Prediction of cold chain logistics temperature using a novel hybrid model based on the mayfly algorithm and extreme learning machine

Abstract

Purpose-The transportation of fresh food requires cold chain logistics to maintain a low-temperature environment, which can reduce food waste and ensure product safety. Therefore, temperature control is a major challenge that cold chain logistics face.

Design/methodology/approach- This research proposes a prediction model of refrigerated truck temperature and air conditioner status (air speed and air temperature) based on hybrid mayfly algorithm (MA) and extreme learning machine (ELM). To prove the effectiveness of the proposed method, the mayfly algorithm-extreme learning machine (MA-ELM) is compared with the ELM and ELM optimized by classical biological inspired algorithms, including the genetic algorithm (GA) and particle swarm optimization (PSO). The assessment is conducted through two experiments, including temperature prediction and air conditioner status prediction, based on a case study.

Findings- The prediction method is evaluated by five evaluation indicators including the mean relative error (*MRE*), mean absolute error (*MAE*), mean squared error (*MSE*), root mean square error (*RMSE*), and coefficient of determination (R^2). It can be concluded that the biological algorithm, especially the MA, can improve the prediction accuracy. This result clearly proves the effectiveness of the proposed hybrid prediction model in revealing the nonlinear patterns of the cold chain logistics temperature.

Research limitations/implications- The case study illustrates the effectiveness of the proposed temperature prediction method, which helps to keep the product fresh. Even though the performance of MA is better that GA and PSO, the MA has the disadvantage of premature convergence. In the future, the modified MA can be designed to improve the performance of MA-ELM.

Originality/value-In prior studies, many scholars have conducted related research on the subject of temperature monitoring. However, this monitoring method can only identify temperature deviations that have occurred that harmed fresh food. As a countermeasure,

research on the temperature prediction of cold chain logistics that can actively identify temperature changes has become the focus. Once a temperature deviation is predicted, temperature control measures can be taken in time to resolve the risk.

Keywords: Cold chain logistics, temperature prediction, extreme learning machine, mayfly algorithm

Paper type Research paper

1. Introduction

With the improvement of living standards, residents have an increasing demand for fresh food such as fruits and vegetables (Li et al., 2019). Compared with ordinary goods, fresh food still has vital signs during the transportation process and will consume organic matter (sugars and starch) through respiration thereby reducing the nutrient content (Han et al., 2021). It is well known that the respiration intensity of fresh food is affected by the transportation environment (temperature, vibration, oxygen and sunlight), and the temperature is the most influential factor (Han et al., 2021). Too high of a temperature will accelerate the spoilage of fresh food, and too low of a temperature will give fresh food freezer burn. Moreover, some temperature-sensitive fresh foods that are not transported within the required temperature range will produce harmful substances that threaten the health of consumers (Konovalenko et al., 2021). Therefore, the use of cold chain logistics to transport fresh food is an effective means to reduce food waste and ensure food safety (Lim et al., 2021; Liu et al., 2020a).

In response, temperature control in cold chain logistics has been the subject of extensive research and applications in the fresh food industry (Konovalenko et al., 2021). In the academic field, the current research hotspot is the temperature monitoring of refrigerated trucks during cold chain logistics transportation (Feng et al., 2019; Tang et al., 2021). These studies have developed a monitoring system that relies on emerging technologies such as wireless sensor networks (WSNs) and the Internet of Things (IOT) to store and transmit the temperature during transportation, thereby realizing visual monitoring (Li, 2021). In addition to vigorous academic research, this temperature monitoring method has been widely used in cold chain logistics practice. For example, Xiao et al. (2017b) achieved real-time monitoring of table grapes in cold chain logistics through a WSN. However, the current temperature monitoring mechanism in cold chain logistics can only be notified after temperature deviations. In fact, a temperature deviation that occurred has already damaged the quality of fresh food (Han et al., 2021). In this case, temperature prediction, which can actively identify upcoming errors and adjust the temperature in time to ensure food quality, is particularly important (Konovalenko et al., 2021).

At present, research on cold chain logistics temperature prediction is very limited, and there is no research on the temperature prediction of refrigerated trucks. In view of the existing research shortcomings, a question is raised: how can the temperature in a refrigerated truck beaccurately predicted and the temperature deviation be adjusted in time? There are many factors that affect the refrigerated truck temperature, so it is difficult to establish a mathematical temperature model, which makes temperature prediction a difficult and complicated task (de Micheaux et al., 2015). To address this problem, machine learning has shown good prospects. Machine learning does not need to understand the physical relationship between various variables and can predict the temperature using driving data, which avoids the establishment of complex mathematical models (Mercier and Uysal, 2018). In machine learning algorithms, extreme learning machines (ELMs), due to their fast learning rate and strong generalization ability, have been widely used in the field of prediction (Khan et al., 2021; Wu et al., 2019). However, the parameters (input weight and hidden bias) of the ELM have a great influence on the prediction results, so how to optimize the parameters has become a key issue (Liu et al., 2020b).

This research proposes the mayfly algorithm (MA) to optimize the parameters of the ELM, and the MA-ELM is designed to predict the refrigerated truck temperature. On the basis of the predicted temperature, the air conditioner status (air speed and air temperature) is further predicted so as to realize the timely control of the refrigerated truck temperature. Furthermore, in order to prove the superiority of the MA-ELM method, the MA-ELM is compared with the standard ELM, the genetic algorithm with the ELM (GA-ELM), and particle swarm optimization with the ELM (PSO-ELM). To the best of our knowledge, this research is an early study to predict the temperature of refrigerated trucks, which has contributed to both academia and industry. In the academic field, a multifactor prediction model for temperature and air conditioner status is established. To the best of our knowledge, this research is the first to propose the MA to optimize the ELM for prediction. In practice, accurate temperature prediction can reduce food waste and ensure food quality while accurate temperature control can reduce energy waste to save energy.

The structure of this research is as follows. This section introduces the research background and content. Section 2 provides a literature review of temperature prediction in cold chain logistics. The prediction method, the MA-ELM, is proposed in Section 3. Section 4 introduces the case study, including data preparation, parameter setting and evaluation index. Section 5 compares the prediction results of different methods, and a discussion is presented. Finally, Section 6 summarizes this research and proposes limitations and future research directions.

2. Literature review

As this research studies the prediction method of cold chain logistics temperature, the literature review is divided into two fields: the cold chain logistics temperature theme and the cold chain logistics temperature prediction method.

