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Monitoring and assessing fruit freshness in IOT-based e-commerce delivery using scenario analysis and interval number approaches

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ABSTRACT

We are concerned with the monitoring and assessment of in-transit fruit freshness in e-commerce deliveries. After comparing the fulfillment processes of fresh fruit transportation in traditional retailing and e-retailing, we formulate an Internet of Things–based framework for monitoring fruit e-commerce deliveries. Based on the fulfillment operations and monitoring modules of the framework, we propose an approach based on a two-stage scenario for assessing the freshness of in-transit fruits. In the first stage, we use a learning-by-doing mechanism to develop a scenario construction method to automatically obtain the most appropriate delivery environment and the occurrence probability for each scenario. In the second stage, we integrate the interval comparison technique into the scenario analysis method to address the freshness assessment of in-transit fruits. The effectiveness and advantages of our approach are verified using numerical simulations.

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1. Introduction

With the development of e-commerce and advanced information technologies, retailing has experienced a revolution. Currently, e-retailing has advantages over traditional retailing in many areas, such as books, music, clothing and electrical appliances. However, fresh produce presents many challenges for e-retailing due to characteristics such as perishability and high-cost logistics, especially in developing countries [3,17]. Recently, the Chinese government and e-commerce giants have tried to break into fresh produce e-retailing. One of the difficulties encountered is determining how to monitor and control the freshness of in-transit fresh produce [12]. Obviously, these tasks are especially difficult without help from advanced information technologies [16,20,30]. In an empirical study, Shin and Eksioglu [32] observed that the application of radio frequency identification devices (RFIDs) considerably improves labor productivity in U.S. retail supply chains.

In the literature, some recent studies have applied related information technologies to the monitoring and control of in-transit fresh produce, presenting specific solutions. For example, Ruiz-Garcia et al. [28] applied ZigBee-based wireless sensors to the monitoring of fruit logistics, analyzed the battery life of the sensors, and evaluated the reliability of the whole system. Abad et al. [1] presented a monitoring system consisting of a smart RFID tag subsystem located in the delivery trucks and a commercial reader/writer subsystem located in the delivery nodes, reporting advantages of this system in an intercontinental

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fresh fish supply chain. Kang et al. [11] presented a simulation method to assess the performance of optimization models and to determine the key parameter values in a RFID sensor–based cold transportation system, while Mainetti et al. [18] applied radio frequency technologies and EPCglobal standards to develop a traceable system of fresh vegetable products. Mejjaoulia and Babiceanu [19] presented an integrated RFID sensor network system for optimizing the transportation of perishable products, indicating that the system was helpful for reducing operation costs. Xiao et al. [40] argued that heavy sensory data needs in traditional monitoring systems reduced data transmission efficiency; thus, they integrated a wireless sensor network (WSN) with compressed sending (CS) to develop a temperature monitoring system for frozen and chilled aquatic products. Finally, Trebar et al. [37] used RFID sensors to monitor the temperatures of styrofoam boxes during the transport of fresh fish and proposed a time- and energy-saving method for packing fish.

The above studies have made specific contributions to the monitoring and control of fresh produce by applying advanced information technologies and providing practical support for the transportation of fresh produce. However, most studies have focused on conventional supply chains, paying little attention to the e-commerce delivery of fresh produce. In e-retailing, the delivery of fresh produce is quite different from traditional transportation, which creates new challenges [13]. Meanwhile, different kinds of fresh produce have specific characteristics in e-fulfillment [16]. Motivated by these observations, in this work, we are concerned with the monitoring of fresh fruit in e-commerce deliveries.

Monitoring and control systems aim to maintain the freshness of perishable products while in transit. However, loss of freshness may result at any point during the e-fulfillment process of fresh fruit orders. Thus, real-time assessment of these products is key to controlling their freshness. The e-fulfillment of fruit orders often involves multiple participants conducting their respective delivery services [25]. The complexity of and uncertainty in this process make monitoring and assessing of the freshness of in-transit fruits difficult. Scenario analysis is an effective method for analyzing complex uncertainty by considering both possible events and their occurrence probabilities [5,8,15]. As mentioned above, the e-fulfillment of fresh fruit orders involves multiple operation links and service participants, creating a process that is full of uncertainty. The freshness of in-transit fruits will vary in different fulfillment situations. Thus, scenario analysis is suitable for recognizing different e-fulfillment situations for fruit orders.

Similarly, it is increasingly popular to develop models using fuzzy or interval information in the literature due to uncertainty [14,31,34,35]. The data, such as temperature and humidity information, produced by fruit monitoring sensors are often interval values. Classic scenario analyses cannot be directly used to address these interval data in each possible scenario. Fortunately, a body of literature addresses interval comparison methods [4,45,47]. The integration of interval comparison methods into classic scenario analysis may provide feasible solutions for assessing the freshness of in-transit fruits in different interval situations.

Motivated by the above observations, in this work, we present an Internet of Things (IOT)-based framework for monitoring fruit e-commerce delivery. We use scenario analysis methods to construct delivery scenarios in the e-fulfillment of fruit orders to provide corresponding assessments of freshness at each step in the delivery process. Meanwhile, based on the characteristics of the sensor data, we integrate interval comparison into the scenario-based freshness assessment approach.

To sum up, in this work, we make the following contributions:

(i) We compare fresh fruit transportation in traditional retailing and e-retailing and present an IOT-based framework for monitoring fruit e-commerce deliveries. Detailed descriptions of fruit e-fulfillment operations, as well as of the modules in the IOT-based monitoring framework, provide a basis for developing a scenario-based approach to assessing in-transit fruit freshness.
(ii) We divide the freshness assessment scenario into a scenario construction stage and a freshness assessment stage. We then use a learning-by-doing mechanism to develop a scenario construction method that can automatically obtain both the most suitable environment for each scenario and the occurrence probability of each scenario from practical delivery operations.
(iii) We integrate interval comparison techniques into scenario analysis methods to assess the freshness of in-transit fruits. This integrated approach assesses freshness by comparing the similarity of the sensing environment to the most suitable environment for each scenario.

The remainder of this paper is organized as follows. Section 2 presents an IOT-based framework for monitoring fruit e-commerce deliveries, providing the basis for the scenario analysis portion of the freshness assessment. In Section 3, we propose a scenario-based approach for assessing the freshness of in-transit fruits, which is divided into a scenario construction stage and a freshness assessment stage. Section 4 presents the experimental results showing the effectiveness and advantages of our contributions. Section 5 concludes the work and provides recommendations for future study.

