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An improved artificial neural network using multi-source data to estimate food temperature during multi-temperature delivery

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Abstract: Product temperature deviation is an important concern in the cold chain management and monitoring of food. Existing "rule-based" monitoring solutions are limited to the direct use of air temperature data of the vehicle used for transport, which can differ significantly from the real temperature of the food being assessed. Thus, this study focuses on developing a new artificial neural network model to precisely estimate the temperature of food products that are stored in multi-temperature refrigerated transport vehicles with minimum sensors. In addition to identifying the temperature in the car, the model also receives input from a multi-source dataset that includes various information such as the outside temperature, initial food temperature, door status, loading and unloading times, etc. The result of the study suggests that the proposed model could substantially enhance estimation accuracy and reliability with fewer temperature sensors in the transport vehicle. It was found that the root mean square error of food temperature estimation based on this model could be decreased by 77% and 79% for chilled and frozen zones, respectively. Moreover, long short-term memory and deep neural networks could avoid overfitting and reduce their estimation errors by about 55% and 48%, when compared to a back propagation neural network. Based on sensitivity analysis, food temperature estimation is significantly influenced by the product's initial temperature and the cumulative time that a door is open. The proposed model could precisely track the real-time food temperature even with sudden ambient changes, thus enabling precautions to take place when required.

Keywords: Cold chain monitoring; Temperature estimation; Urban delivery; Machine learning; Multi-source data

Nomenclature

SL_0	Initial shelf life (day)	***Symbols***	
SL	Remaining shelf life (day)	IoT	Internet of things
Q_{10}	The ratio of the reaction rate	WSN	Wireless sensor network
T_{ref}	The reference temperature	ANN	Artificial neural network
ΔT	The temperature deviation value	RMSE	Root mean square rror
t	At a certain time	BP	Back propagation
$k\ (T_{ref})$	The quality change rate at the reference temperature	LSTM	Long short-term memory
R_{SL}	The error rate of food shelf-life estimation		

1. Introduction

Around one-third of all human-produced food worldwide is lost or wasted in the supply chain, with poor temperature management being one of the main contributors (Blakeney, 2019; Mercier et al., 2017). Temperature-controlled delivery is an integral segment of the cold chain for perishable foods. Globally, over 4 million refrigerated vehicles are currently in operation with an annual growth rate of 2.5% (Artuso et al., 2019). In China, the annual growth rate of refrigerated vehicles reached 19.1%, with over 340,000 units in 2021; which is likely due to the increasing demand for perishable food cold chains (Cold Chain Logistics Committee of CFLP, 2021).

The Internet of Things (IoT) technology has been explored as a potential solution to achieve real-time temperature monitoring throughout food cold chains (Aghbashlo et al., 2015; Tang et al., 2021). As part of Industry 4.0, the IoT is an Internet-based global architecture that can analyze the digital identity connection between goods and services through the use of data networks (Birkel and Hartmann, 2020; E.S.A. et al., 2022; Hosseinpour et al., 2014, 2013). Cold chain logistic companies could collect a series of data by deploying global positioning system-based tracking technology and the wireless sensor network (WSN), which could gather important information on the geographical locations, velocities, temperatures, and relative humidities of the food transport vehicles. However, it is neither economical nor desirable to install a temperature sensor for each food item (Han et al., 2021). Badia-Melis et al. (2016) showed that the accuracy of equivalent temperatures using fewer sensors was assured by data mining techniques for cold chain transportation. Evidence of IoT's effectiveness in optimizing perishable food product quality has been explored by Salinas Segura and Thiesse (2017) and is based on a supply chain model of manufacturers, distribution centers, and retailers. The studies mentioned show that IoT-based delivery significantly reduces food spoilage. Furthermore, data mining could enable early alert and proactive temperature control systems by extracting rules from large-scale operational datasets (Li et al., 2010; Wang and Yue, 2017). Overall, it can be concluded that data mining technology can effectively be used to optimize cold chain processes by investigating the information underlying the sampling data to maintain the quality of food products (Ruiz-Garcia et al., 2009; Ting et al., 2014).

Product temperature deviation is a concern in food cold chain monitoring that is based on IoT technology. A study conducted by Ruiz-Garcia et al. (2010) recorded a maximum temperature of 8.52°C and a minimum of -3.0°C in a refrigerated vehicle that had a temperature setpoint of 0 °C. Around 98% of the time, the vehicle's temperature exceeded the industry's recommended range (setpoint ± 0.5°C). Konovalenko and Ludwig (2021) experimented with several scenarios for a large cold chain logistics company by analyzing a dataset consisting of 19,146 recorded temperature values at multiple subcontractor stages. They found that only 16.55% of the values were correct because the temperatures were observed by sensors and evaluated by event-driven, rules-based monitoring across the multimodal supply chain (including ocean and air transport, warehousing, and distribution).

As summarized in Table 1, previous studies mainly applied information technology to analyze sensor data for food temperature estimation (e.g., the mean value method, kriging algorithm, capacitor algorithm, and artificial neural network (ANN)) (Badia-Melis et al., 2016; Jedermann et al., 2009; Palafox-Albarran et al., 2015). These studies suggest that adopting suitable algorithms could reduce the number of temperature sensors while increasing temperature estimation accuracy. For example, the mean value method, cross-attribute kriging, and ANN were used for food temperature estimation in a reefer, which required 16, 8, and 8 sensors, respectively, and the corresponding Root Mean Square Errors (RMSE) were 3.97°C, 1.0°C, and 0.1°C (Badia-Melis et al., 2016; Palafox-Albarran et al., 2015). The same algorithms used in the previous studies could reduce estimation errors when investigating the reefer's temperature database once additional attribute data is added. For example, it was found that adding humidity data as input variables to the Kriging algorithm reduces estimation errors (Jedermann et al., 2009; Palafox-Albarran et al., 2015). Proper temperature monitoring and alert are vital in ensuring the effectiveness of the cold chain in order to avoid food quality and safety issues (Tang et al., 2021). However, it is challenging to implement a traditional "rule-based" temperature estimation model along food cold chains because the temperature in a transport vehicle is often unevenly distributed and can experience significant fluctuations (Badia-Melis et al., 2018; Konovalenko et al., 2021). The rule-based methodology consists of assigning key thresholds (relying on the available data sources) that are verified versus the received measurement values; the system yields a notification before corrective action is taken in the event of deviating values.

Significant gaps remain in the literature as existing studies mainly focus on food temperature estimation for the refrigerated transport segment and not the other segments of the cold chain like urban delivery. Many food cold chain studies assume that only single loading and unloading operations occur during the entire transit. This would suggest that the carriage temperature is relatively constant throughout the transit. Additionally, the temperature of fresh food delivered by trucks could be affected by the following: 1) food characteristics, including heat transfer properties and initial temperatures; 2) technical variables, including the thermal leakage rate of the vehicle envelope, internal partitions, and door seals; 3) operational factors, including frequency and accumulation time of loading and unloading, pre-cooling, and packaging. The models built by data mining that use the internal temperature of the carriage to estimate the food temperature could have large errors because they disregard the varying nature of multi-temperature vehicles. Thus, there is a significant challenge in accurately estimating the temperature of delivered food.