2.1 Cold chain logistics temperature theme

Fresh food is perishable, and cold chain logistics is used to transport fresh food to maintain a low-temperature environment. Due to the positive role of cold chain logistics in protecting fresh food quality, cold chain logistics research has attracted the attention of scholars in many fields including engineering, food and supply chains (Leng et al., 2020; Tang et al., 2021; Wu and Hsiao, 2021). Through the analysis of the existing literature, it is found that the research on cold chain logistics temperature mainly focuses on the temperature monitoring of refrigerated trucks. In earlier research, Xiao et al. (2017a) developed a quality tracking system for aquatic products that integrates a WSN and quick response codes to realize automatic temperature collection, transmission and monitoring. However, WSNs have shortcomings. That is, their network topology is easily affected by the external environment, and their data processing capabilities are weak. As a solution, the IOT has good potential in solving the above questions. Tsang et al. (2018) built a cold chain logistics system based on the IOT that includes three functions multitemperature packaging optimization, real-time product monitoring, and distribution route optimization. The results showed that implementing the proposed system can reduce food spoilage, improve customer satisfaction and increase operational efficiency. As the research has deepened, many scholars have conducted temperature warning research based on the temperature monitoring results in cold chain logistics. For example, Tang et al. (2021) used supervised machine learning models to classify the refrigerated truck door status and refrigeration system status to detect inappropriate behaviour. However, stakeholders can only be notified after a temperature deviation occurs in the abovementioned research. For temperature-sensitive products, once a temperature deviation occurs, the quality of fresh food can be reduced (Yong et al., 2020). Therefore, it is necessary to predict the temperature change trend in cold chain logistics, which can actively identify potential risks to avoid causing temperature deviations.

Some scholars have conducted research on cold chain logistics temperature prediction, but the research is not comprehensive. Regarding prediction objects, pallets (Mercier and Uysal, 2018) and containers (Konovalenko et al., 2021) have received attention in the existing research, and refrigerated trucks have not been studied thus far. This research focuses on the temperature prediction of refrigerated trucks. In terms of the factors affecting temperature, Mercier and Uysal (2018) used a neural network model to predict the perishable food temperature along the supply chain, and the results show that a sensor placed in the pallet corner can maximize the temperature prediction accuracy. However, their research has a limitation, that is, the temperature data in a pallet are collected by a single sensor. Indeed, they also stated that the number of sensors in the space should be increased in future research to increase the input of the neural network. This research fully considers this factor and sets up five sensors in different spatial positions in the refrigerated truck. Konovalenko et al. (2021) used the adapted Newton's law of cooling to predict pharmaceutical cold chain logistics temperatures and proved that the proposed method is superior to artificial neural networks and autoregressive moving average models through prediction errors and execution time. However, their research only collected temperature data and did not consider variables that cause temperature changes. They proposed that factors that cause temperature changes, including shocks, humidity and light, can be considered in future research.

This research draws on the ideas from Konovalenko et al. (2021) and attempts to find the factors that affect the temperature of refrigerated trucks from the existing research. Artuso et al. (2019) established a dynamic thermal model of a refrigerated truck considering the outside temperature, and the result showed that the outside temperature is the most important factor affecting the temperature inside the refrigerated truck. Therefore, it is indispensable to consider the outside temperature in the research on the refrigerated truck temperature. Furthermore, they proposed that the influence of load layout changes on internal temperature should be studied in the future. Correspondingly, Guo et al. (2012) studied the numerical simulation of temperature field distribution in refrigerated track based on computational fluid dynamics (CFD), and the results showed that different load layout affect the airflow, resulting in different temperature field distributions. In reality, the goods can be placed arbitrarily, which results in a variety of layouts. Therefore, a unified load layout is adopted in this research to reduce the influence of the cargo layout on the experimental results. In addition, unlike ordinary cargo, fresh food will continue to breathe during transportation, releasing heat and carbon dioxide, which will cause the temperature in the refrigerated truck to rise (Ertan et al., 2019). The degree of respiration is related to the load of the cargo, so this research uses the load to reflect the temperature change caused by respiration. During the delivery process, the refrigerated truck inevitably needs to open the door to unload the cargo, and this process will affect the temperature in the refrigerated truck. de Micheaux et al. (2015) carried out the experimental and numerical investigation of the infiltration heat load during the opening of refrigerated truck body, and the result showed that opening the door caused external heat to enter and affected the interior temperature of the refrigerated truck. Therefore, the factor of whether to open the door or not is considered when conducting the refrigerated truck temperature research. At this stage, air conditioners are widely used to control the refrigerated truck temperature, which includes two adjustment variables, the air conditioning speed and air conditioning temperature (Gao et al., 2021). Based on the analysis above, five factors that affect the refrigerated truck temperature can be determined, which are the outside temperature, load, whether the door is open, air conditioning speed and air conditioning temperature.

2.2 Cold chain logistics temperature prediction method

Recently, temperature prediction methods have been continuously discussed by scholars with the development of artificial intelligence. Initially, a neural network was used to predict the cold chain logistics temperature. Specifically, Chen and Shaw (2011) used a back propagation network to predict the temperature change of cold chain logistics, and the control center can immediately perform operations when an abnormality occurs. However, the traditional back propagation neural network has a slow convergence speed, which is prone to overfitting and underfitting (Khan et al., 2019). In addition, the learning rate and learning weight parameters need to be set based on experience, which can easily have a serious impact on the model effect if the parameters are set unreasonably (Khan et al., 2021). To overcome the shortcomings of the back propagation neural network, Huang (2014) proposed the ELM algorithm in which the input weight and hidden bias are generated randomly without being manually set. Their research results show that compared with feedforward neural networks (such as back propagation network), the ELM has a faster learning rate and better generalization capabilities. Since then, the ELM has been widely used in various fields, including photovoltaic power prediction (Zhou et al., 2020), evapotranspiration prediction (Wu et al., 2019), aircraft trajectory and associated fuel consumption prediction (Khan et al., 2021) and traffic flow prediction (Cai et al., 2020), due to its good performance However, it has not been applied in the cold chain logistics field thus far.

Even though the ELM model has many advantages, it is worth noting that the parameters of the input weight and hidden bias are randomly generated, which may produce nonoptimal parameters during the training process (Liu et al., 2020b). In response to this shortcoming, scholars began to seek to optimize the input weight and hidden bias through the good global search capabilities of biologically inspired algorithms. At present, the research is mainly focused on the combination of the ELM and classic biologically inspired algorithms. For example, Kumar et al. (2019) predicted indoor temperatures through the PSO-ELM, and the results showed that their proposed PSO-ELM improved the prediction accuracy compared with the ELM. Zhou et al. (2020) proved that the GA-ELM model has higher accuracy and stability in photovoltaic power prediction than the ELM. However, research on the optimization of the ELM with a new biologically inspired algorithm is still very limited. In response, this research proposes using the MA to optimize the parameters. The MA inspired by the mayfly mating process, was proposed by Zervoudakis and Tsafarakis (2020); and they proved that the performance of the MA is better than those of PSO and the GA in terms of solution quality.

Based on the above analysis, the innovations of this research are summarized as follows.