2. An IOT-based framework for monitoring fruit e-commerce delivery

2.1. Fruit e-commerce delivery

In traditional commerce, fresh fruits are often sold to end consumers through multiple intermediaries, such as wholesalers, distributors and retailers, as Fig. 1 shows. In the traditional retailing channel, fresh fruits are first picked on farms and then transported to local processing centers (LPCs) where fruits are washed, cooled, packaged, and so on. Then, the processed fruits are often purchased by wholesalers who will either store the fruits in their warehouses or directly transport

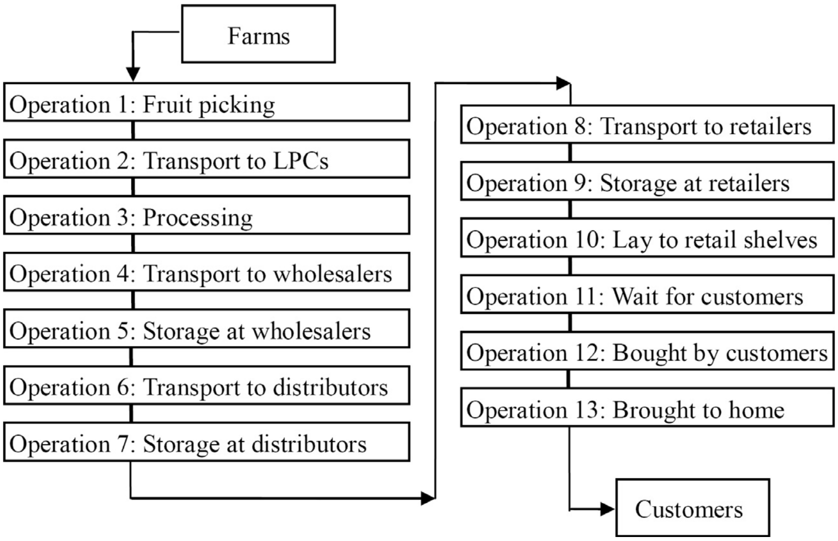


Fig. 1. Traditional fruit commerce delivery.

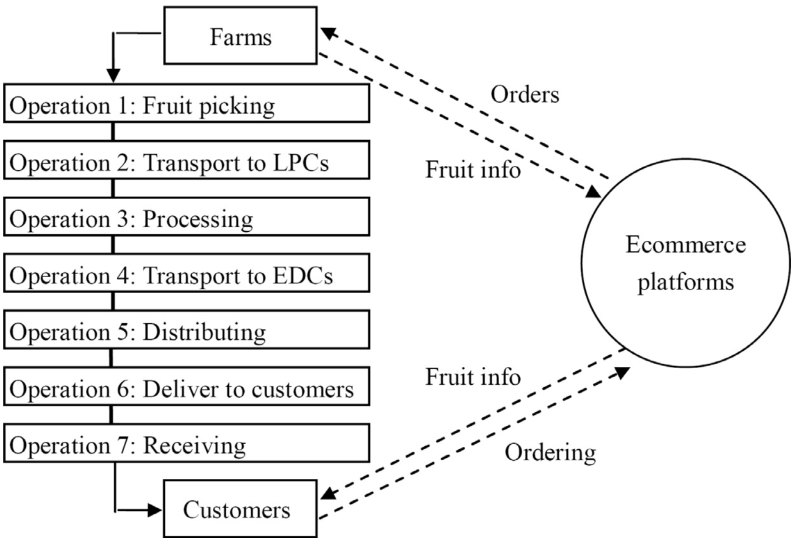


Fig. 2. Farm-to-table fruit e-commerce delivery.

them to their distributors. After receiving the fruits, distributors in consumption areas often deliver fruits to their respective retailers. Finally, these retail-ready fruits have to be stocked on retailers' shelves until customers come into the stores and buy them.

Due to the complicated process of moving produce from farmers to retailers illustrated above, it often takes a long time and high costs before retailers can stock fruits on their shelves for end consumers to buy. In order to maintain freshness, fruits are often transported in cold chain systems, although a large proportion of fruits will spoil during transport and be thrown away regardless [44]. As a result, fresh fruits often have relatively high retail prices. However, e-commerce is changing this picture.

Having reshaped common product retailing, e-commerce is shifting to live and fresh products. In fruit e-commerce, the long traditional supply chain from farm to end customer shown in Fig. 1 is often greatly shortened. One typical fruit type of e-retailing is "farm-to-table" commerce [43]. Fig. 2 shows the basic process involved in farm-to-table fruit e-commerce (at end distribution centers (EDCs), fruits are transited from the trunk transport to the last mile delivery): farms post fruit supply information on e-commerce platforms when, or even before, the fruits ripen; customers submit orders to farms through e-commerce platforms; finally, farms pick the fruits based on the orders they receive and deliver them to the appropriate end customers.

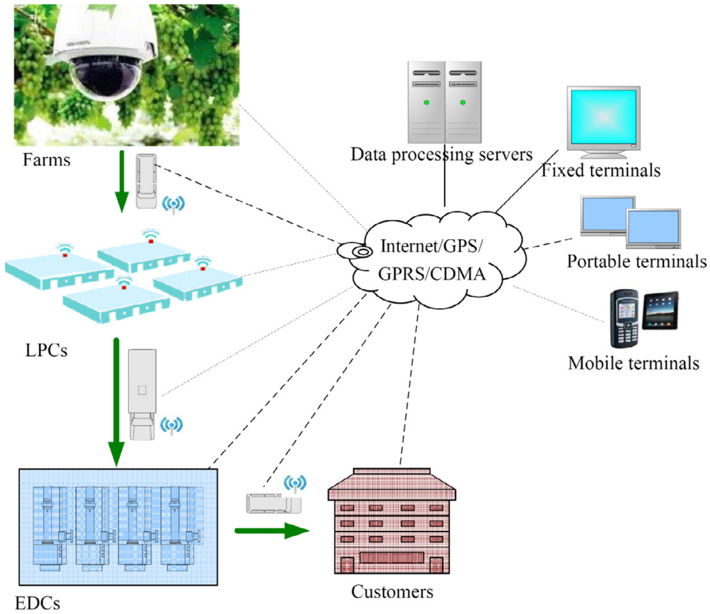


Fig. 3. IOT-based monitoring framework of fruit e-commerce delivery.

