trimf(parameter, $[x_1, x_2, x_3]$). In addition, the fuzzy rules, which are defined by the domain experts to express the relationship between inputs and outputs, are managed by ctrl.Rule(), while all the rules can be controlled by ctrl.ControlSystem() to aggregate the results by entering the specific input values. Therefore, the adjustments on the assigned customer satisfaction level, importance factors $\alpha_i$ and $\beta_i$ for a customer compared to all other customers can be obtained, while the delivery routes can be re-optimized by considering the adjusted parameters in the delivery planning, as shown in Figure 8. By combining the above results, multi-temperature delivery planning can be established. On the one hand, the delivery routes are predetermined according to the shipment pre-alerts, and thus the truckers can view their optimized delivery route, which is identified by the vehicle registration number. On the other hand, if unexpected incidents occur, the fuzzy logic approach is then activated for the transportation team to update the delivery routes automatically. Consequently, the truckers can check the updated delivery route by using their vehicle registration number.

To examine the data volume and network size of the proposed system, the entire trail run is lasted for 3 months to fulfil the e-commerce orders of perishable goods. Also, the case company offers up to five cargo vans to complete the orders in the daily operations, and thus five corresponding wireless sensor networks are built to connect sensor nodes and IBM Cloud via the 4G network, which provides an extensive geographical coverage of Internet. Although the environmental conditions are collected in real-time, the data storage in Cloudant is conducted in a specific time interval, namely 1 minute, for 12-hour daily transportation operations. Each data payload contains identity, firmware version, timestamp, a series of environmental condition. Subsequently, approximately 14.68GB and 250.57MB data are handled in the IBM Cloud for real-time monitoring and data management in Cloudant, respectively. On the other hand, enabling GPS functions in the mobile devices may consume approximately 5MB per hour for driving, and therefore about 26.37GB data regarding traffic conditions are used for the operations within this 3-month period. On average, each truck for the perishable food e-fulfilment needs about 0.98GB per month and 1.758GB per month for the data collection on environment and traffic conditions, respectively. The extent of the data consumption for implementing the proposed system in the real-life situation is relatively reasonable and applicable, while the long-term implementation is considered in the case company in future.

## 5. Results and Analysis

The system performance resulting from implementing the proposed system in the case company is analysed in this section. The core functions of IoT-MTDPS include (i) multi-objective optimization in delivery route planning, and (ii) dynamic re-routing by fuzzy logic using IoT technologies. In addition, the performance of the proposed delivery planning system is compared to the traditional VRP model. Also, the sensitivity analysis for parameter configurations of 2PMGAO is conducted through experimental design. Finally, the managerial implications of using the proposed system are also described.

### *5.1 Performance for IoT-MTDPS*

To validate the performance of IoT-MTDPS, there are three scenarios set to investigate the average and the best results by means of multi-objective optimization in IoT-MTDPS, the traditional VRP and the manual approach. The details of three scenarios are (i) 10 customers, (ii) 25 customers, and (iii) 50 customers, where the data for the scenarios are collected from the case company. The traditional multi-temperature VRP model (MTVRP), which is a single objective optimization, is referred to the previous study on delivery route planning for multi-temperature food distribution (Tsang et al., 2018). The maximum number of iterations in the genetic algorithm is defined in three cases, namely (i) 5,000 times, (ii) 10,000 times, and (iii) 20,000 times. Table 3 shows the performance comparison among IoT-MTDPS and the MTVRP regarding the travelling distance which is standardised by Google Maps Distance Matrix API. It is found that the results from IoT-MTDPS and traditional VRP are obviously better than the traditional approach regarding the travelling distance, with 13% to 27% improvement. For the larger size of the customer pool, a higher number of iterations is required to obtain the better solutions for the delivery route planning. Merely maintaining 5,000 iterations cannot fulfil the requirements in scenarios 2 and 3 and search for the optimal solutions. On the other hand, the proposed system is not only optimizing the travelling time between depot and nodes, but also minimizing the number of vehicles used and maximizing the customer satisfaction in the aspects of service time window and product cooling time window. Thus, although the proposed system considers three objectives simultaneously to search for optimal solutions, the deviations of the results are less than 10%.