First, the acquisition of temperature data considers the different spatial positions in the refrigerated truck to improve the prediction accuracy. Second, the five factors that affect the refrigerated truck temperature, i.e., the outside temperature, air conditioning speed, air conditioning temperature, load and whether the door is open, are fully considered to make the model in line with the actual situation. The third innovation is that the research realizes the prediction of the air conditioner status based on the temperature prediction to achieve temperature control. The fourth innovation is that the research innovatively proposes the MA-ELM method for prediction.

3. Proposed methodology

This research uses the MA-ELM to predict the temperature and air conditioner status. The ELM is introduced in Section 3.1, Section 3.2 explains the MA, Section 3.3 describes the solution steps of the MA-ELM, and Section 3.4 introduces the evaluation indicators of the prediction results.

3.1 Extreme learning machine (ELM)

The ELM is an advanced single hidden layer feedforward neural network algorithm that overcomes the situation in which the results easily fall into the local optimum and the convergence speed is slow due to the use of the gradient descent algorithm in the traditional feedforward neural network (Huang, 2014). The input layer, hidden layer and output layer constitute the ELM model; and the network structure of the ELM is shown in Figure I. The ELM is used to train N arbitrary samples (x_i, y_i), in which x_i represents input variable, y_i represents the expected output, and the expression of the predicted output value o_j is shown in Equation (1), where β_i, $g(x)$, w_i, b_i, and L represent the output weight, activation function, input weight, , hidden bias, and number of hidden layer nodes, respectively.

$$\sum_{i=1}^{L} \beta_i \, g(w_i \cdot x_i + b_i) = o_j \tag{1}$$

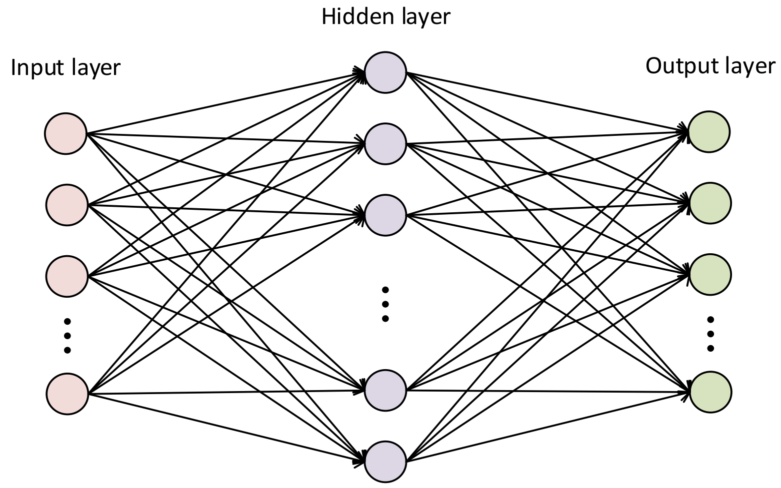


Figure I. The structure of the ELM.

The goal of the ELM is to minimize the output error, which can be expressed as Equation (2), that is, w_i, b_i and β_i are required make Equation (3) hold. The matrix form of Equation (3) is $H\beta = T$, where H represents the output matrix of the hidden layer, as shown in Equation (4); and β, and T represent the weight matrix and output matrix respectively, as shown in Equation (5).

$$\sum_{i=1}^{L} \left\| o_j - t_j \right\| = 0 \tag{2}$$

$$\sum_{i=1}^{L} \beta_i \, g\left(w_i \cdot x_j + b_i\right) = t_j \tag{3}$$

$$\mathrm{H}(w_1, \dots, w_L, b_1, \dots, b_L, x_1, \dots, x_L) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \dots & g(w_L \cdot x_1 + b_L) \\ \vdots & \dots & \vdots \\ g(w_1 \cdot x_N + b_1) & \dots & g(w_L \cdot x_N + b_L) \end{bmatrix}_{N*L} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L*m} \quad T = \begin{bmatrix} T_1^T \\ \vdots \\ T_L^T \end{bmatrix}_{L*m} \tag{5}$$

In the process of ELM training, input weight w and hidden bias b are randomly generated, and their values do not change. Therefore, the output matrix H of the hidden layer is determined according to Equation (4). For any w and b, the ELM can approximate the training sample with zero error when the number of neurons in the hidden layer is the same as the number of samples in the training set (Zhou et al., 2020). Therefore, the approximate output weight β^* can be obtained according to Equation (6), where H^+ represents the Moore-

Penrose generalized inverse of matrix H.

$$\beta^* = H^+T \tag{6}$$

3. 2 Mayfly algorithm (MA)

The analysis in Section 3.1 shows that w and b affect the performance of the ELM, and the MA is proposed to optimize the above two parameters in this research. The optimization process of the MA includes three stages, namely, the movement of male mayflies, the movement of female mayflies, and the mating of male and female mayflies (Zervoudakis and Tsafarakis, 2020).

Stage 1. Movement of male mayflies. The male mayflies gather together, and each male mayfly adjusts its position according to the experience of himself and the surrounding mayflies. The position is updated as Equation (7), where $x_i(t)$ is the position of male mayfly i at time t and $x_i(t+1)$ and $v_i(t+1)$ represent the position and velocity of mayfly i at time $t+1$ respectively. At time 0, $x_i(0) \in [x_{min}, x_{max}]$. In this algorithm, male mayflies perform the nuptial dance at a constant speed, and the speed is calculated as Equation (8).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{7}$$

$$v_{id}(t+1) = v_{id}(t) + p_1 e^{-\alpha r_m^2}\left(pbest_{id} - x_{id}(t)\right) + p_2 e^{-\alpha r_n^2}\left(gbest_d - x_{id}(t)\right) \tag{8}$$

where $v_{id}(t)$ and $x_{id}(t)$ represent the speed and position of mayfly i in dimension *d* *(d=1, 2...n)* at time *t*, respectively; p_1 and p_2 are positive attraction constants; and α is the visible range of each mayfly. When solving the minimization problem, the calculation formula of the historical optimal position $pbest_i$ of mayfly i is shown in Equation (9), where $f(\cdot)$ is the objective function (fitness function). $gbest$, as shown in Equation (10), is the global optimal position of the mayfly, where *N* represents the total number of male mayflies in the population. r_m represents the distance between the current position and $pbest$, calculated as Equation (11). r_n represents the distance between the current position and $gbest$, calculated as Equation (12).