Compared with traditional fruit retailing, the farm-to-table fruit e-commerce described in in Fig. 2 has some of the following specific advantages:

(1) Online farms can sell their fruits before picking them. In the traditional business model, farms have to pick their fruits and transport them to retailers through multiple intermediaries before customers select from among the fruits on the retailers' shelves. Obviously, the retailing time is much longer in the e-commerce model.
(2) Fruits are directly delivered from the farms to the end customers. Thus, fruit retailing is changing from "push" to "pull" modes with the introduction of e-commerce. In the "pull" mode, the flow of fruits is directed, which often greatly improves freshness and reduces costs.
(3) The number of intermediate links is greatly reduced. As Fig. 2 shows, farm-to-table fruit e-commerce delivery generally consists of seven operations—nearly one-half of the number of delivery links as in traditional fruit commerce delivery, as shown in Fig. 1. This change not only shortens transportation times but also reduces costs.
(4) Due to directed transportation and fewer intermediaries, it is also easier to track the supply chain in fruit e-commerce, which is helpful when addressing fruit safety concerns.

However, fruit e-commerce inevitably encounters some challenges during the fulfillment of online orders. One prominent issue is monitoring and controlling the freshness of multiple kinds of fruits in transit. This point is the key to fruit e-commerce success.

2.2. An IOT-based monitoring framework

Based on the farm-to-table fruit e-commerce delivery process shown in Fig. 2, we present a corresponding monitoring framework using IOT-related technologies, such as global position systems (GPS), RFID sensor tagging, wireless sensor networks, mobile communication networks (e.g., GRPS/CDMA) and the Internet, as indicated in Fig. 3.

This framework consists of eight main modules. Each module has a specific role and is equipped with corresponding IOT-related technologies.

(1) Farm module. With the wide application of advanced information and control technologies on farms, extensive contributions have been made to intelligent farming (i.e., precision agriculture). For details, the readers are referred to the extant works [6,10,33]. In our framework, the farm module could collect environment data on farms using equipment such as temperature sensors, humidity sensors, photosensitive sensors, CO_2 sensors, soil sensors and cameras. The sensor information collected in this module is transferred to data processing servers and stored in the servers.
(2) Vehicle module. The vehicle module is used to physically connect the farm, LPC, EDC and customer modules. Vehicles are equipped with cooling and sensing subsystems. The objective of the cooling subsystem is to maintain the vehicle environment within the most suitable conditions for maintaining the freshness of in-transit fruits. The sensing subsystem is a precondition for controlling the vehicle environment. In our framework, the sensing subsystem is part of a common RFID sensor-based system [11,19,46].

(3) LPC module. After being picked on farms, fruits are transported to LCPs. As mentioned above, fresh fruit processing includes washing, cooling, and packaging in the LPC module. Another key operation in the LPC module is the tagging of RFID sensors to fruits. Information written in the RFID sensors might include places of origin, growth conditions, processing procedures, transport service providers, designated EDCs, and end customers. Using this information, fruit orders can be smoothly transported from LPCs to customers.
(4) EDC module. In this module, fruits are collected from various LPCs and distributed to their corresponding customer areas. A specific EDC often receives fruit orders from various farms, and a specific transport vehicle often visits multiple EDCs at which fruits need to be transferred from large transport trucks to medium-sized or small vehicles. Traditional manual sorting at EDCs is often time consuming. In our framework, RFID readers, which can automatically recognize and sort tagged fruits into batches, are used in the EDC module to reduce the time needed to transfer fruit orders at EDCs.
(5) Customer module. Currently, there are three main receiving modes: home delivery, intelligent reception, and third-party receiving [2,9,24,39]. In the home delivery mode, fruit orders are delivered directly to customers. This mode is currently the most common mode. In intelligent reception, fruit orders are delivered to boxes that are equipped with cooling and messaging systems, and customers receive text message alerts as soon as their fruit orders are placed into the reception boxes. In the third-party receiving mode, fruit orders are delivered to third parties, such as community service centers and local retail stores.
(6) Communication module. The communication module consists of various subsystems, such as local area networks, wireless sensor networks, GPS, mobile communication networks and the Internet. This module connects all related parties, including farms, transport service providers, LPCs, EDCs and customers, and almost all the information is disseminated via the communication module.
(7) Server module. The server module is the heart of the information processing framework. The data are stored and processed by data processing servers, which can be either centralized or decentralized [41]. The key role of this module is to assess the freshness of the monitored fruits and send timely operation commands. Thus, the accuracy of freshness assessment is very important to the overall framework [38]. In the following section, we will provide specific solutions to this problem.
(8) Terminal module. All information and operation commands for the in-transit fruits should be accessible at any time and place through various terminals, such as fixed, portable and mobile terminals. These terminals can be used by farms, transporters, LPCs, EDCs, and customers.

3. A scenario-based approach for assessing the freshness of in-transit fruits

As mentioned in the Introduction, scenario analysis is a prediction and assessment technique for analyzing both the possible events and the occurrence probability of each event. This technique has been widely used for complicated decision-making issues. Although fresh fruit e-retailing is significantly simpler than traditional fruit retailing, uncertainties remain, and loss of freshness will differ based on the operations and environments of the e-fulfillment process. Thus, in this work, we analyze scenarios for assessing the freshness of in-transit fruits and then develop a two-stage scenario-based assessment approach.

3.1. Scenario analysis of freshness assessment

Determining how to represent scenarios is a precondition of scenario analysis. As we can see in Fig. 2, fruit e-commerce delivery consists of multiple operations implemented in the corresponding environment, and each operation often has an impact on the total delivery time. In addition, different kinds of fruits often have different shelf lives. We thus present a scenario representation method for assessing the freshness of in-transit fruits along four dimensions:

$$S = \{(F, O, E, T)\} \tag{1}$$

where S represents the scenario consisting of four dimensions for which fruit freshness is assessed: Fruit (F), Operation (O), Environment (E) and Time (T). Each dimension has specific effects on the freshness of in-transit fruits, as detailed in the following.

F represents the characteristics of fruits. For example, fruits have specific attributes, such as perishability and pressure resistance. These attributes directly impact their shelf lives in both refrigerated and conventional environments. In this work, we divide fruits into eight categories based on their characteristics, as shown in Table 1.

We can also express fruit categories using the following set form:

$$F = \{(ResiT, ResiH, ResiP)\} \tag{2}$$

where $ResiT = \{good, bad\}$ represents resistance to temperature, $ResiH = \{good, bad\}$ represents resistance to humidity, and $ResiP = \{good, bad\}$ represents resistance to pressure. Obviously, F includes 8 (2^3) fruit categories, that is, $F = \{F_i, 1, 2, ..., 8\}$.

O indicates the current module of the in-transit fruits. As analyzed in Section 2.2, the delivery of fruit orders consists of eight main operations that affect the freshness of in-transit fruits. For example, the same fruit will have a different shelf life

Table 1
Fruit categories based on their characteristics.