After reviewing the existing literature, it was found that only a few studies have been conducted to estimate food products' real temperatures in multi-temperature vehicles during urban delivery. To tackle the challenge and fill the gaps in the literature as identified above, this study develops a new ANN model by using multi-source datasets to precisely estimate temperatures with minimum requirements for the sensors and the transmission bandwidth. Specifically, the contributions of this study are threefold:

- A novel and innovative ANN model is developed to estimate real-time temperatures of food products in delivery vehicles. To estimate real-time load temperature in lightly refrigerated transport vehicles using wireless temperature sensors, effective temperature control management by machine learning using ANN is critical. This may enable cold chain logistic organizers to implement strategies (such as reducing energy consumption and ensuring food quality) based on the proposed ANN model when reliable temperature data is available.
- A comprehensive multi-source dataset following Fishbone Diagram Analysis Framework is selected to overcome the inadequacies of existing rule-based studies. The proposed ANN model takes into account key parameters that affect the food products' temperatures. such as outside

temperature, initial food temperature, door status and loading/unloading time.

- Lastly, the validity of the proposed ANN model is verified by conducting sensitivity and uncertainty analyses.

2. Methodology

This study develops and proposes an ANN monitoring model based on a multi-source dataset to effectively estimate the temperatures of delivered food using a reduced number of sensors. First, multi-source data streams were selected based on the Fishbone Diagram Analysis Framework to identify the main factors that could affect temperature estimation (see Supplementary Material: Annex 2). Then the multiple-temperature monitoring system was established to simulate the food delivery process for collecting on-site experimental training data. Lastly, an improved ANN model was developed and verified by the multi-source data to precisely estimate the food products' temperatures in the urban multi-temperature delivery truck.

2.1 Experimental Development

2.1.1. Truck Parameters

A multi-temperature refrigerated truck experiment was designed in this study to simulate cargo loading deliveries for obtaining training data. Figure 1 shows the structure of the multi-temperature refrigerated truck, with a load of 2 tons and dimensional parameters of 5.0×2.0×2.0 m^3. The truck was divided into chilled and frozen zones, with an air outlet speed of 6m/s and an onboard mechanical refrigeration system. The different sections in the same carriage were separated by a thermal insulation partition. Heat exchange between the zones is achieved by dust within the air at the top of the carriage.

2.1.2. Layout of Temperature Sensors

Figure 2a shows the layout of ambient temperature sensors inside the carriage. The temperature-controlled carriage was divided into six sections. Five temperature sensors (10cm away from the inside carriage body) were arranged in each section. Figure 2b depicts the sensors' layout to monitor food temperature. Twenty sensors were positioned in each of the chilled and frozen zones. Temperature sensors were placed externally on both the left (sun side) and right (shade side) sides of the different sections. Before testing was done, all the temperature sensors were calibrated, and time lag was tested. The data acquisition interval of the sensor was set as 10s. The sensors were RC-5 temperature and humidity sensors (manufactured by Shenzhen Jingchuang Company, with a temperature measurement range of -40°C to 70°C and an accuracy of ±0.2°C).

2.1.3. Cargo Loading and Assumptions

Figure 3 shows the layout of the simulated carriage at its rated full load. The chilled zone was loaded with four pallets, each with six boxes and four layers of fruits (citrus and bananas) which were packed in corrugated cartons and stacked in tight piles. Meanwhile, the frozen zone was loaded with four standard pallets, each stacked with six boxes and four layers of frozen goods (corn, carrots, and cucumbers). The middle of pallets was reserved for ventilation gaps. The specific setup, process and assumptions are as follows:

(1) The trial was conducted in both the summer and winter seasons. Inside the carriage, the air temperatures of the chilled and frozen zones were set at 0℃ and -18℃ for a period of 5 days during the winter. During the summer, the temperatures of the chilled and frozen zones were set to 12℃ and -18℃ for a period of 8 days.

(2) It was assumed that the carriage had 10 delivery points each day. According to a survey conducted by the Guangzhou Transportation Group's cold chain delivery center, the intervals between cargo loading and unloading were generated by random numbers between 35–60mins.

The truck door was open at each delivery point for a duration of 2-6 minutes.

(3) The food products had both pre-cooled and non-precooled thermal states. Three days of non-precooling were assumed for the delivery of citrus, whilst two days of non-precooling were assumed for bananas. The product's initial temperature varied depending on the food category and thermal state.

(4) Figure 4 illustrates a delivery scheme to prevent overfitting and ensure full data coverage of the space. The detailed loading/unloading scheme is shown in Supplementary Material: Annex 1. The test procedure is designed as follows: the refrigeration system had a fault state of 15h. The fan failure was 5h. The return air tank was partially blocked for 5h and the air supply tank was partially blocked for 5h. Finally, the study tested different load/unload times when the door would remain open (12min, 16min, and 20min) in non-standard operating conditions to validate the effectiveness of the proposed model. A total of 22,750 valid records were collected for the two experiments, each containing data from 72 temperature sensors and 2 door status sensors. A detailed analysis of the temperature data can be found in Supplementary Material: Annex 3.

2.1.4. Shelf-life Estimation Model

As shown in Eq. 1, this study used a simple calculation method for the edible food threshold based on a residual shelf life estimation model proposed by Jedermann et al. (2013) and Zou et al. (2022).

$$SL = SL_0 - \left[1 + (Q_{10} - 1) \cdot \frac{\Delta T}{10}\right] \times k(T_{ref}) \times t \qquad (1)$$

where t is time, T_{ref} is the reference temperature, k (T_{ref}) is the mass change rate at the reference temperature, ΔT is the temperature deviation value, and SL_0 and SL represent the initial shelf life and the remaining shelf life after t, respectively. Q_{10} is the ratio of the reaction rate at the temperature T_{ref}+10 and that at temperature T_{ref}, ranging from 2 to 4 at a temperature of 0-10°C. Given the complexity and *variance of the relation between shelf life and temperature, Q_{10} is set to be 3 in this study.*

Equation 2 shows how the reduced shelf life in time *t* was calculated.

$$SL(T_{ref} + \Delta T) = SL_0 - SL = \left[1 + (Q_{10} - 1) \cdot \frac{\Delta T}{10}\right] \times k\left(T_{ref}\right) \times t \qquad (2)$$

Equation 3 shows how to calculate the error rate of food shelf-life estimation R_{SL} versus the temperature deviation value.

$$R_{SL} = \frac{SL(T_{ref}+\Delta T) - SL(T_{ref})}{SL(T_{ref})} = (Q_{10} - 1)\frac{\Delta T}{10} \qquad (3)$$

The general temperature error was between 0.5°C and 1.0°C, which corresponds to 10% and 20% shelf-life estimation errors, respectively. Assuming that the temperature error reaches 1.5°C and 2.0°C, the relative shelf-life estimation errors would be 30% and 40%. For this study, the error of shelf-life estimation is considered to be within 10%, while temperature estimation error shall not exceed 0.5°C.