$$pbest_i = \begin{cases} x_i(t+1), if\ f\left(x_i(t)\right) < f(pbest_i) \\ pbest_i, if\ f\left(x_i(t)\right) \geq f(pbest_i) \end{cases} \tag{9}$$

$$gbest \in min\{f(pbest_1), f(pbest_2), \cdots, f(pbest_N)\} \tag{10}$$

$$r_m = \sqrt{\sum_{d=1}^{n}(x_{id} - pbest_{id})^2} \tag{11}$$

$$r_n = \sqrt{\sum_{d=1}^{n}(x_{id} - gbest_d)^2} \tag{12}$$

To obtain the best solution, the best male mayfly in the population will continuously change the speed to perform a continuous up and down nuptial dance, which introduces a random element to the algorithm. In this case, the speed calculation formula at time $t+1$ is shown in Equation (13), where *v* is the dance coefficient and *r* is a random number from [-1,1].

$$v_{id}(t+1) = v_{id}(t) + vr \tag{13}$$

Stage 2. Movement of female mayflies. Female mayflies will not gather; instead, they will fly to males to mate. The calculation formula for the position of female mayfly i at time $t+1$ is shown in Equation (14), where $y_i(t)$ represents the position of female mayfly i at time t, and $v_i(t+1)$ represents the speed of female mayfly i at time $t+1$. At time 0, $y_i(0) \in [y_{min}, y_{max}]$.

$$y_i(t+1) = y_i(t) + v_i(t+1) \tag{14}$$

This algorithm sets the attraction as a fixed process, that is, the mating partner is selected based on performance, which means that the best performing female is attracted to the best performing male. When solving the minimization problem, the speed of the female is calculated as Equation (15), where $y_i(t)$ and $v_{id}(t)$ represent the position and velocity of female mayflies i in dimension *d (d=1, 2...n)* at time t respectively; p_2 is a positive attraction constant; α is a visibility constant; r_0 is the distance between male mayflies and female mayflies; l represents the random walk coefficient when the female is not attracted by the male; and r is a random number from [-1,1].

$$v_{id}(t+1) = \begin{cases} v_{id}(t) + p_2 e^{-\alpha r_o^2}\left(x_{id}(t) - y_{id}(t)\right), if\ f(y_i) > f(x_i) \\ v_{id}(t) + lr,\ if\ f(y_i) \le f(x_i) \end{cases} \tag{15}$$

Stage 3. Mating of mayflies. According to the principle of mayfly attraction, one of the male mayflies is produced as the male parent, one from the female mayflies is produced as the female parent, and then the cross operation is performed. The generation of fathers and mothers can be random or according to the fitness function. The two offspring (s_1 and s_2) generated are shown in Equations (16) and (17), where μ represents a random value within a specific range. The initial speed of the offspring is 0.

$$s_1 = \mu \times male + (1-\mu) \times female \tag{16}$$

$$s_2 = \mu \times female + (1-\mu) \times male \tag{17}$$

3. 3 Steps of the mayfly algorithm-extreme learning machine (MA-ELM)

The following five steps are used in the MA-ELM to predict the temperature and air conditioner status, and the specific solution steps are shown in Figure II.

Step 1: Normalize the collected data and divide the dataset into a training set and a test set.

Step 2: Enter the dataset into the ELM model, initialize the mayfly population (set the parameters including population size *N*, positive attraction constants p_1 and p_2, visibility constant α, random walk coefficient l, dance coefficient *v* and crossover coefficient), and calculate the fitness function value. In this research, the fitness function is the minimum average of the sum of the mean squared errors of the output variables in the test set, as shown in Equation (18). X_c and X_{cz} represent the true and predicted values of the output variable *c*, respectively; and X_d and X_{dz} represent the true and predicted values of the output variable *d*, respectively. h represents the group number of data in the test data set.

$$f(x) = \frac{1}{2}\left(\frac{\sum_{a=1}^{h}(X_c - X_{cz})^2}{h} + \frac{\sum_{a=1}^{h}(X_d - x_{dz})^2}{h}\right) \quad a = 1,2,\dots,h \tag{18}$$

Step 3: Update the positions of mayflies according to Equations (7) - (17), and perform the cross operation to obtain new *w* and *b* for calculating the new fitness value, thereby updating the optimal fitness value of the individual and the whole.

Step 4: Judge whether the maximum number of iterations is reached. If the condition is met, the optimal solution will be output; otherwise, skip to step 4 until the stopping condition is reached.

Step 5: Obtain the optimal parameters of the ELM through the MA and input the result into the ELM prediction model to output the predicted value and evaluate the performance of the model.

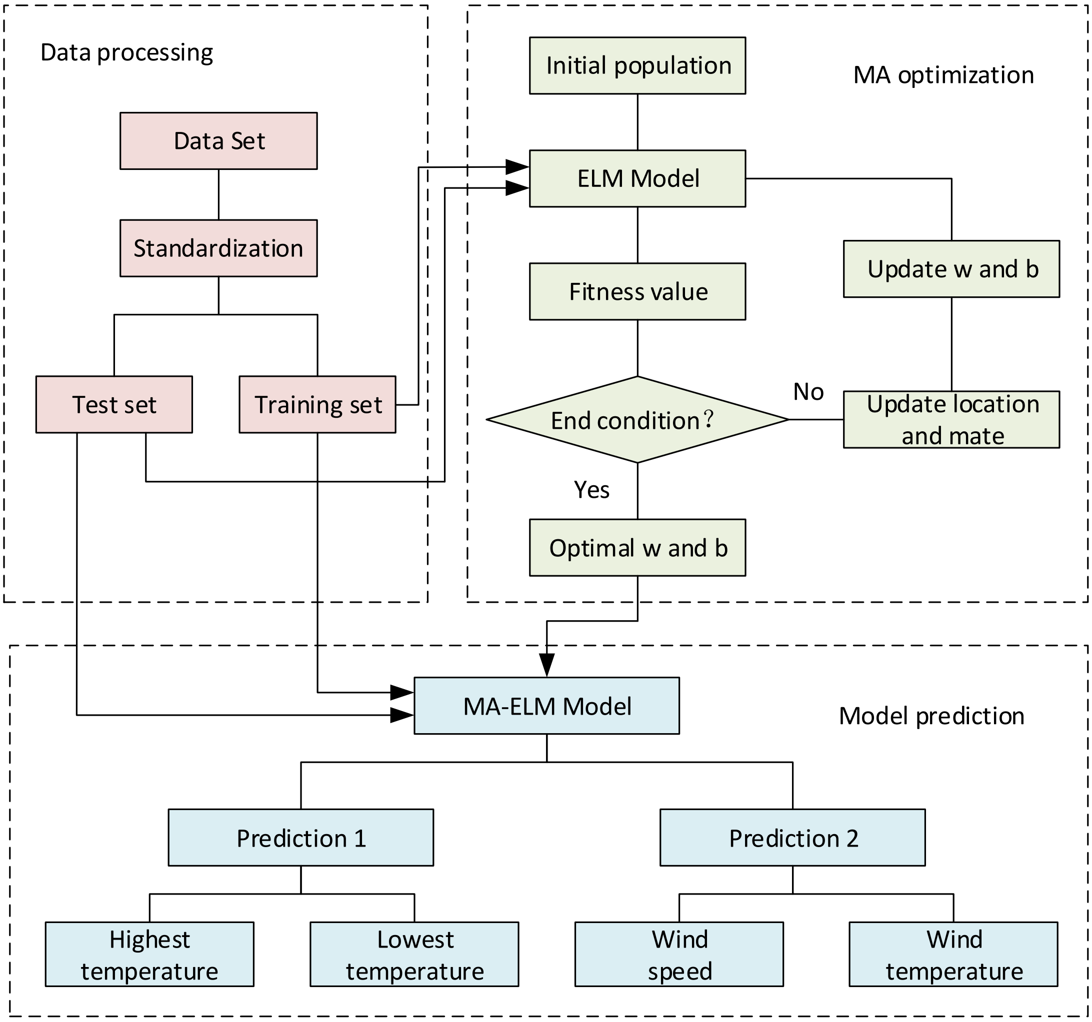


Figure II. The solution steps of the MA-ELM.