Resistance to temperature	Resistance to humidity	Resistance to pressure	Categories
Good	Bad	Bad	F_1
		Good	F_2
	Good	Bad	F_3
		Good	F_4
Bad	Good	Good	F_5
		Bad	F_6
	Bad	Good	F_7
		Bad	F_8

depending on its maturity when it is picked. Unripe fruits often have longer shelf lives than ripe ones. Other operations are affected by whether they occur in a cooling environment. We express the detailed operating situations as follows:

$$O = \{(Oper1, Oper2, Oper3, Oper4, Oper5, Oper6, Oper7)\} \tag{3}$$

where $Oper1 = \{unripe, ripe\}$ represents the maturity of the fruits when they are picked, $Oper2 = \{cooling, non-cooling\}$ represents whether Operation 2 (i.e., Transport to LPCs) in Fig. 2 occurs in a cooling environment, and $Oper3 \sim Oper7$ have the same meaning as $Oper2$. As we can see, O includes 128 (2^7) operating situations, that is, $O = \{O_j, j = 1, 2, ..., 128\}$.

E represents the environment in which in-transit fruits are kept. Deterioration mainly results from the actions of enzymes in the fruits, and temperature and humidity directly impact the activation of these enzymes [12]. Meanwhile, pressure also impacts the loss of freshness, especially for fragile or ripe fruits. Thus, there are often ideal temperature, humidity and pressure ranges for maintaining the shelf life of a given kind of fruit. We express the environment situation as:

$$E = \{(Temp, Humi, Pres)\} \tag{4}$$

where $Temp$, $Humi$ and $Pres$ represent the temperature, humidity and pressure, respectively, in the environment. In this work, we categorize these environmental factors as good and bad. Thus, E also includes 8 (2^3) environment situations, that is, $E = \{E_k, k = 1, 2, ..., 8\}$.

T represents the time needed for each operation. The same fruits in the same operation and environment situation may lose their freshness at different rates if operations take varying amounts of time. Generally, the longer the operation time, the more freshness is lost in transit. Based on the fruit e-commerce delivery process described in Fig. 2, we express the time situation using the following set:

$$T = \{(Time1, Time2, Time3, Time4, Time5, Time6, Time7)\} \tag{5}$$

where $Time1 \sim Time7$ represent the time needed for each operation. For convenience, we express time using two levels, long and short, that is, $Time1 = \{long, short\}$. Other time situations are also described. Thus, T includes 128 (2^7) time situations, that is, $T = \{T_l, l = 1, 2, ..., 128\}$.

To sum up, the freshness of in-transit fruits will depend on the scenario. Although we express the four dimensions of each scenario using simple levels, there are still up to 2^{20} ($2^3 \times 2^7 \times 2^3 \times 2^7$) scenarios. Thus, it is not feasible to conduct a freshness assessment of in-transit fruits conditional on delivery service providers knowing all the scenarios. Additionally, the translation of a practical status into the corresponding levels is not easy due to the uncertainty in real-world situations. Based on these observations, we divide scenario-based freshness assessment into two stages: scenario construction and freshness assessment. In the following subsections, we detail each stage.

3.2. Stage I: scenario construction

In the scenario construction stage (shown in Fig. 4), we consider the Fruit (F) and Operation (O) situations. According to the addition principle in probability theory, we obtain the following formulas:

$$\sum_{i=1}^{8} p(F_i) = 1 \tag{6}$$

$$\sum_{j=1}^{128} p(O_j/i) = 1 \quad \forall i = 1, 2, ..., 8 \tag{7}$$

where $p(F_i)$ represents the probability of $F_i, i = 1, 2, ..., 8$, O_j/i represents the jth O situation under the ith F situation, and $p(O_j/i)$ represents the conditional probability of O_j, $j = 1, 2, ..., 128$ under F_i, $\forall i = 1, 2, ..., 8$.

The aim of the scenario construction stage is to determine the most suitable Environment (E) and the probabilities of the $2^{10}(2^3 \times 2^7)$ scenarios, that is, to determine $E_{best/j/i} = \{Temp_{best/j/i}, Humi_{best/j/i}, Pres_{best/j/i}\}$, $p(F_i)$ and $p(O_j/i)$.

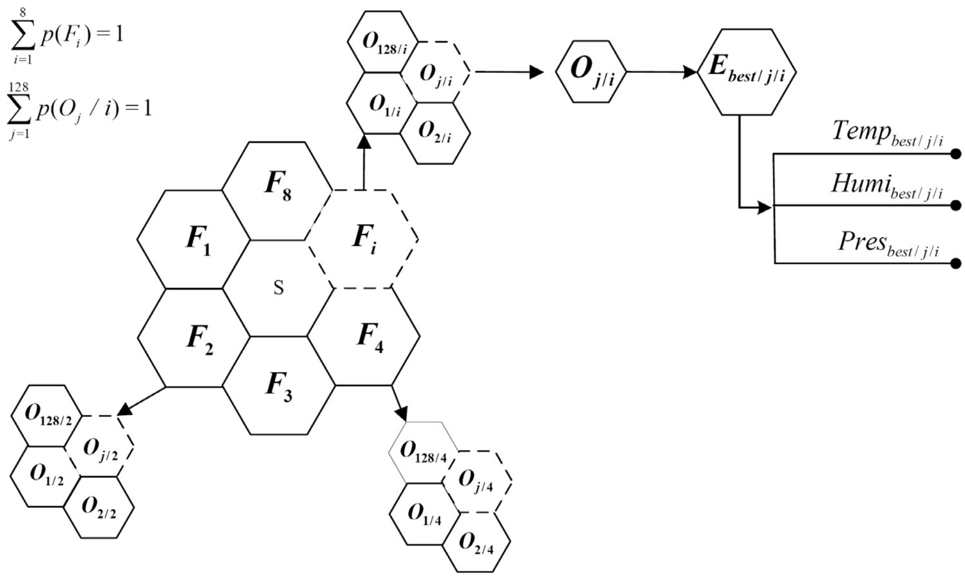


Fig. 4. Scenario construction stage.

In this stage, we use the learning-by-doing mechanism to obtain $p(F_i)$, $p(O_j/i)$ and $E_{best|j|i}$. In the IOT-based framework in Fig. 3, the detailed process for a given fruit e-commerce company is as follows:

Step 1: Initialization. Set $p(F_i) = 0$, $p(O_j/i) = 0$, and $E_{best/j/i} = \{0, 0, 0\}$, $i= 1, 2, ..., 8, j= 1, 2, ..., 128$. Use G_i^t and H_{ij}^t to record the occurrence frequency of F_i and O_j/i, respectively (where t is a counter, $G_i^0 = 0$, and $H_{ij}^0 = 0$). Use $Temp_{t|j|i}$, $Humi_{t|j|i}$ and $Pres_{t|j|i}$ to record the temperature, humidity and pressure at t, respectively. These variable values and the whole process are stored in the server module and are editable.