2.2 Artificial Neural Network (ANN) Model

2.2.1. Data Selection

This study used multi-source data to manage the temperature in the cold chain delivery of food. The multi-source data stream included ambient temperature sensors inside the carriage and information collected on logistics operation, food characteristics, environment, and equipment. The analysis framework of the fishbone diagram was applied, including "human, machine, material, law, and environment" elements to identify the main factors that could affect food temperature estimation. This study did not consider the influence of human factors on temperature estimation because they would be difficult to predict and control. The specific method used for determining the multi-source data stream is shown in Supplementary Material: Annex 2. Based on the assumptions, availability and applicability of the data, the multi-source data stream was selected and included the ambient temperature inside the carriage, precooling or not, car door status, outside temperatures, initial food temperatures, and the cumulative loading and unloading times.

2.2.2. ANN Model Structure

The ANN model has been widely recognized to effectively estimate the temperature patterns of heat-generating fresh fruits and vegetables (Nunes, et al., 2014). As shown in Figure 5, this ANN model consisted of an input layer, a hidden layer, and an output layer. The number of nodes in the input and output layers was relatively fixed in the specific example presented. Given that this estimation used all structured temperature state data, the number of hidden layers should be adjusted based on the target performance requirements. Therefore, the ANN model can estimate the real food temperature by relying on multisource data streams (Figure 5). Twenty food temperature sensors are located in each chilled and frozen zone, resulting in 20 neurons in the ANN output layer. The input layer neuron of the chilled zone consists of three types of data sources: 1) door status, including one sensor that detects the open/close door status and a counter that calculates the accumulative time that the door is open 2) food parameters, including initial temperature and heat status (two of these parameters were acquired when leaving the warehouse, so there was no need to increase the sensing equipment in the carriage); 3) temperature information, including one outside temperature sensor, one frozen zone ambient temperature sensor, and one to six chilled compartment ambient temperature sensors. The overall ANN structure of the frozen zone was the same as the chilled zone. A temperature sensor in the carriage was added as needed: (1) one neuron was used to observe the estimation error between the estimated temperature and the real temperature; and (2) the number of temperature sensors in the carriage was increased to two until the estimation accuracy was achieved (RMSE$\leqslant$0.5°C).

2.2.3. Machine Learning Algorithms and Training Methods

The Back Propagation (BP) neural network is a multi-layer feedforward neural network that could learn and store a wide range of input-output pattern mapping relationships (Shih and Wang, 2016). BP neural networks use the fastest descent method to continuously adjust weights and thresholds, which ultimately minimizes the network's squared errors (Leng et al., 2019). Typical learning algorithms are the Levenberg Marquardt (LM) algorithm, the bayesian regularization algorithm, and the conjugate gradient algorithm (Chen et al., 2013). Based on the performance comparison of algorithms, this study selected the LM algorithm (see Supplementary Material: Annex 4 for an explanation). Samples were divided into three parts: training sets (70%), validation sets (15%), and test sets (15%) based on preliminary analysis (Tang et al., 2021; Xu et al., 2013).

3. Results and Discussion

Developing an improved ANN model using multi-source data to achieve precise food temperature estimation during urban delivery requires balancing the performance and information technologies (i.e., sensor configuration, bandwidth demand, and computational resource consumption). The effects this has on food temperature estimation results are analyzed and discussed in the following sections.

3.1. Food Temperature Estimations

Table 2 shows that the estimation error decreases with an increase in the number of sensors. The test set error is 2.35°C with only one ambient temperature sensor deployed in the chilled zone. The test set error is then reduced to 1.32°C once six sensors are installed. Overall, the estimation error between one and six sensors was decreased by 43.0%. This indicates that there is a significant increase in estimation accuracy when more temperature monitoring sensors are used. Badia-Melis et al. (2016) implemented the ANN model to achieve a temperature estimation error of 1.49°C, using only one sensor in a single-temperature reefer (the results are compared Table 1). However, for this study, six sensors were required to reach an acceptable level of accuracy which indicates that temperature estimation is considerably more demanding for multi-temperature reefer than for a single-temperature one. Additionally, the shelf-life estimation error could reach around 30% according to Eq. (3) when using 2 × 6 sensors to monitor food temperature. Therefore, improving the temperature estimation accuracy by merely increasing the number of onboard temperature sensors is economically unfeasible.

3.2. The Effect of Food Temperature Estimation Based on Multi-Source Data

Table 3 presents the performance results of an ANN estimation of RMSE based on multi-source data after 100 epochs. The results show that the RMSE of training and validation sets is 0.54°C, while the RMSE of the test set data is 0.53°C. This error value is reduced by around 77% when compared to only using ambient temperature sensor data. The results from the frozen zone show a temperature estimation error of 0.61°C for the test set. This error value is reduced by around 79% when compared to only using ambient temperature sensor data. As shown in Tables 2 and 3, the error in the ANN model based on multi-source data is reduced by about 60% when compared to the conventional rule-based methods (6 sensors used).

Error distribution plots were created to verify the results. As shown in Figure 6, the multi-source data temperature estimation errors are well-distributed. Temperature estimation errors are predominantly distributed between -0.5°C and 0.3°C in the chilled zone and between -0.35°C to 0.60°C in the frozen zone. The percentage of absolute temperature estimation errors beyond 1.0°C is very rare. Thus, this ANN model using multi-source data could lead to significantly improved food temperature estimation performance.

3.3. Experimental Verification

Figure 7a compares temperature changes with time (i.e., ambient temperature, real food temperature, and estimated temperature) inside the multi-temperature carriage. The estimated temperature roughly coincides with the real temperature, which suggests that the ANN model using multi-source data performs well in the case of sudden changes in food temperature. To further demonstrate this finding, an indirect precooling test was designed, i.e., bananas were not pre-cooled before day 8, but were pre-cooled to 11°C before loading for distribution on day 9. It can be found from the results shown in Figure 7b that although the difference between the ambient temperature values for those two days is minor, the real food temperature varies dramatically, especially at the jump-change point (circled in red). When the food temperature suddenly drops by 8°C or more, such changes are well-tracked with a multi-source data approach based on this improved ANN model. However, the difference between the ambient and real temperature values is significant, with a maximum error of over 10°C.

Figure 8 shows a significant difference between the ambient temperature and the real temperature of the food in the frozen zone. This is because the sensor was incapable of quickly detecting the real food temperature, while the temperature difference exceeds 15°C between the initial food temperature (around -15°C) and the ambient temperature of the carriage (>0°C) during the daily loading. The food temperature estimation largely agrees with the precise temperature curve (Figure 8). This indicates that the food temperature in the frozen zone could also be accurately predicted based on the improved ANN model.

3.4. Sensitivity Analysis

3.4.1 Effect of Multi-Source Data Variability in Two Temperature Zones

Table 4 shows the RMSE of the test set as the variation in multi-source data of the chilled zone compared to the original results. The factors influencing the estimation performance in descending order are initial food temperature, cumulative time that the door is open, frozen zone temperature, precooling, door status, and outside temperature. The initial food temperature has the most significant impact on the estimation outcome. However, previous studies did not include initial food temperature data in the ANN model, potentially causing significant estimation error (Mercier et al., 2017). Secondly, the pre-cooling stage and process is crucial in maintaining the quality of perishable foods (Do Nascimento Nunes et al., 2014). It is noted that the initial food temperature data included the pre-cooling data of food products in this study. Next, the cumulative time that the door is open considerably contributes to food temperature estimation. Without considering this factor, the error is increased by 0.21°C. Food temperature rises rapidly during distribution due to door-opening operations, which is consistent with the findings of Abad et al. (2009), Koutsoumanis et al. (2010), and McKellar et al. (2014). For example, Abad et al. (2009) monitored a temperature increase of 2°C during the loading and unloading fresh fish. The temperature could increase by 10°C in summer during the loading and unloading of lettuce (McKellar et al., 2014). However, Abad et al. (2009) and Tsang et al. (2018) only focused on temperature changes in single loading and unloading operations rather than the cumulative time that the door is open. Lastly, the temperature difference between zones influences the food temperature estimation error (about 0.1°C) in the chilled zone because the partitions are not thoroughly heat-insulated (Liu et al., 2019; Tsang et al., 2018). When considering the non-linear interaction of the temperatures between frozen and chilled zones in the same carriage (Konovalenko et al., 2021), integrated analysis of the temperature sensor data synthesis is imperative.