In addition, the pareto-optimal set of the weighted sum approach for the multi-objective optimization can be obtained from a priori articulation of user preferences (Marler and Arora, 2010). This method has advantages of simplicity and flexibility of the optimization process, which can be fully under the control of end users. In this study, 25 sets of preference in weight assignment are collected to formulate the pareto-optimal solution set in the three scenarios defined above, as shown in Figure 9. It is found that a convex-like shape of the pareto-optimal front is formulated such that the relationship and tendency between three objectives can be revealed. In this study, the customer satisfaction is proportional to the number of trucks, and inversely proportional to the transportation cost, that is, the time required for completion of the delivery.

Table 3. Performance comparison among IoT-MTDPS and traditional VRP

| | | **IoT-MTDPS** | | | **MTVRP** | | |
|---|---|---|---|---|---|---|---|
| | | N | Average | Best | N | Average | Best |
| S1 | 5,000 | 4137 | 179.13 | 163.45 | 3892 | 179.61 | 171.12 |
| | 10,000 | 4877 | 181.33 | 165.14 | 3995 | 173.32 | 162.74 |
| | 20,000 | 4635 | 168.45 | 164.39 | 3761 | 176.28 | 165.82 |
| Average: | | | 176.30 | 164.33 | | 176.403 | 166.56 |
| S2 | 5,000 | 5000 | 325.13 | 316.84 | 4885 | 301.21 | 291.63 |
| | 10,000 | 9327 | 298.67 | 283.15 | 6339 | 299.14 | 294.11 |
| | 20,000 | 10102 | 298.61 | 292.48 | 7005 | 302.62 | 293.68 |
| Average: | | | 307.47 | 297.49 | | 300.99 | 293.14 |
| S3 | 5,000 | 5000 | 432.18 | 412.32 | 5000 | 410.36 | 396.5 |
| | 10,000 | 10000 | 400.48 | 386.72 | 9764 | 383.68 | 352.43 |
| | 20,000 | 15634 | 356.83 | 341.63 | 10568 | 360.18 | 343.32 |
| Average: | | | 396.50 | 380.22 | | 394.74 | 364.08 |

Remark: S1: Scenario 1 with 10 customers; S2: Scenario 2 with 25 customers; S3: Scenario 3 with 50 customers