Step 2: After finishing a delivery, all the environment information is transmitted to the server module by the communication module, and $Temp_{t|j|i}$, $Humi_{t|j|i}$ and $Pres_{t|j|i}$ are recorded into the server module. Meanwhile, customers in the customer module evaluate whether the received fruits are fresh. If the evaluation indicates that the fruits are fresh, $t = t + 1$, go to Step 3; if not, ignore this delivery and proceed to Step 5.

Step 3: Decision-makers in the terminal module determine which of the 1024 scenarios the delivery belongs to, according to the fruit characteristics and operations that took place in the farm, vehicle, LPC, EDC and customer modules. Based on this judgement, update $G_i^t = G_i^{t-1} + 1$ and $H_{ij}^t = H_{ij}^{t-1} + 1$ if F_i and O_j/i occur; otherwise, keep $G_i^t = G_i^{t-1}$ and $H_{ij}^t = H_{ij}^{t-1}$.

Step 4: Update $p(F_i) = G_i^t / \sum_{i=1}^{8} G_i^t$ and $p(O_j/i) = H_{ij}^t / \sum_{i=1}^{8} \sum_{j=1}^{128} H_{ij}^t$ in the server module. If $H_{ij}^t \neq 0$, update $Temp_{best/j/i} = \sum_1^t Temp_{t/j/i} / H_{ij}^t$, $Humi_{best/j/i} = \sum_1^t Humi_{t/j/i} / H_{ij}^t$ and $Pres_{best/j/i} = \sum_1^t Pres_{t/j/i} / H_{ij}^t$ in the server module, Otherwise, update $Temp_{best/j/i} = 0$, $Humi_{best/j/i} = 0$ and $Pres_{best/j/i} = 0$ in the server module.

Step 5: If $G_i^t \neq 0, H_{ij}^t \neq 0, \forall i = 1, 2, ..., 8, j=1, 2, ..., 128$ or $t = Max_t$, go to Step 6. Otherwise, proceed to Step 2. Here, Max_t expresses the maximum learning time. As we can see, we use two stopping criteria. One is $G_i^t \neq 0, H_{ij}^t \neq 0, \forall i = 1, 2, ..., 8, j=1, 2, ..., 128$, which means that all the situations are traversed. The other is the maximum learning time.

Step 6: Termination. Store $p(F_i)$, $p(O_j/i)$ and $E_{best/j/i} = \{Temp_{best/j/i}, Humi_{best/j/i}, Pres_{best/j/i}\}$ in the server module as the rules for conducting fruit freshness assessment of future e-fulfillment orders.

Using the above learning-by-doing process, we could specify the 1024 scenarios automatically. Similarly, we could specify 2^{20} ($2^3 \times 2^7 \times 2^3 \times 2^7$) scenarios by considering the four situations in farm-to-table fruit e-commerce delivery and 2^{32} ($2^3 \times 2^{13} \times 2^3 \times 2^{13}$) scenarios in traditional fruit commerce delivery. We will use experimental simulations to compare the efficiency of the three scenario construction methods in Section 4.

3.3. Stage II: freshness assessment

In Stage I, we could use a learning-by-doing mechanism to determine the most suitable Environment (E), as well as the probabilities of the 2^{10} scenarios, that is, $E_{best/j/i} = \{Temp_{best/j/i}, Humi_{best/j/i}, Pres_{best/j/i}\}$, $p(F_i)$ and $p(O_j/i)$. Then, it is our final aim to assess the freshness of in-transit fruits by comparing the current situation with the scenarios constructed in Stage I. In this subsection, we will address the assessment issue.

As Kang et al. stated [11], there are two main sensing types: interval sensing and immediate sensing. In our IOT-based monitoring framework, we use the interval sensing method. Sensors located in the delivery environment send temperature, humidity and pressure information in a given interval. Here, we use three interval variables to represent the sensing environment:

$$E_{sensing/j/i} = \{\bar{T}emp_{sensing/j/i}, \bar{H}umi_{sensing/j/i}, \bar{P}res_{sensing/j/i}\} \tag{8}$$

$$\bar{T}emp_{sensing/j/i} = [Temp^{lower}_{sensing/j/i}, Temp^{upper}_{sensing/j/i}] \tag{9}$$

$$\bar{H}umi_{sensing/j/i} = [Humi^{lower}_{sensing/j/i}, Humi^{upper}_{sensing/j/i}] \tag{10}$$

$$\bar{P}res_{sensing/j/i} = [Pres^{lower}_{sensing/j/i}, Pres^{upper}_{sensing/j/i}] \tag{11}$$

where $\bar{T}emp_{sensing/j/i}$, $\bar{H}umi_{sensing/j/i}$ and $\bar{P}res_{sensing/j/i}$ are intervals representing the temperature, humidity and pressure, respectively, of situation O_j/i. $Temp^{lower}_{sensing/j/i}$, $Humi^{lower}_{sensing/j/i}$ and $Pres^{lower}_{sensing/j/i}$ are the lower bounds, while $Temp^{upper}_{sensing/j/i}$, $Humi^{upper}_{sensing/j/i}$ and $Pres^{upper}_{sensing/j/i}$ are the upper bounds. The widths of $\bar{T}emp_{sensing/j/i}$, $\bar{H}umi_{sensing/j/i}$ and $\bar{P}res_{sensing/j/i}$ are fixed due to the sensing settings.

As we can see, the closer the sensing environment $E_{sensing|j|i}$ is to the most suitable environment $E_{best|j|i}$, the fresher the fruits will be. To measure the proximity of $E_{sensing|j|i}$ to $E_{best|j|i}$, we should first determine how to compare $Temp_{best|j|i}$ and $\bar{T}emp_{sensing/j/i}$, $Humi_{best|j|i}$ and $\bar{H}umi_{sensing/j/i}$, and $Pres_{best|j|i}$ and $\bar{P}res_{sensing/j/i}$. That is, we should determine how to compare crisp and interval numbers.