Table 5 demonstrates the effects of multi-source data variability on food temperature estimation in the frozen zone. The magnitude of the influence of the RMSE on food temperature estimation is in the same order as the results for the chilled zone. The estimation error is increased from 0.61℃ to 1.01℃ (the initial temperature of food is excluded). Similarly, the error goes up by 0.73°C when not taking into account the cumulative time that the door is open. Other factors, such as door status and outside temperature data, hardly influence the estimation results. Based on benchmark results, the location of the temperature sensor also has little impact on temperature estimation. However, this is not the case when using Kriging-based algorithms (Badia-Melis et al., 2016; Jedermann et al., 2009; Palafox-Albarran et al., 2015).

3.4.2 Effect of the Data Acquisition Interval on the Estimation Performance

In addition to potentially using fewer sensors, temperature monitoring systems aim to transmit a smaller volume of data to the cloud, which requires maintaining a relatively longer data acquisition interval while ensuring temperature estimation accuracy (Tang et al., 2021). As such, this study analyzed the influence that different data acquisition intervals had on the temperature estimation errors by focusing on the chilled zone. As seen in Table 6, the overall impact that the data acquisition interval had on the temperature estimation errors is relatively low. It grows slightly as the data acquisition interval increases, for example, the average values at 10s, 1min, and 2min are 0.50℃, 0.50℃, and 0.52℃, respectively. Assuming that the acquisition interval is extended to 5 min, the average error in food temperature estimation is only 0.57°C. It increases by 14% over 10s under the corresponding control, but the amount of transmitted data is reduced to 1/30. Although the short data acquisition intervals (<1s) can be achieved by the development of 5G and IoT technologies, it implies that higher bandwidth requirements are associated with energy consumption (Li et al., 2018; Zhu et al., 2022). The recommended criterion for temperature data acquisition interval in China is 5 minutes or less (GB/T 24616, 2019). Thus, it is suggested that a data acquisition interval of 2-3 min is reasonable (the error shall be limited to about 0.5℃). Additionally, future studies on data acquisition intervals shall consider fault warnings for building an efficient temperature monitoring system (Tang et al., 2021).

3.4.3 Effect of Machine Training Models on the Estimation Performance

This study also examines the effectiveness of BP, long short-term memory (LSTM), and deep learning networks on temperature estimation error values. The RMSE of food temperature estimation for different ANN models is presented in Table 7. The LSTM contains one hidden layer by employing the "Adam" optimizer for the dataset training test. The temperature estimation error is 0.24°C without the dropout layer. A dropout layer with a regularization process is then added to avoid overfitting, yielding a test set RMSE output of 0.53°C for the estimation error. This outcome is essentially the same as the one from the BP network. Considering that the LSTM network generates up to thousands of parameters, the study recommends a more accessible BP network in case there is no particularly high demand for temperature estimation accuracy.

A deep learning network model was built to examine the performance of adding hidden layers on the reliability of temperature estimation. A dropout layer is added after each hidden layer to prevent overfitting. The RMSE of the test set is 0.51°C when there are two hidden layers in the network, which is a similar result to the BP network. When the network has three hidden layers, the RMSE of the test set decreases to 0.33°C. As such, the deep neural network enables better temperature estimation, but it is complicated because of the significant number of parameters, memory usage, and computation time.

3.5. Uncertainty Analysis

An uncertainty analysis was conducted to determine how uncertainties in multi-source data affect the reliability of the temperature estimation results. The Pearson correlation coefficient (R) was utilized to measure a linear correlation between the estimated and real food temperatures. As shown in Figure 9, the overall R of the chilled and frozen zones is 0.995 and 0.990 in the same carriage. This indicates that estimated temperature highly correlates with the real temperature in a multi-temperature carriage. These results show that the model proposed in this study presents a lower level of uncertainty in food temperature estimations.

3.6. Practical Implication and Limitations

To estimate real-time loading temperatures in refrigerated transport vehicles using wireless temperature sensors, precise temperature control management by machine learning using ANN is critical. The option for machine learning to only be trained by air temperature inside the vehicle is limited when using one or a few sensors in transit. As an alternative, increasing the number of sensors is essential to reduce the uncertainty related to the applied assumptions. However, the ANN is hampered by the deployment cost, which could also result in expensive human resource costs, as analysing the data patterns sampled from the multi-temperature vehicle is very complicated. Therefore, cold chain logistic organizers must consider how to improve the model's precision using fewer temperature sensors. Furthermore, although experimental data (collected from the laboratory and field) are often incomplete (i.e., few measured food products and uncertain environmental conditions) the first-hand data generated by the experiment are more robust to construct a training dataset for the machine learning model. This may enable cold chain logistic organizers to implement strategies (such as reducing energy consumption and ensuring food quality) based on the proposed ANN model when reliable temperature data is available. Thus, the findings from this study can be used as a basis for temperature management across the food cold chain and as a reference for decision-making systems of food and pharmaceutical cold chain operations.

However, it is important to note that there are several research limitations in this study. First, the representativeness of the food samples used in the study is limited due to high financial costs and long testing periods. The samples tested were oranges, bananas, and several frozen vegetable products. Future research requires the inclusion of a wider variety of raw food products to improve the generalization of the estimation model. In addition, the theoretical construction of multi-temperature refrigerated vehicles is limited by environmental conditions and other realistic delivery factors - all of which have an influence on the temperature of the food products. The temperature profiles of the food products are also influenced in a multi-directional manner, with the external environment and the internal heat generated by the product having an effect. Further research is needed to increase the accuracy of the estimation model by considering variables representing predictive concerns, such as the number of delivery points, loading and unloading times, reefer models, and load capacities.

4. Conclusions and Prospects

This study proposes an improved ANN model using multi-source data to precisely estimate the temperature of delivered food products based on an experimental set-up. The main conclusions are:

1) The proposed ANN model could substantially enhance estimation accuracy and reliability in comparison to the models trained with only the internal air temperature dataset. Compared to the traditional ANN models trained with one temperature sensor dataset, the RMSE of food temperature estimation using the improved ANN model could be decreased by 77%-79%. Most importantly, the improved ANN model can precisely track the real-time food temperature under sudden temperature changes, thus enabling precautions to take place when required.
2) Different multi-source dataset categories could affect food temperature estimation to various extents. Thus, it is important to rank their influence based on a sensitivity analysis. The results suggest the following ranking in ascending order: initial food temperature, cumulative door opening time, frozen zone temperature, pre-cooled temperature, external temperature, and door status.
3) The recommended data acquisition interval is 2-3 minutes. It was found that extending the data acquisition interval does not significantly reduce temperature estimation errors.
4) Different ANN models like LSTM and deep learning networks can improve estimation accuracy

and prevent overfitting. Compared to the BP network, the temperature estimation error of LSTM without the dropout layer and deep learning networks with three hidden layers could be decreased by around 55% and 48%, respectively.