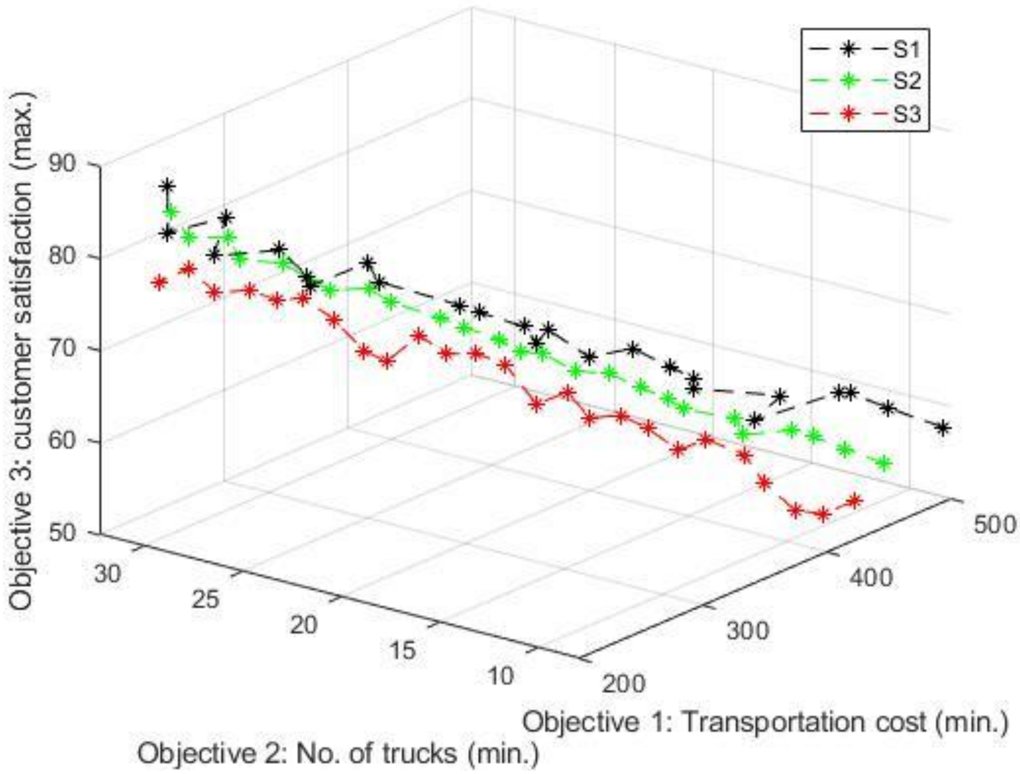

Figure 9. Pareto-optimal solution set by the articulation of user preferences

*5.2 Sensitivity Analysis for 2PMGAO*

To validate the parameter configuration of 2PMGAO, a sensitivity analysis is conducted to investigate its performance and effectiveness using the Taguchi experimental design. The analysis is performed for different values of crossover rate ($R_c$ = 0.4/0.6/0.8), mutation rate ($R_m$ = 0.05/0.1/0.15), and population size ($S_p$ = 100/250/500). By using a traditional experimental design (Srinivas et al., 2014), the entire analysis requires $3^3 = 27$ experiments to fully investigate the differences and changes, and it is not easy to compare the findings. To conduct the sensitivity analysis in a systemic manner, the Taguchi method is applied, which requires only nine experiments (L9 Taguchi array), to select the best parameter configuration. Conforming to the optimization process, the 'smaller-is-better' quality characteristics are selected to measure the iteration for the optimal results obtained from 2PMGAO. Table 4 shows the Taguchi experimental design and findings for parameter configuration of 2PMGAO in the case study scenario. After conducting the Taguchi analysis, the signal-to-noise ratio (S/N) between parameters and their levels are obtained, as shown in Figure 10. The best parameter configuration of 2PMGAO is crossover rate of 0.6 (S/N: −72.59), mutation rate of 0.10 (S/N: −66.12), and population size of 500 (S/N: −73.28). Therefore, the parameter configuration in the case study outperforms the other configurations, in which the solution quality and efficiency of optimization process can be guaranteed.

Table 4. Taguchi experimental design for parameter configuration

| Crossover rate ($R_c$) | Mutation rate ($R_m$) | Population size ($S_p$) | Iteration for optimal result |
|---|---|---|---|
| 0.4 | 0.05 | 100 | 13862 |
| 0.4 | 0.10 | 250 | 3546 |
| 0.4 | 0.15 | 500 | 26705 |
| 0.6 | 0.05 | 250 | 5137 |
| 0.6 | 0.10 | 500 | 980 |
| 0.6 | 0.15 | 100 | 15375 |
| 0.8 | 0.05 | 500 | 3756 |
| 0.8 | 0.10 | 100 | 2380 |
| 0.8 | 0.15 | 250 | 13558 |