Due to real-world uncertainty, interval and fuzzy numbers have been widely used in the literature [21–23,27,36,42]. Sengupta and Pal [29] proposed an interval comparison index, and Giove [7] extended it to an index for comparing crisp and interval numbers. Further, in our previous work, we have considered decision-maker optimism to develop a preference-based method for comparing crisp and interval numbers [26]. We showed the advantage of our method over those of Sengupta and Pal [29] and Giove [7]. In this work, we use our preference-based method to compare $Temp_{best|j|i}$ in $E_{best|j|i}$ (crisp) with $\bar{T}emp_{sensing/j/i}$ in $E_{sensing|j|i}$ (interval) as follows:

$$\delta(Temp_{best/j/i}, \bar{T}emp_{sensing/j/i}) = \frac{o(Temp_{best/j/i}) - o(\bar{T}emp_{sensing/j/i})}{\omega(Temp_{best/j/i}) + \omega(\bar{T}emp_{sensing/j/i}) + 1} \tag{12}$$

where $o(Temp_{best/j/i}) = \gamma Temp_{best/j/i} + (1-\gamma)Temp_{best/j/i} = Temp_{best/j/i}$, and $o(\bar{T}emp_{sensing/j/i}) = \gamma Temp^{lower}_{sensing/j/i} + (1-\gamma)Temp^{upper}_{sensing/j/i}$ denote the perceived values of $Temp_{best|j|i}$ and $\bar{T}emp_{sensing/j/i}$, $\omega(Temp_{best/j/i}) = \frac{1}{2}(Temp_{best/j/i} - Temp_{best/j/i}) = 0$ and $\omega(\bar{T}emp_{sensing/j/i}) = \frac{1}{2}(Temp^{upper}_{sensing/j/i} - Temp^{lower}_{sensing/j/i})$ denote the half-widths of $Temp_{best|j|i}$ and $\bar{T}emp_{sensing/j/i}$, respectively. That is:

$$\delta(Temp_{best/j/i}, \bar{T}emp_{sensing/j/i}) = \frac{Temp_{best/j/i} - (\gamma Temp^{lower}_{sensing/j/i} + (1-\gamma)Temp^{upper}_{sensing/j/i})}{\frac{1}{2}(Temp^{upper}_{sensing/j/i} - Temp^{lower}_{sensing/j/i}) + 1} \tag{13}$$

where γ denotes the degree of decision-maker optimism. As we can see, the smaller $\left|\delta(Temp_{best/j/i}, \bar{T}emp_{sensing/j/i})\right|$, the closer $\bar{T}emp_{sensing/j/i}$ is to $Temp_{best|j|i}$.

Similarly, we have:

$$\delta(Humi_{best/j/i}, \bar{H}umi_{sensing/j/i}) = \frac{Humi_{best/j/i} - (\gamma Humi^{lower}_{sensing/j/i} + (1-\gamma)Humi^{upper}_{sensing/j/i})}{\frac{1}{2}(Humi^{upper}_{sensing/j/i} - Humi^{lower}_{sensing/j/i}) + 1} \tag{14}$$

$$\delta(Pres_{best/j/i}, \bar{P}res_{sensing/j/i}) = \frac{Pres_{best/j/i} - (\gamma Pres^{lower}_{sensing/j/i} + (1-\gamma)Pres^{upper}_{sensing/j/i})}{\frac{1}{2}(Pres^{upper}_{sensing/j/i} - Pres^{lower}_{sensing/j/i}) + 1} \tag{15}$$

After obtaining the above $\delta(Temp_{best/j/i}, \bar{T}emp_{sensing/j/i})$, $\delta(Humi_{best/j/i}, \bar{H}umi_{sensing/j/i})$ and $\delta(Pres_{best/j/i}, \bar{P}res_{sensing/j/i})$, we can calculate the proximity of $E_{sensing|j|i}$ and $E_{best|j|i}$ using:

$$C(E_{sensing/j/i}, E_{best/j/i}) = w_1\left|\delta(Temp_{best/j/i}, \bar{T}emp_{sensing/j/i})\right| + w_2 \left|\delta(Humi_{best/j/i}, \bar{H}umi_{sensing/j/i})\right| + w_3\left|\delta(Pres_{best/j/i}, \bar{P}res_{sensing/j/i})\right| \tag{16}$$

where w_1, w_2 and w_3 represent the weights of temperature, humidity and pressure, respectively, for maintaining the freshness of in-transit fruits. According to probability theory, we could use the $p(O_j/i)$ to calculate the weights as follows:

$$w_1 = \frac{DW_1}{DW_1 + DW_2 + DW_3} \tag{17}$$

$$w_2 = \frac{DW_2}{DW_1 + DW_2 + DW_3} \tag{18}$$

Table 2
Comparison of the three scenario construction methods.

Method	Situations considered	Number of scenarios
IOT-based FO method	Fruit, Operation	2^{10} $(2^3 \times 2^7)$
IOT-based FOET method	Fruit, Operation, Environment, Time	2^{20} $(2^3 \times 2^7 \times 2^3 \times 2^7)$
Traditional FOET method	Fruit, Operation, Environment, Time	2^{32} $(2^3 \times 2^{13} \times 2^3 \times 2^{13})$

$$w_3 = \frac{DW_3}{DW_1 + DW_2 + DW_3} \tag{19}$$

where DW_1, DW_2 and DW_3 represent the impact difference of temperature, humidity and pressure, respectively, that is:

$$DW_1 = \left| \sum_{i=1,2,3,4} \sum_{j=1}^{128} p(O_j/i) - \sum_{i=5,6,7,8} \sum_{j=1}^{128} p(O_j/i) \right| \tag{20}$$

$$DW_2 = \left| \sum_{i=3,4,5,6} \sum_{j=1}^{128} p(O_j/i) - \sum_{i=1,2,7,8} \sum_{j=1}^{128} p(O_j/i) \right| \tag{21}$$

$$DW_3 = \left| \sum_{i=2,4,5,7} \sum_{j=1}^{128} p(O_j/i) - \sum_{i=1,3,6,8} \sum_{j=1}^{128} p(O_j/i) \right| \tag{22}$$

Here, (20)–(22) are consistent with the categories in Table 1. As we can see, the greater the impact the of temperature on the freshness, the larger DW_1 will be; this is also so for DW_2 and DW_3.

After obtaining $C(E_{sensing|j|i}, E_{best|j|i})$ using (16)–(22), we can assess the freshness of fruit deliveries using $f = \sum C(E_{sensing/j/i}, E_{best/j/i})$, where i and j depend on the actual delivery situation. As we can see, the smaller $C(E_{sensing|j|i}, E_{best|j|i})$, the closer $E_{sensing|j|i}$ is to $E_{best|j|i}$ and the fresher the in-transit fruits.

4. Numerical simulations

In this section, we use numerical experiments to demonstrate the efficiency and advantages of applying our two-stage approach to assessing the freshness of in-transit fruits in an IOT-based framework.