The implementation of the proposed ANN model in urban food delivery can lead to the construction of a multi-decision system for the agrifood supply chain, including real-time food quality monitoring, temperature alerting, and refrigeration system fault detection. Given the complexity of the ANN model, the critical focus for future research should be optimizing the model database and strengthening the generalization capability. This would help cold chain operators to detect and prevent temperature chain breaks on time and ultimately reduce food loss.

Credit Authorship Contribution Statement

Yifeng Zou: Conceptualization, Methodology, Data curation, Software, Writing original draft. **Junzhang Wu**: Formal analysis, Experiment, Validation, Revision, and Editing. **Xinfang Wang**: Analysis, Revision, and Editing. **Kimberly Morales**: Revision and Editing. **Guanghai Liu**: Funding acquisition. **Alessandro Manzardo**: Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in the study.

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Supplementary Materials

The detailed data associated with this article can be found in Supplementary Material−Annex.

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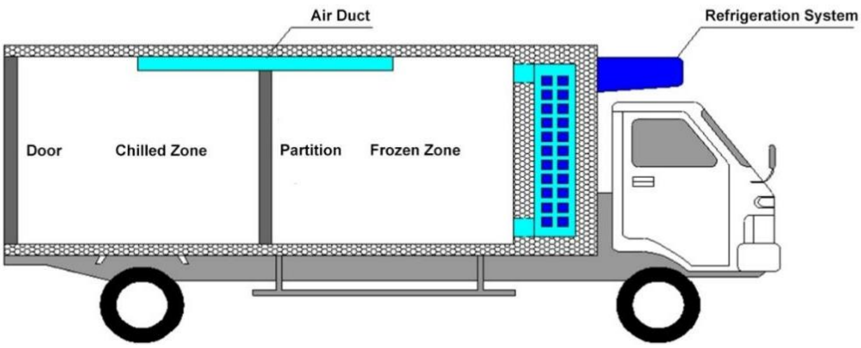
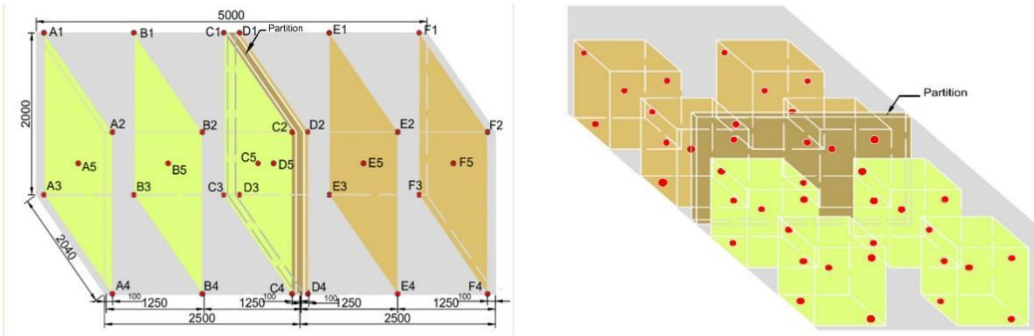


Figure 1 Structure of the multi-temperature refrigerated truck



(a) (b)

Figure 2 Layout of temperature sensors (a: ambient temperature sensors inside the carriage; and b: food temperature sensors) *Note:* The capital letters A, B, C, D, E, and F indicate the layout of the temperature sensors inside the vehicle from rear to front, where A, B, and C is in the chilled zone and D, E, and F in the frozen zone. No. 1 to 5 indicates the number of sensors in the same section. The red dots in the Figure represent sensors.

(a) Chilled zone (b) Frozen zone

Figure 3 Cargo stacking diagram in the carriage

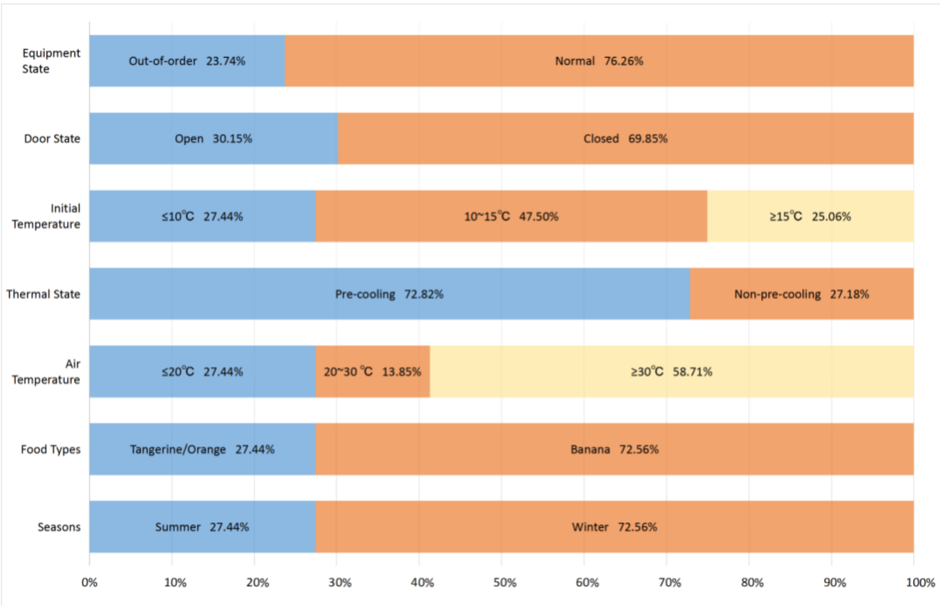


Figure 4 Percentage of collected data influenced by various factors (chilled zone)