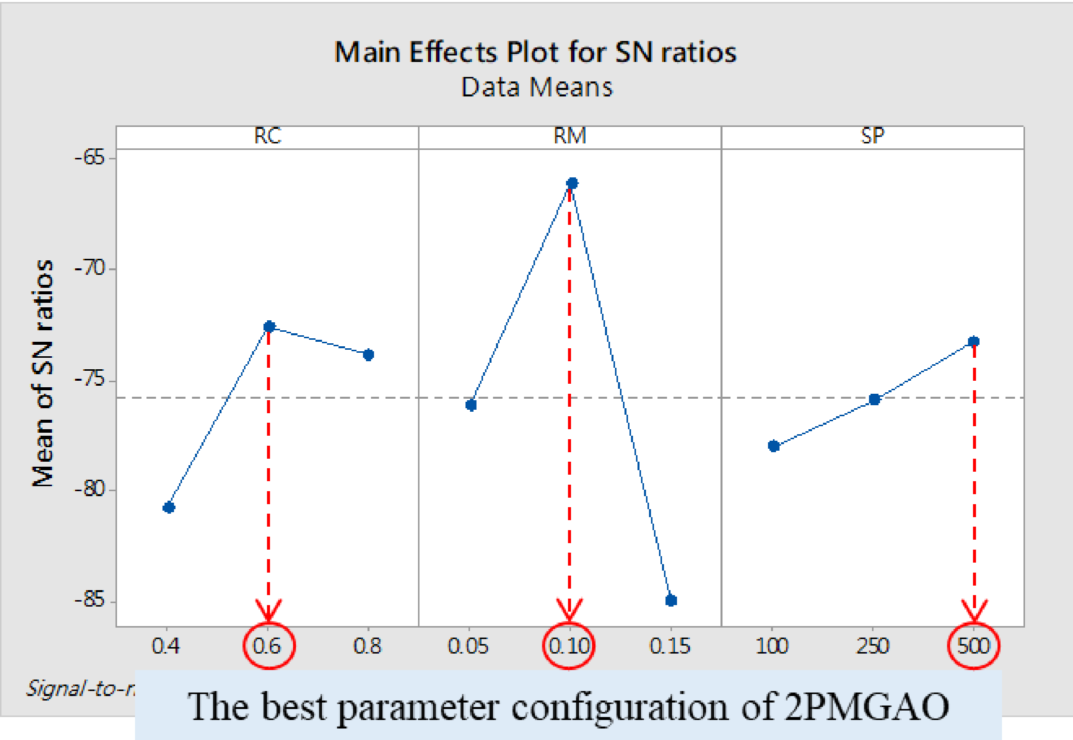


Figure 10. Signal-to-noise ratios of sensitivity analysis

*5.3 Comparison with the Existing Studies*

In this section, the proposed system is compared with other existing work to demonstrate its advantages for multi-temperature last-mile delivery in perishable food e-commerce logistics. Existing work that applies the approaches of IoT and multi-objective optimization are chosen for comparison and are summarized in Table 5.

*(i) Comparing IoT-MTDPS with IoT approaches*

IoT is a promising method in the collection of real-time information from physical objects to the digital world, and more and more research studies have revealed the framework and deployment of IoT technologies. To compare the proposed system, the studies of Ruan and Shi (2016) and Liu et al. (2019) are selected in which IoT approaches in assisting e-commerce delivery and logistics management were developed. The recent research studies lack sufficient consideration of the multi-temperature characteristics of food products during the distribution process, and the data collection processes are not structured by the modern IoT frameworks. Therefore, the proposed work in this study explores the multi-temperature characteristics at a product-dependent parcel level, which matches operational concerns in the business-to-customer (B2C) e-order fulfilment process. Also, the IoT implementation in this study follows the modern structure of SOA showing the data transmission, selection of IoT devices, and PaaS platform in a systematic manner. Liu et al. (2019) also stressed that the use of IoT technologies can facilitate route planning with additional dynamic capability. Such a consideration is also included in the proposed work, covering unexpected incidents during the delivery process additionally. This study, with an in-depth case study, brings the academic and practical values from the existing approaches to benefit the research and operations of perishable food e-commerce logistics in the data collection and acquisition of using IoT technologies.

*(ii) Comparing IoT-MTDPS with multi-objective optimization approaches*

To control multiple essential factors in the route planning, multi-objective optimization is needed to consider a number of objective functions in the optimization process. The studies of Guo et al. (2017) and Chan et al. (2020), which provide robust route planning for handling perishable food, are selected for the comparison. Several existing routing models for multi-objective optimization consider cost, food quality, sustainability, but the multi-temperature characteristics are still under-researched in recent years. To cope with the nature of perishable food e-commerce logistics, the multi-temperature characteristics using cold chain packaging are embedded in the delivery planning to assure the process of meeting environmental requirements. Also, the importance of effective data collection and case study to examine the model performance is illustrated, and this is regarded as the trend in the modern research studies to be theoretically and practically feasible. Moreover, this study proposes the 2PMGAO to determine static and dynamic routing to enhance the practicality and adaptability in the complex scenarios. Therefore, the proposed work on multi-objective optimization is not only catching up with the modern trends, but also including the novel elements to enrich the delivery planning.