4.1. Effectiveness analysis of our scenario construction method

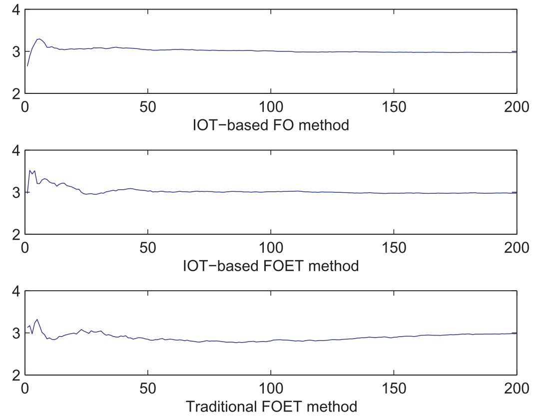
As mentioned in 3.2, there are three kinds of scenario construction methods: (1) the two-stage method considering Fruit and Operation situations in an IOT-based monitoring framework (IOT-based FO method, for short), (2) the full method considering Fruit, Operation, Environment and Time situations in an IOT-based monitoring framework (IOT-based FOET method, for short), and (3) the full situation method in traditional fruit commerce delivery (Traditional FOET method, for short). Table 2 compares the three scenario construction methods.

From the comparison in Table 2, we can see that the IOT-based FO method has greatly reduced complexity, which could consequently increase the efficiency of constructing the freshness assessment scenarios. The question is then how effective is the IOT-based FO method? To answer this question, we implemented Monte Carlo simulations in Matlab using the "learning-by-doing" mechanism described in Section 3.2.

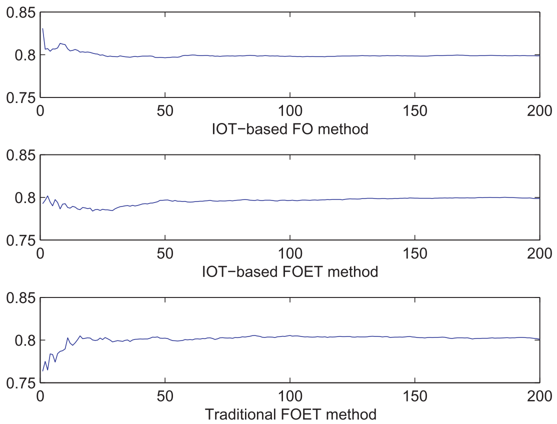
In the simulations, we create the following settings: (i) The occurrence probabilities of the scenarios for the three methods similarly obey a normal distribution whose range is consistent with the number of scenarios. Taking the IOT-based FO method as an example, there are 1024 scenarios. We first label these scenarios from 1 to 1024 and assume that scenarios 512 and 513 have the maximal occurrence probability. (ii) The temperature, humidity and pressure in the most suitable environment obey the following normal distributions: $N(3, 0.8^2)$, $N(0.8, 0.05^2)$ and $N(6000, 1000^2)$, respectively. (iii) The stopping criterion is set to $Max_t = 1000$.

Using the above settings, we obtained the simulated environments produced by the three scenario construction methods. Based on Fig. 5, we can observe:

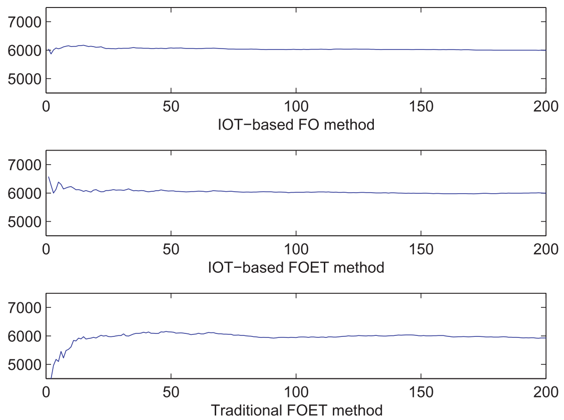
(1) With increasing learning times, all three scenario construction methods approached the most suitable environment. This consistency verified the effectiveness of our IOT-based FO method. In other words, our IOT-based FO method achieves an equivalent level of effectiveness using a greatly reduced number of scenarios. Thus, our IOT-based FO method has advantages over the IOT-based FOET method and the traditional FOET method.



(a) Simulated temperature $\max_{i=1,\ldots,8,j=1,\ldots,128}\{Temp_{best/j/i}\}$ where the x-coordinate expresses the learning time and the y-coordinate expresses the simulated temperature



(b) Simulated humidity $\max_{i=1,\ldots,8,j=1,\ldots,128}\{Humi_{best/j/i}\}$ where the x-coordinate expresses the learning time and the y-coordinate expresses the simulated humidity



(c) Simulated pressure $\max_{i=1,\ldots,8,j=1,\ldots,128}\{Pres_{best/j/i}\}$ where the x-coordinate expresses the learning time and the y-coordinate expresses the simulated pressure

Fig. 5. Simulated environment by the three kinds of scenario construction methods.

Table 3
Sensing data and assessment results when $\gamma = 0.5$.

Delivery No	Sensing environments			Assessment
	$\bar{Temp}_{sensing/64/4}$	$\bar{Humi}_{sensing/64/4}$	$\bar{Pres}_{sensing/64/4}$	results
1	[2.60, 2.95]	[0.75, 0.85]	[5800, 6100]	0.1861
2	[2.55, 2.90]	[0.75, 0.85]	[5800, 6100]	0.2003
3	[2.55, 2.90]	[0.70, 0.80]	[5800, 6100]	0.2161

(2) The simulated temperature, humidity and pressure values using the IOT-based FO method exhibited the smallest fluctuations. The traditional FOET method simulated environments with the largest fluctuations, especially at the beginning of the learning period. This results from the varying numbers of scenarios constructed using the three methods.

In short, the IOT-based FO method outperforms both the IOT-based FOET method and the traditional FOET method in terms of efficiency and stability, with equivalent effectiveness.

4.2. Freshness assessment using our scenario-based approach

In Section 4.1, we obtained the most suitable environment for each scenario $E_{best/j/i} = \{Temp_{best/j/i}, Humi_{best/j/i}, Pres_{best/j/i}\}$, as well as the probabilities $p(F_i)$ and $p(O_j/i)$. Then, we can use these learning rules to assess the freshness of in-transit fruits. As there are 1024 scenarios, it is impossible to illustrate the assessment using every scenario. Here, we select the following scenario as an example:

$$E_{best/64/4} = \{Temp_{best/64/4}, Humi_{best/64/4}, Pres_{best/64/4}\} = \{2.989, 0.801, 6006.647\}$$

Then, given the three sensing delivery data points shown in Table 3, we can obtain the assessment results.