3.4 Evaluation indicators

Selecting the appropriate evaluation indicators is very important for the analysis of prediction results. This research evaluates the prediction results through five indicators, including the mean relative error (*MRE*), mean absolute error (*MAE*), mean square error (*MSE*), root mean square error (*RMSE*), and coefficient of determination (R^2), as shown in Equations (19) - (23), respectively, where Y_i is the true value, Y_{ia} is the predicted value, Y_{ib} is the average value of the true value, and *i* is the sample ($i = 1,2,\dots,n$). The closer the values of the

MRE, *MAE*, *RMSE* and *MSE* are to 0, the higher the prediction accuracy. The closer the value of the R^2 is to 1, the better the model fit.

$$MRE = |Y_i - Y_{ia}|/nY_i \tag{19}$$

$$MAE = 1/n \sum_{i=1}^{n} |Y_i - Y_{ia}| \tag{20}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} (Y_i - Y_{ia})^2/n} \tag{21}$$

$$MSE = \sum_{i=1}^{n} (Y_i - Y_{ia})^2/n \tag{22}$$

$$R^2 = \sum_{i=1}^{n} (Y_{ia} - Y_{ib})^2/\sum_{i=1}^{n} (Y_{ia} - Y_{ib})^2 \tag{23}$$

4. Case study

To evaluate the effectiveness of the proposed prediction method, this research takes Enterprise A (anonymous) as the object to conduct a case study. Enterprise A is a third-party cold chain logistics enterprise in Southwest China that has sufficient cold chain logistics equipment. In recent years, Enterprise A has continued to develop applications using emerging technology to provide customers with high-quality urban distribution services. Among these applications, the temperature prediction and air conditioner status prediction proposed in this research are included. Next, the preparation work of the case study, including data preparation, parameter setting and evaluation indicators, is introduced.

4.1 Data preparation

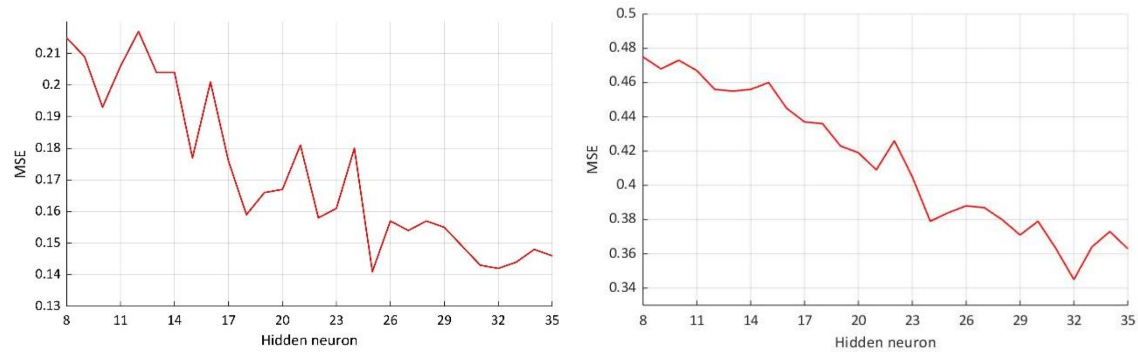
The temperature field distribution of the refrigerated truck is irregular, which will cause the temperatures at different locations in the refrigerated truck to be different. This research combines the internal temperature measurement method of related standards, namely, the 'Technical conditions and test methods of insulated and refrigerated vehicles' (Ministry of Industry and Information Technology of the People's Republic of China, 2010), and the actual situation to establish a temperature measurement program. That is, a temperature measuring point is set at the center of the inner surfaces of the other five compartments except for the surface where the door is located. In addition to temperature, it is also necessary to collect data on the five variables that affect the refrigerated truck temperature identified in the literature review, including the outside temperature, air conditioning speed, air conditioning temperature, load, and whether the door is open.

During the operations of a refrigerated truck, the data are sampled every 15 minutes, which means that this study can realize the temperature prediction after 15 minutes. The outside temperature, air conditioning speed, air conditioning temperature, load, and temperature of the refrigerated truck are all actual values. A total of 450 pieces of valid data were collected, of which 400 pieces were randomly selected as the training set, and the remaining 50 pieces were used as the test set. To eliminate the influence of different units on the results, the data need to be normalized. That is, all variables are converted into dimensionless values within (0, 1), as shown in Equation (24), where x_{ai} represents the converted value, x_a represents the *a-th* input, and x_{max}, and x_{min} represent the maximum and minimum values of x_a, respectively. Whether the door is open is measured as a 0-1 variable, where 0 means that the door is closed, and 1 means that the door is open.

$$x_{ai} = \frac{x_a - x_{min}}{x_{max} - x_{min}} \quad a = 1, 2, \dots, n \tag{24}$$

4.2 Parameter settings

The parameters that need to be set include the ELM parameters and biologically inspired algorithm parameters. In the ELM model, the settings of the input neuron and output neuron are based on actual needs. According to the above, the temperatures of the five measurement points are different, and these temperatures need to be within the specified temperature range. In this case, it is only necessary to require that the maximum temperature and the minimum temperature be within the specified interval to ensure that the temperatures of all temperature measurement points are within the specified range. Therefore, in Model 1 (temperature prediction), the number of input neurons is 5, including the outside temperature, air conditioning speed, air conditioning temperature, load, and whether the door is open; and the number of output neurons is 2, including high temperature and low temperature. Model 2 (air conditioner status prediction) also uses the same setting. The input neurons include the outside temperature, load, whether the door is open, high temperature and low temperature; and the output neurons include the air conditioning speed and air conditioning temperature. The number of hidden nodes has an important impact on the performance of the ELM. Specifically, too few hidden nodes will lead to insufficient model accuracy, and too many hidden nodes will cause model overfitting. According to experience, the optimization range of the initial number of hidden nodes is set to [8,35], and the mean squared error of the training set is used as the evaluation index to find the optimal number of hidden nodes. The images of the mean squared errors of the two models are shown in Figure III (a) and (b). Figure III shows that the models work the best when the numbers of hidden nodes are 25 and 32, respectively. Finally, the sigmoid function is used as the activation function of the hidden layer in this research. The specific parameter settings of the ELM are shown in Table I.