Table 5. Comparison of IoT-MTDPS with other existing work

| | | **IoT approaches** | | **Multi-objective optimization approaches** | |
|---|---|---|---|---|---|
| | **IoT-MTDPS** | Ruan and Shi (2016) | Liu et al. (2019) | Guo et al. (2017) | Chan et al. (2020) |
| Objectives | To formulate a systematic approach to facilitate multi-temperature last-mile delivery in e-commerce logistics | To monitor and assess fruit freshness in e-commerce delivery | To enable dynamic optimization strategy by considering real-time information for smart vehicles and logistics tasks | To formulate a route planning model for fresh food e-commerce logistics | To develop a production inventory routing planning for perishable food logistics |
| Methods | IoT, GA for multi-objective optimization, fuzzy logic | IoT, scenario analysis | IoT, single objective optimization | GA and PSO for multi-objective optimization | Modified PSO for multi-objective optimization |
| Multi-temperature feature | Product-dependent parcel-level | Fruit-dependent | No | No | No |
| Routing support and dynamicity | Yes, static and dynamic routing | No | Yes, static and dynamic | Yes, static | Yes, static |
| Structured data collection | SOA for IoT implementation | General IoT framework | Self-proposing data collection model | No | Provision from the case company |
| Case study | Yes | No | Yes | No | Yes |

## 6. Discussion

To summarize the value and implications from this study, this section includes discussion on (i) academic implications, (ii) managerial and operational implications, (iii) contribution and novelty, (iv) limitation of this study, and (v) future work.

### *6.1 Academic Implications*

This study proposes a new paradigm of MTJD-based perishable food e-commerce logistics to address the research gap in e-commerce logistics. In the past, a number of research studies were conducted on distribution planning in the perishable food supply chain, using cold chain equipment, such as refrigerated trucks and temperature monitoring. However, orders in the perishable food e-commerce are fragmented, small in order volume, and high in SKU variety, so that adoption of typical refrigeration systems during delivery is ineffective to meet all food products' requirements. Subsequently, the MTJD was proposed to manage product-dependent monitoring requirements during the distribution, which can be further extended to the business of perishable food e-commerce in this manuscript. Therefore, the product-dependent multi-temperature characteristics should be explored to support the formulation of delivery routes, in order to fulfil customers' requirements on food quality. Through this study, the research gap in perishable food e-commerce logistics has been filled by integrating the MJTD to consider the product-dependent multi-temperature characteristics. Research on the distribution and delivery planning of the perishable food supply chain in e-commerce logistics can be completed with the addition of this study, and thus the food quality and temperature requirements can be considered throughout the entire supply chain. The consideration of using general trucks, active containers, refrigerated trucks, multi-temperature trucks, and multi-temperature last-mile delivery can be integrated as a whole in perishable food e-commerce logistics. Moreover, the MTJD-empowered perishable food e-commerce logistics opens a novel research domain to satisfy environmental requirements for food, such as temperature, relative humidity, level of carbon dioxide, in various logistics and supply chain models. The synergy of adopting different cold chain equipment in supply chain management can be obtained, which can derive the corresponding logistics and supply chain models. The studies on the enhancement of storage and transportation effectiveness in the food supply chain can be further established. Last, but not least, the study provides a case study of MTJD-based perishable food e-commerce, which is a valuable reference for system deployment and implementation by means of emerging technologies.

### *6.2 Managerial and Operational Implications*

With the help of IoT-MTDPS, it is found that the delivery route planning process can be done automatically by considering not only travelling time or distance, but also truck utilization and customer satisfaction. Customer satisfaction is measured through two components, namely service time window and maximum transportation duration of the cold chain packaging. This is particularly important and meaningful in managing perishable food e-commerce logistics due to the high transaction volume, fragmented orders, and high environmental sensitivity. Differing from the traditional logistics process, the companies need to pay more attention to handling the occurrence of unexpected events, such as food spoilage, order cancelations, and urgent order creation. The proposed system provides flexibility for re-optimizing the delivery routes once unexpected incidents occur. Therefore, the effectiveness and efficiency of handling the e-commerce orders can be enhanced. Since the numbers of customers for e-commerce logistics have been rapidly growing in recent years, maintaining good service quality on transportation and product quality assurance during delivery are two major challenging tasks for most LSPs. Poor transportation performance may cause damage to a company's reputation, or even loss of the customers' confidence in the logistics services. In LSPs, the most time-consuming task is to determine the delivery routes based on the pre-alert information. Therefore, most companies are willing to invest in transportation management systems with delivery route planning, but existing systems are designed for handling general road transportation in the freight forwarding industry, rather than handling e-commerce logistics and perishable food. By using IoT-MTDPS, companies can take advantage of automatically determining the delivery routes, real-time updating of the delivery routes for special cases, and the total monitoring of the trucks. On the other hand, end consumers can also enjoy the benefits of order management and a high transparency in the delivery process. They can not only check the logistics information, which is a milestone in showing the real-time delivery status, but also can visualize the real-time truck location and their delivery sequence. Therefore, material and information flow in perishable food e-commerce can be effectively managed and smoothed, while customer satisfaction can also be enhanced.