Here, we use the first set of sensing environment data to provide a detailed example. For the sensing environment data:

$$\bar{Temp}_{sensing/64/4} = [2.60, 2.95]$$

$$\bar{Humi}_{sensing/64/4} = [0.75, 0.85]$$

$$\bar{Pres}_{sensing/64/4} = [5800, 6100]$$

we use (13)–(15) to compare the interval sensing environment with the crisp best environment (here, $\gamma = 0.5$):

$$\delta(Temp_{best/64/4}, \bar{Temp}_{sensing/64/4}) = \frac{2.989 - (0.5 \times 2.60 + 0.5 \times 2.95)}{\frac{1}{2}(2.95 - 2.60) + 1} = 0.1821$$

$$\delta(Humi_{best/64/4}, \bar{Humi}_{sensing/64/4}) = \frac{0.801 - (0.5 \times 0.75 + 0.5 \times 0.85)}{\frac{1}{2}(0.85 - 0.75) + 1} = 0.00095$$

$$\delta(Pres_{best/64/4}, \bar{Pres}_{sensing/64/4}) = \frac{6006.647 - (0.5 \times 5800 + 0.5 \times 6100)}{\frac{1}{2}(6100 - 5800) + 1} = 0.3751$$

Then, we can calculate the distance between $E_{sensing/64/4}$ and $E_{best/64/4}$:

$$C(E_{sensing/64/4}, E_{best/64/4}) = \frac{1}{3} \times |0.1821| + \frac{1}{3} \times |0.00095| + \frac{1}{3} \times |0.3751| = 0.1861$$

where we consider approximately $w_1 = w_2 = w_3$ because the occurrence probabilities of the scenarios have normal distributions.

Similarly, we can obtain assessment results for the first set of sensing environment data using varying degrees of optimism, as Fig. 6 shows. Fig. 7 presents the assessment results for all sets of sensing environment data with varying levels of optimism.

Comparing the results in Table 3 and Figs. 6– 7 yields the following observations:

(1) When the degree of optimism is held at $\gamma = 0.5$ in Table 3, the fruits in the first sensing environment (that is, {[2.60, 2.95], [0.75, 0.85], [5800, 6100]}) are assessed as the freshest of the three environments, as its sensing environment approximates the best environment {2.989, 0.801, 6006.647} compared to the other two sensing environments (that is, {[2.55, 2.90], [0.75, 0.85], [5800, 6100]} and {[2.55, 2.90], [0.70, 0.80], [5800, 6100]}). These results verify the effectiveness of our interval comparison method in fruit freshness assessment.

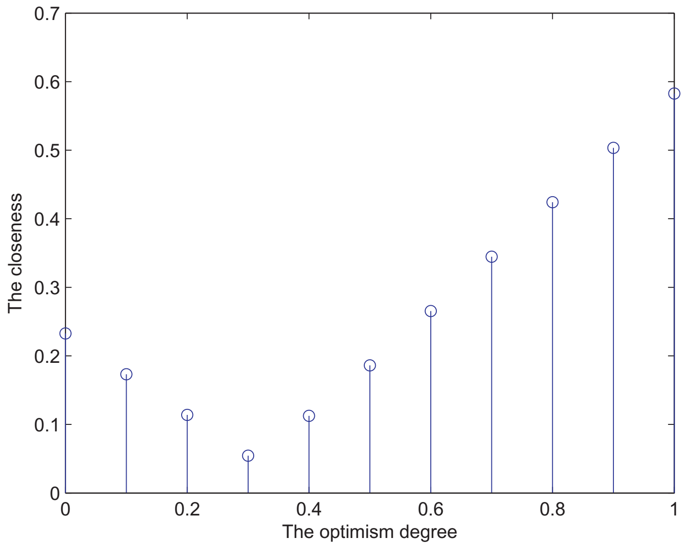


Fig. 6. The impact of the degree of optimism on the assessment results for the first set of sensing data, where the x-coordinate expresses the optimism degree and the y-coordinate expresses the closeness.

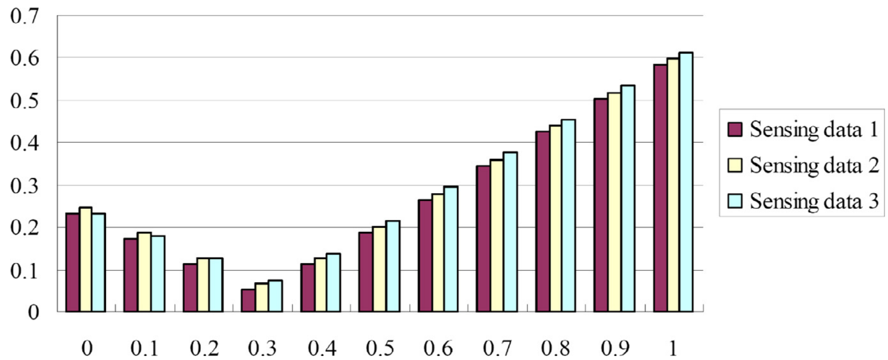


Fig. 7. The impact of the degree of optimism on the assessment results of all sets of sensing data, where the x-coordinate expresses the optimism degree and the y-coordinate expresses the closeness.

(2) For a given set of sensing environment data, the degree of optimism affects the comparison of the crisp best environment with the interval sensing environment, which consequently impacts the assessment results. As Figs. 6 and 7 show, every sensing environment is assessed with the smallest value when $\gamma = 0.3$.

From the results in Sections 4.1 and 4.2, we observe that the combination of scenario analysis and our interval comparison technique is effective for assessing the freshness of in-transit fruits under interval conditions. In fact, the integrated method can also be used to address other assessment and prediction problems in complicated and uncertain scenarios.

5. Concluding remarks

In this work, we investigated the monitoring and assessment of fruit freshness in e-fulfillment. For the monitoring aspect, we provided a comparison of the traditional fruit retailing and e-retailing transportation processes and applied IOT-related technologies, such as GPS, RFID sensor tagging and wireless sensor networks, to formulate a monitoring framework for e-commerce fruit delivery. For the fruit freshness assessment, we presented a two-stage scenario-based approach for assessing the freshness of in-transit fruits. This approach yielded the most suitable environment in each scenario and the occurrence probability of each scenario from the practical delivery operations. Freshness was assessed by comparing the similarity of the sensing environment to the most suitable environment for each scenario.

Although the effectiveness and advantages of our contributions are verified by numerical experiments, further work is required to produce practical benefits and extend the application fields. One such project might collect practical e-fulfillment data for fresh fruits to establish the most suitable environment for each scenario.

Acknowledgments

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