（a）Model 1 （b）Model 2

Figure III. Mean squared error changes with the number of hidden layer nodes increases.

Table I. The parameters of the ELM.

Model	Input neuron	Hidden neuron	Output neuron	Activation function
Model 1	5	25	2	Sigmoid
Model 2	5	32	2	Sigmoid

Furthermore, to verify the effectiveness of the MA for the parameter optimization of the ELM, the MA is compared with the GA and PSO in this research. Integrating the research of Zervoudakis and Tsafarakis (2020), Li et al. (2020) and Li et al. (2019), as well as the research experience, the parameters of the related biologically inspired algorithm are set as follows: (1) MA: population size $N = 30$, positive attraction constants $p_1 = 1$ and $p_2 = 0.5$, visibility constant $\alpha = 2$, random walk coefficient $l = 0.1$, dance coefficient $v = 0.1$, and crossover coefficient $v = 0.95$. (2) GA: population size $N = 30$, crossover probability $Pc = 0.8$, and mutation probability $Pm = 0.2$. (3) PSO: population size $N = 30$, learning factor $C_1 = 2$, learning factor $C_2 = 2$, and inertia factor $\delta = 0.9$. The maximum number of iterations of the three algorithms is set to 1000.

5. Results analysis and discussions

To verify the effectiveness of the MA-ELM method proposed in this research, many experiments have conducted. In Section 5.1, the temperature prediction results are analyzed, and the air conditioner status (air speed and air temperature) is predicted in Section 5.2.

5.1 Temperature prediction

This section uses four ELM methods (ELM, GA-ELM, PSO-ELM, and MA-ELM) to predict the temperature of refrigerated trucks in cold chain logistics. Figure IV shows the comparison between the target value and predicted value of low and high temperatures under the four ELM methods. Figure IV shows that regardless of high temperature or low temperature, the predicted value of the MA-ELM is closer to the target value. This finding can also be confirmed by the low- and high- temperature prediction error map in Figure V. Figure V shows that the error fluctuations predicted by the MA-ELM are closer to the zero line compared with the other three models. Furthermore, in order to increase the accuracy of the analysis, the five indicators *MRE, MAE, RMSE, MSE* and R^2 introduced in Section 4.3 are used to evaluate the prediction results, as shown in Table II.

Table II shows that when predicting the minimum temperature, the prediction effect of the MA-ELM (*MRE*=0.057, *MAE*=0.169, *RMSE*=0.218, *MSE*=0.047, and R^2=0.909) is better than that of the GA-ELM (*MRE*=0.063， *MAE*=0.185, *RMSE*=0.246, *MSE*=0.060, and R^2=0.909), the PSO-ELM (*MRE*=0.069, *MAE*=0.25, *RMSE*=0.246, *MSE*=0.060, and R^2=0.909） and the ELM (*MRE*=0.109, *MAE*=0.295, *RMSE*=0.381, *MSE*=0.145, and R^2=0.526). Specifically, in terms of the values of the four indicators of the *MRE*, *MAE*, *RMSE*, and *MSE*, compared with the ELM, the GA-ELM reduces the values by 0.046, 0.11, 0.135, and 0.085, respectively; the PSO-ELM reduces the values by 0.04, 0.09, 0.126, and 0.08, respectively; and the MA-ELM reduces the values by 0.052, 0.126, 0.163, and 0.098, respectively. Regarding the R^2, the three biologically inspired algorithms increase the value by 0.239, 0.158, and 0.383, respectively. The above results show that the use of biologically inspired algorithms (the GA, PSO and the

MA) improves the prediction accuracy of the ELM. Moreover, the MA has the best effect, which demonstrates the important role of the MA-ELM in improving the prediction accuracy. Similarly, the results of high temperature prediction are analyzed, and it is found that the order of the four methods from good to bad is MA-ELM (*MRE*=0.037, *MAE*=0.132, *RMSE*=0.173, *MSE*=0.030, and R^2=0.924) > GA-ELM (*MRE* =0.042, *MAE*=0.147, *RMSE*=0.185, *MSE*=0.034, and R^2=0.797) > PSO-ELM (*MRE*=0.047, *MAE*=0.169, *RMSE*=0.222, *MSE*=0.049, and R^2=0.704) > ELM (*MRE*=0.086, *MAE*=0.299, *RMSE*=0.373, *MSE*=0.139, and R^2=0.543). Therefore, regardless of whether high temperature or low temperature prediction is conducted, the MA-ELM has the best effect, followed by the GA-ELM, PSO-ELM and ELM.

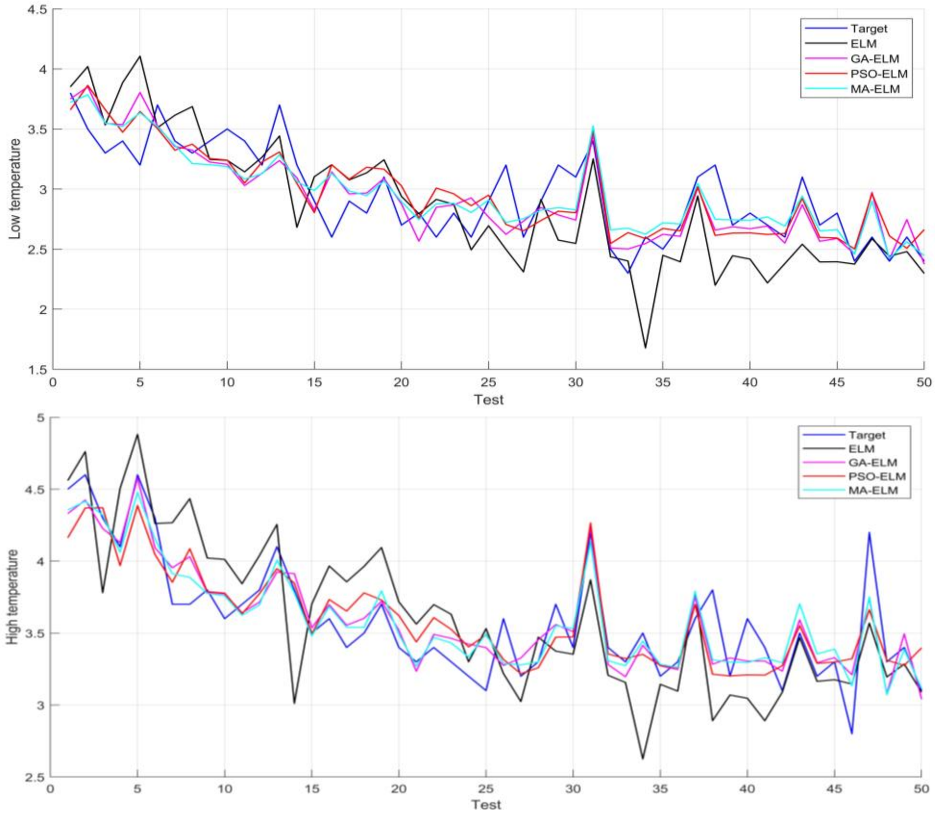


Figure IV. Comparison of target and predicted values at low and high temperatures.