### *6.3 Contribution and Novelty*

The contribution and novelty of this study have three facets. First and foremost, this paper addresses an important research and industrial problem of last-mile delivery in the perishable food e-commerce logistics environment. A new paradigm of MTJD-based perishable food e-commerce logistics is introduced, which is shifted from the generic food supply chain. In the e-commerce logistics environment, the B2C order fulfilment for food products must handle time-critical and temperature-sensitive delivery. The effective systematic approach by integrating IoT, artificial intelligence, and multi-objective optimization is therefore formulated in this study to address the needs in the industry and fulfil the need for further research in this area.

Second, the delivery planning in this study simultaneously considers multi-temperature characteristics, food quality, and customer satisfaction, together with essential factors in VRP, including travelling cost, time window, and flow conversion. Specific to the multi-temperature characteristics, the parcel-level temperature control through the use of passive cold chain packaging is explored for the formulation of delivery planning in the area of perishable food e-commerce logistics.

Third, this paper proposes an IoT-based system architecture and 2PMGAO to integrate IoT technology and optimization of distribution paths in a systematic manner. The real-time information collected by IoT technology, including location and environmental monitoring, can be effectively managed and adopted for the formulation of delivery routes. The GA-based multi-objective optimization with MTJD embedded is used to determine the nearly optimal solutions for vehicle routing. For the sake of coping with unexpected incidents during delivery, a dynamic routing mechanism is also presented in this study to reduce the negative impact from the incidents and to maintain the desired level of customer satisfaction.

Other than the case presented in this study, the proposed work can potentially contribute to other application areas for handling temperature-sensitive and perishable products, for example, pharmaceuticals, life science items, and floral products. The above application areas require consideration not only of fulfilment of time-critical orders, but also assurance of product quality and satisfaction of handling requirements during storage and transportation.

## 7. Conclusions

This study combines the ontology of multi-temperature joint distribution and e-commerce logistics to design and develop an adaptive approach for managing perishable food e-commerce logistics effectively. In this paper, a dynamic multi-temperature transportation management system (IoT-MTDPS), which integrates Internet of Things (IoT) technologies, multi-objective optimization, and fuzzy logic, is presented. The use of IoT technologies enables the real-time tracking of the trucks and automatic data acquisition for optimizing the delivery schedule. In addition, it is also an important source of information in identifying the occurrence of unexpected incidents. To address the needs in perishable food e-commerce, a novel factor, namely product-dependent multi-temperature characteristics, is included in the delivery planning. The 2PMGAO is then developed to solve the multi-objective optimization problem in both a static and dynamic manner. The static routing can be formulated for the transportation team before delivery, while the dynamic routing can be established when unexpected incidents are reported and the fuzzy logic is activated. Generally, the transportation team will follow the predetermined delivery schedule to distribute the e-commerce orders. When meeting unexpected incidents, the proposed system also has a mechanism to re-optimize the delivery schedule by automatically adjusting the parameters in multi-objective optimization by using the fuzzy logic approach. Therefore, the proposed system can alleviate the workload for the routine operation of the transportation team and increase the visibility of the delivery process to the end customers. The formulation of the delivery schedule and transportation management are more efficient and flexible so as to cater to the demands in e-commerce logistics. As this study is confined to the perishable food e-commerce logistics, it is further recommended that the proposed methodology can be utilized in future research in the supply chain of managing temperature-sensitive and perishable products. Using the methodology in this manner would be a crucial step towards the development of a theory for designing a multi-temperature joint supply chain in the aspects of storage and transportation.

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