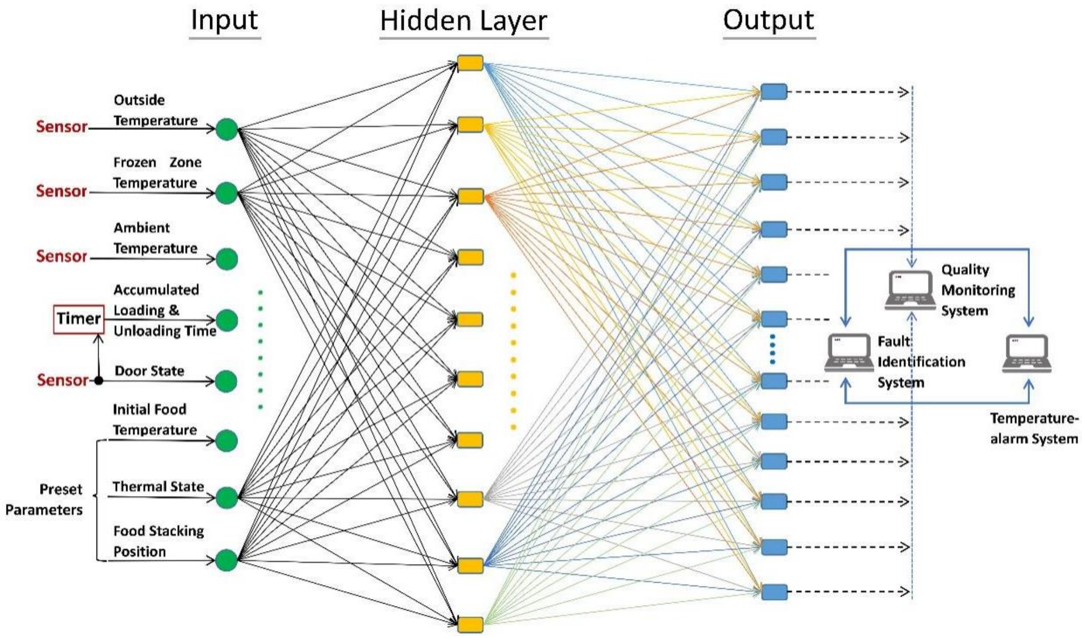
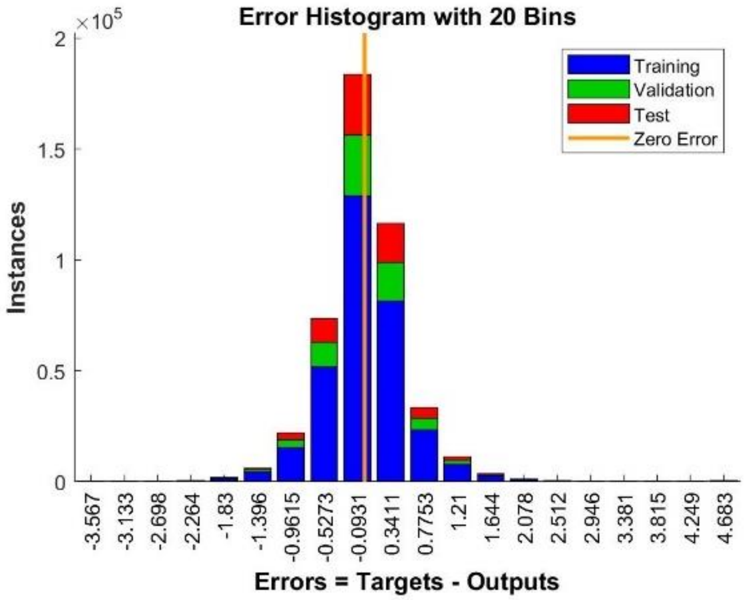
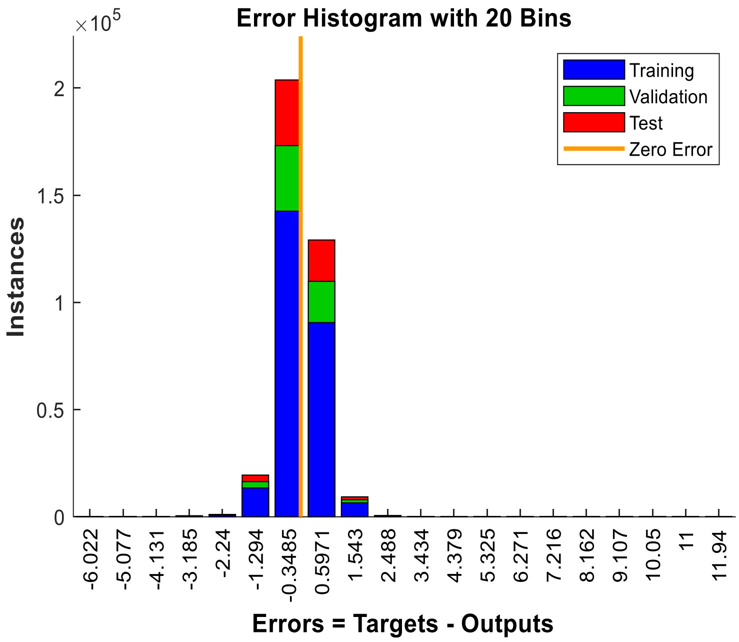


Figure 5 The ANN model for food temperature estimation (chilled zone)

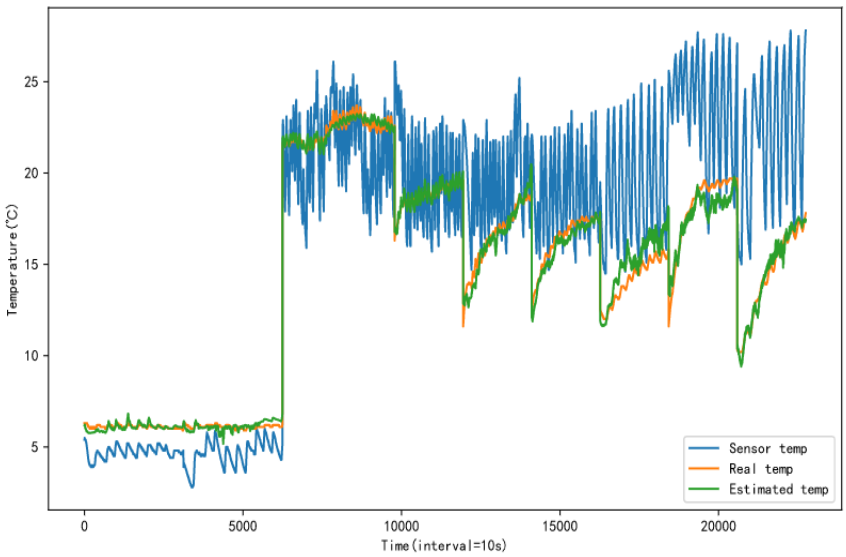


(a) Chilled zone

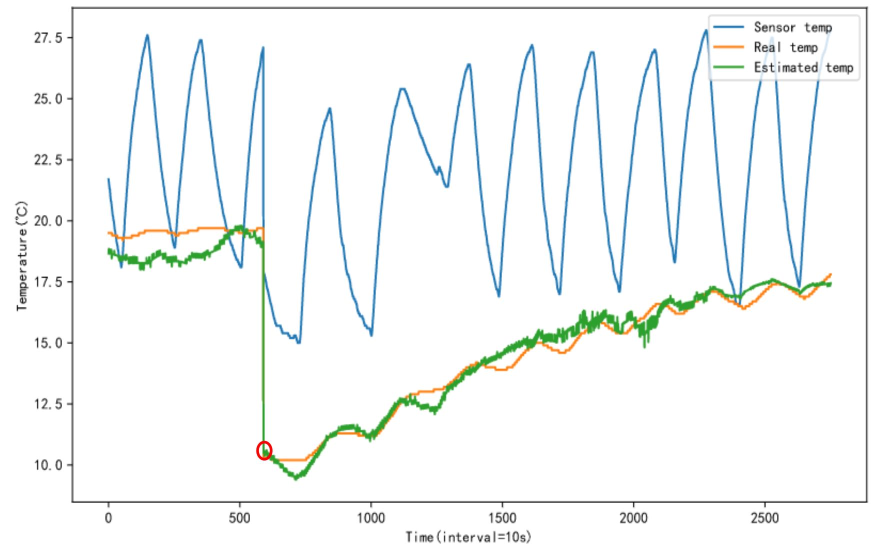


(b) Frozen zone

Figure 6 Error distribution in temperature estimation



(a)