Figure VI shows the fitness convergence curve of the GA, PSO and the MA in the process of optimizing the parameters of the ELM, which can further illustrate the superiority of the MA. The convergence curves of the fitness functions of the three biologically inspired algorithms follow the same trend. That is, the fitness values are first greatly reduced, and then the decreasing trend continues to decrease until it approaches stability. This process shows that the

MA reaches a steady state in less time, and the fitness value when the MA reaches a steady state is lower. These results show the effectiveness of the MA proposed to optimize the parameters of the ELM.

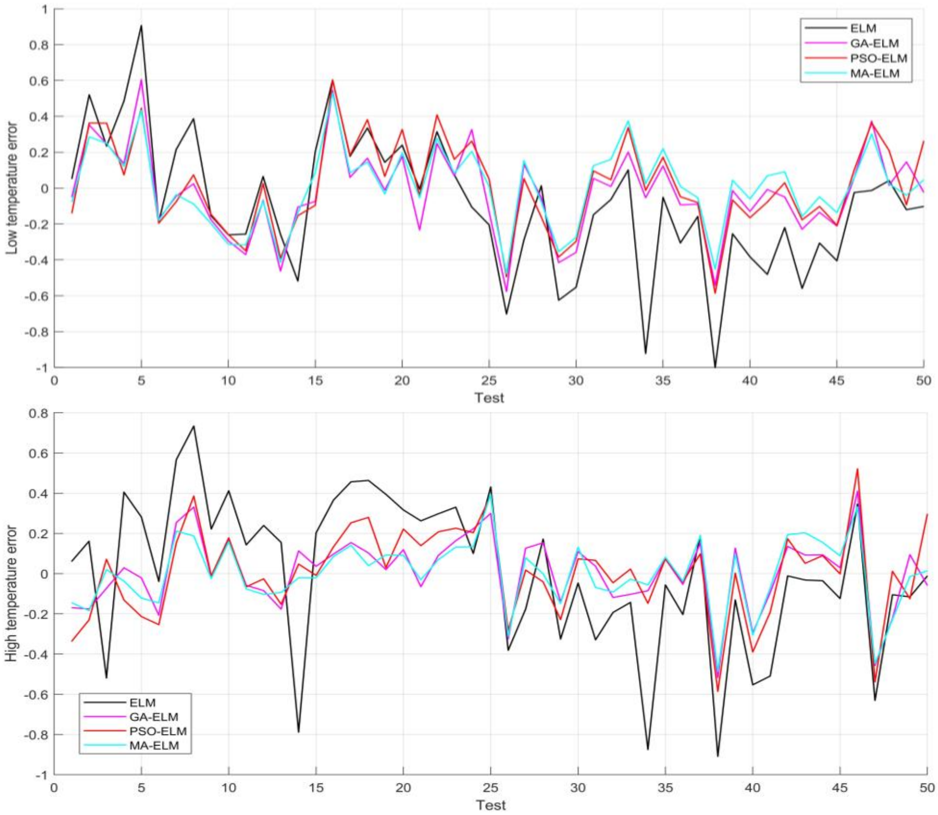


Figure V. Prediction error of low and high temperature.

Table II. The prediction evaluation results at low temperatures and high temperatures.

Prediction object	Method	*MRE*	*MAE*	*RMSE*	*MSE*	R^2
Low temperature	ELM	0.109	0.295	0.381	0.145	0.526
	GA-ELM	0.063	0.185	0.246	0.060	0.765
	PSO-ELM	0.069	0.205	0.255	0.065	0.684
	MA-ELM	0.057	0.169	0.218	0.047	0.909
High temperature	ELM	0.086	0.299	0.373	0.139	0.543
	GA-ELM	0.042	0.147	0.185	0.034	0.797
	PSO-ELM	0.047	0.169	0.222	0.049	0.704
	MA-ELM	0.037	0.132	0.173	0.030	0.924

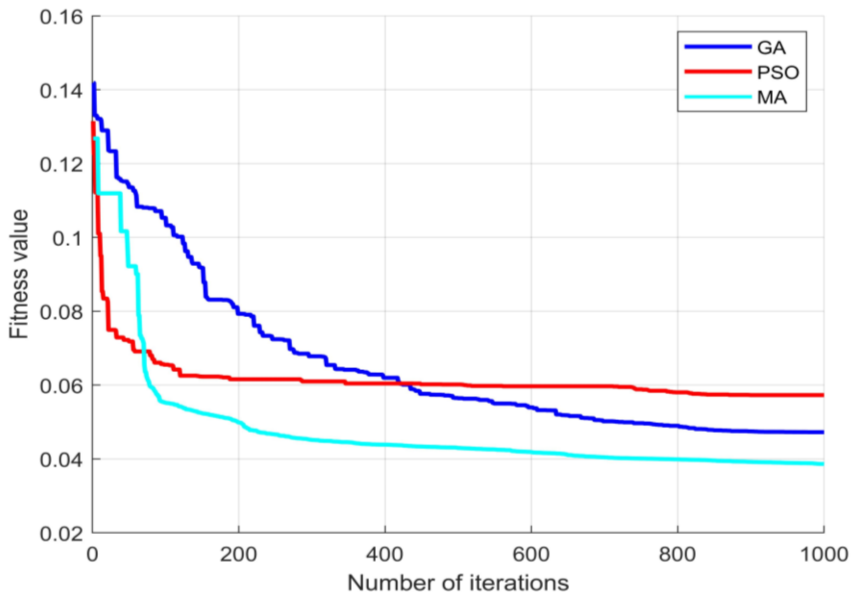


Figure VI. The fitness convergence curve of the GA, PSO and the MA for temperature prediction.