(b)

Figure 7. Three temperature profiles in the chilled zone. (a: normal refrigerated temperature; and b: a sudden change in refrigerated temperature at a certain period of time)

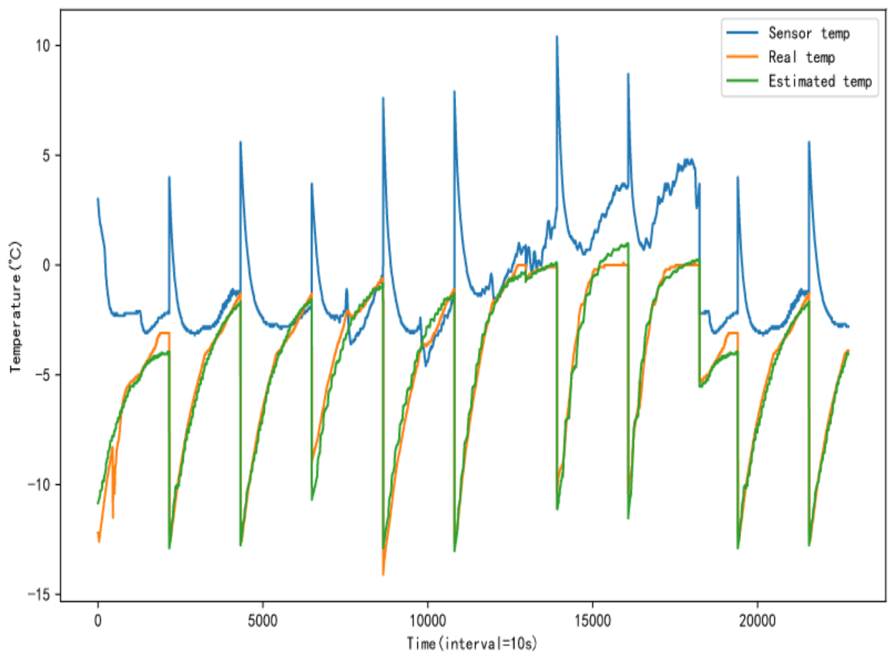
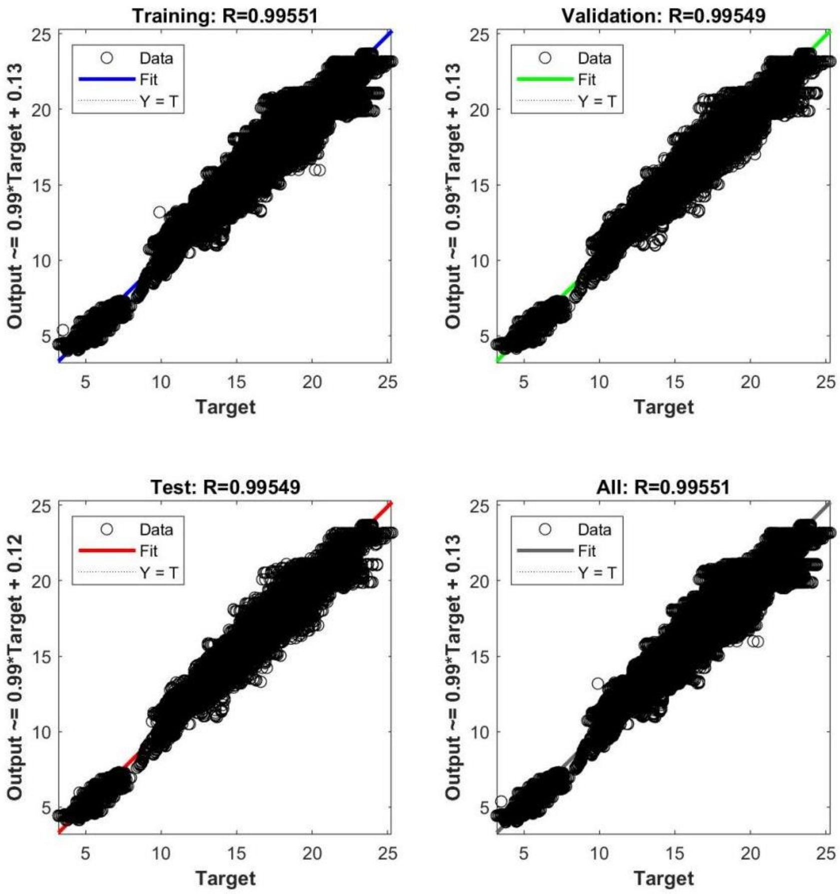
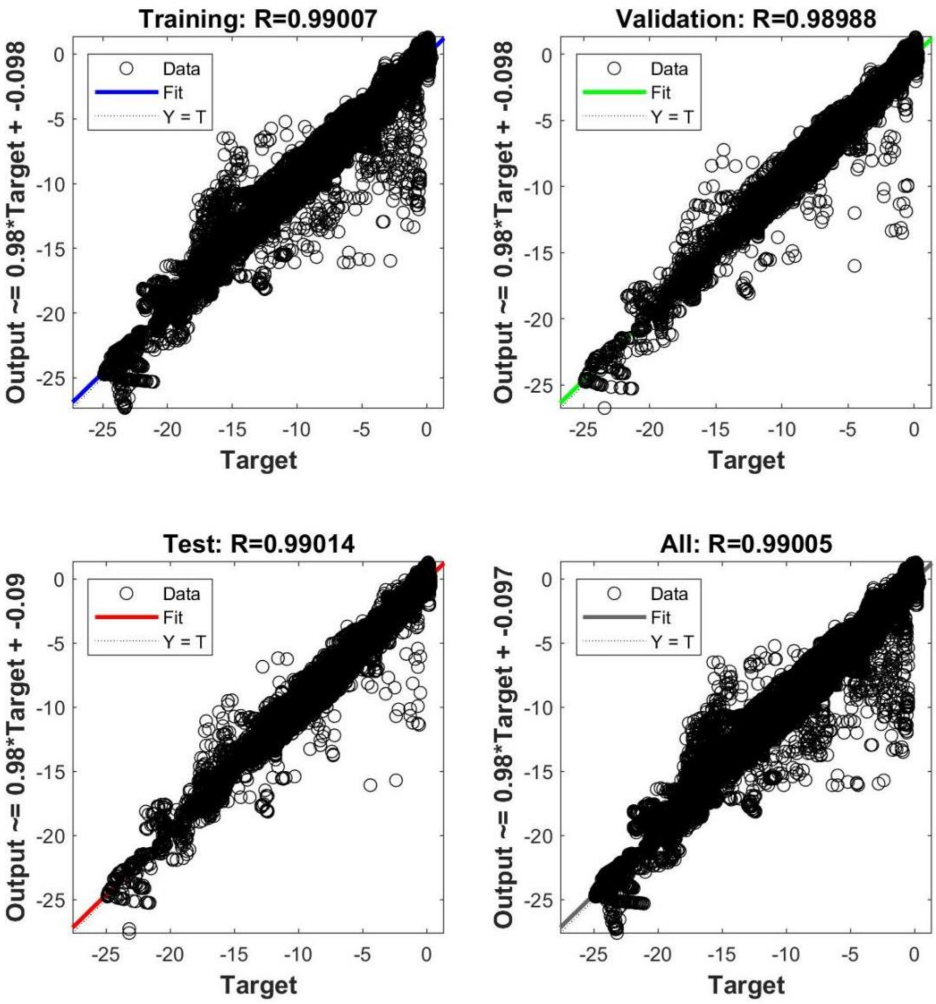


Figure 8. Three temperature profiles in the frozen zone



(a) Chilled zone



(b) Frozen zone

Figure 9. The linear correlation (R) between estimated and real temperatures

Table 1 The main methods for temperature estimation and performance analysis from the existing literature

Methods	**Objects**	**Logistics**	**Temp.* sensors**	**RMSE* (°C)**	**Data source**	**Reference**
Mean value	Reefer containers	Trans.*	16	3.97	Exp.*	(Badia-Melis et al., 2016)
Simple interpolation	Pallets	Trans.	28	0.2	Exp.	(Jedermann and Lang, 2009)
Kriging	Reefer containers	Trans.	16	1.32	Exp.	(Badia-Melis et al., 2016)
Kriging	Truck	Trans.	30	0.5	Exp.	(Jedermann et al., 2009)

Kriging	Truck	Trans.	8	2.2	Exp.	(Jedermann and Lang, 2009)
Cross-attribute Kriging	Reefer containers	Trans.	8	1.0	Exp.	(Palafox-Albarran et al., 2015)
Fuzzy multiple objective decision making	Truck	Trans.	7	1.79	Exp.	(Liu et al., 2014)
Capacitor method	Reefer containers	Trans.	1	1.28	Exp.	(Badia-Melis et al., 2016)
ANN*	Reefer containers	Trans.	8	0.11	Exp.	(Badia-Melis et al., 2016)
ANN	Reefer containers	Trans.	1	1.49	Exp.	(Badia-Melis et al., 2016)
ANN	Reefer containers	Trans.	4	0.32	Exp.	(Badia-Melis et al., 2016)
ANN	Reefer containers	Trans.	3	0.37	Exp.	(Badia-Melis et al., 2016)
ANN	Pallet	Sup. *	1/each pallet	<0.5	Exp.	(Mercier and Uysal, 2018)
ANN	Multi-temp. truck	Deliv. *	4	0.54	Exp.	The study
LSTM	Multi-temp. truck	Deliv.	4	0.24	Exp.	The study
Deep learning	Multi-temp. truck	Deliv.	4	0.33	Exp.	The study

Abbreviations: ANN represents Artificial Neural Network; RMSE means Root Mean Square Error; Trans., Deliv., Exp. and Sup. represent transportation, delivery, experiment, and supply chain respectively. Temp. represents temperature.

Table 2 ANN estimation of RMSE using ambient temperature data with four sets of temperature sensors

Sets of temperature sensors *	**Chilled zone (RMSE) /°C**			**Frozen zone (RMSE) /°C**		
	Training	Validation	Test	Training	Validation	Test
One [a]	2.35	2.33	2.35	2.93	2.97	2.96
Two [b]	2.28	2.29	2.31	2.06	2.08	2.10
Three [c]	2.00	2.03	1.98	1.77	1.75	1.78
Six [d]	1.34	1.35	1.32	1.57	1.59	1.58

Note: * The number below represents all temperature sensor sets associated with the smallest estimation error. a. one sensor, i.e., only the current ambient temperature monitoring sensor (A2) is used in the chilled zone; b. two sensors, i.e., A2+B1; c. three sensors, i.e., A2+B1+C2; d. six sensors, i.e., all sensors on the top surface of the compartment are used as the source of sensors, A1+A2+B1+B2+C1+C2. The location of each sensor is shown in Figure 2.

Table 3 ANN estimation of RMSE based on multisource data

Sets of temperature sensors	chilled zone (RMSE) /℃			Frozen zone (RMSE) /℃		
	Training	Validation	Test	Training	Validation	Test
One	0.54	0.54	0.53	0.61	0.62	0.61
Two	/	/	/	0.57	0.58	0.57

Table 4 Effect of various data sources on temperature estimation errors in the chilled zone

Ambient temperature sensor inside the carriage	Outside temp./ ℃	Frozen zone temp./ ℃	Pre-cooled/ ℃	Initial temp./ ℃	Door status/ ℃	Cumulative door opening time/ ℃	Benchmark/ ℃
A1	0.53	0.59	0.56	0.94	0.55	0.73	0.48
A2	0.53	0.62	0.56	0.93	0.53	0.66	0.50
B1	0.51	0.58	0.61	0.89	0.52	0.71	0.53
B2	0.53	0.60	0.54	0.91	0.48	0.67	0.52
C1	0.57	0.53	0.52	0.85	0.50	0.71	0.52
C2	0.55	0.57	0.52	0.93	0.56	0.76	0.46
Average	0.54	0.58	0.55	0.91	0.52	0.71	0.50

Note: The first column is the location of the ambient temperature sensor in the chilled zone (Figure 2). The benchmark is the RMSE of temperature estimated when all multisource data is used as input. The other columns are the RMSE of temperature estimated after excluding the data. All the above data refer to the RMSE of the test set.

Table 5 Effect of various diversity data on temperature estimation errors (frozen zone)

Ambient temperature sensor inside the cabin	Outside temp./ ℃	Frozen zone temp./ ℃	Initial temp./ ℃	Door status/ ℃	Cumulative door opening time/ ℃	Benchmark/ ℃
D1	0.74	0.81	1.06	0.64	0.74	0.62
D2	0.70	0.66	1.09	0.59	0.69	0.58
E1	0.69	0.66	1.03	0.65	0.71	0.64
E2	0.65	0.62	1.09	0.63	0.82	0.62
F1	0.69	0.68	0.96	0.66	0.69	0.63
F2	0.64	0.72	0.84	0.62	0.73	0.58
Average	0.68	0.69	1.01	0.63	0.73	0.61

Note: The first column is the location of the ambient temperature sensor in the frozen zone (Figure 2). The benchmark is the RMSE of temperature estimation when multisource data is input. The other columns are the RMSE of temperature estimation after excluding this data. All the above data refer to the RMSE of the test set.

Table 6 The RMSE of food temperature estimation error at different data acquisition intervals.

Diversity data	10s/ ℃	30s/ ℃	1min/ ℃	2min/ ℃	3min/ ℃	4min/ ℃	5min/ ℃
A1	0.48	0.55	0.50	0.57	0.56	0.57	0.58

A2	0.50	0.56	0.50	0.49	0.57	0.57	0.59
B1	0.53	0.54	0.53	0.51	0.55	0.59	0.56
B2	0.52	0.50	0.48	0.56	0.58	0.59	0.57
C1	0.52	0.57	0.53	0.50	0.51	0.53	0.53
C2	0.46	0.51	0.47	0.50	0.55	0.57	0.57
Average	0.50	0.54	0.50	0.52	0.56	0.57	0.57

Note: The first column indicates that the input diversity data contains one temperature sensor at different locations.

Table 7 The RMSE of food temperature estimation for different ANN models.

		LSTM		**Deep neural network**	
Network types	**BP**	One hidden layer	One hidden layer+ One dropout layer	Two hidden layers + Three dropout layers	Three hidden layers + Three dropout layers
RMSE/ ℃	0.53	0.24	0.53	0.51	0.33