5.2 Air conditioner status prediction

This section makes timely adjustments to the results predicted in Section 5.1. That is, when the high temperature and low temperature are not within the scope of the cold chain logistics requirements, the air speed and air temperature can be adjusted to achieve precise temperature control. In this section, the MA-ELM is used to predict the air conditioner status (air speed and air temperature); and the three methods of the ELM, GA-ELM, and PSO-ELM are used for comparison. The comparison between the prediction values and target value of the four methods is shown in Figure VII. The figure shows that the prediction effect of the MA-ELM is the best because its predicted value is closest to the target value. Figure VIII shows the prediction errors of the four methods, of which the MA-ELM has the smallest fluctuation range, which means that its prediction effect is the best. The fitness convergence curves of the GA, PSO and the MA in Figure IX also show that the MA can maximize the accuracy of the prediction model. Specifically, compared with the GA and PSO, the MA can find a solution with a lower fitness value and reach a stable state earlier.

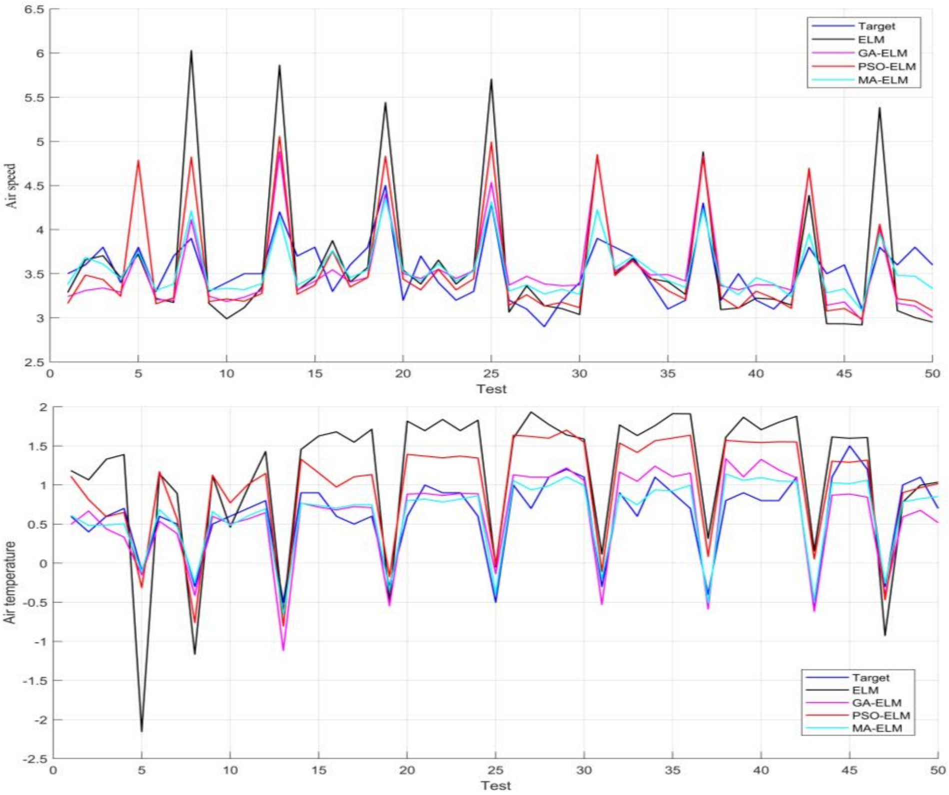


Figure VII. Comparison of the target and predicted values of the air speed and temperature.

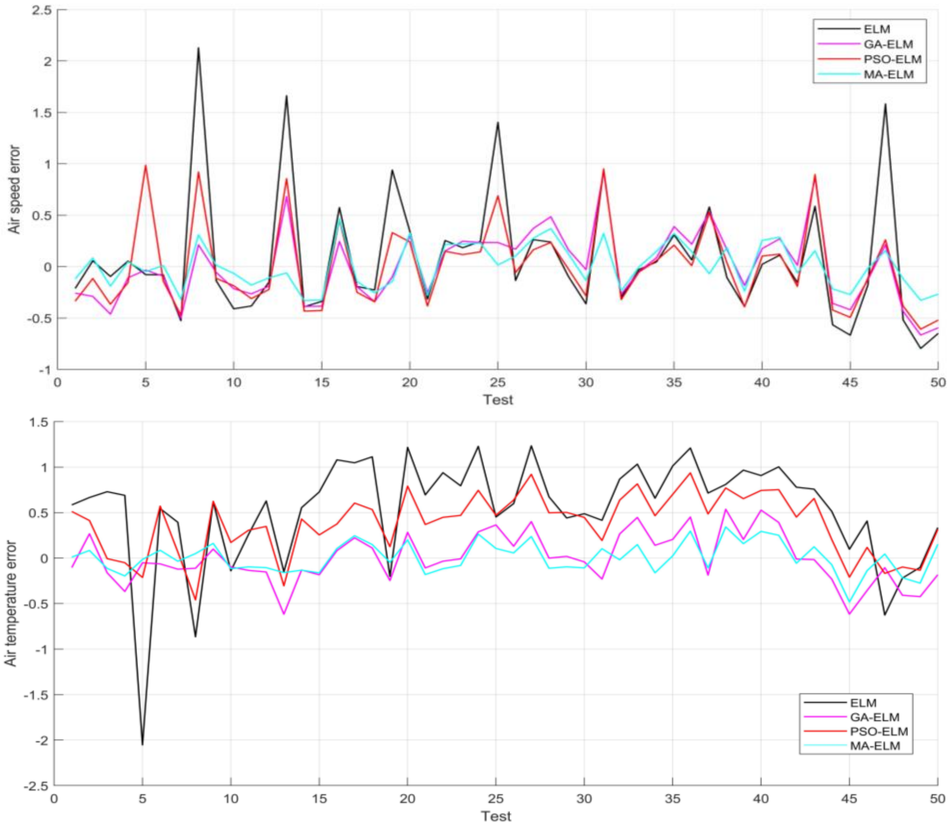


Figure VIII. Prediction error of the air speed and temperature.

Graphically, it is proven that the prediction effect of the MA-ELM is the best, and this conclusion is further verified by numerical methods. Table III lists five indicators, the *MRE*, *MAE*, *RMSE*, *MSE*, and R^2 , for evaluating the predicted values of the air speed and air temperature. In predicting the air speed, compared with the ELM, the MA-ELM (*MRE*=0.053, *MAE*=0.186, *RMSE*=0.217, *MSE*=0.047, and R^2=0.881) can improve the prediction accuracy to the greatest extent, followed by the GA-ELM (*MRE*=0.082, *MAE*=0.292, *RMSE*=0.355, *MSE*=0.126, and R^2=0.843), and finally the PSO-ELM (*MRE*=0.890, *MAE*=0.332, *RMSE*=0.417, *MSE*=0.174, and R^2=0.812). Similarly, in predicting the air temperature, the MA-ELM (*MRE*=0.197, *MAE*=0.142, *RMSE*=0.169, *MSE*=0.289, and R^2=0.920) produced the best performance, the ELM (*MRE*=0.833, *MAE*=0.705, *RMSE*=0.793, *MSE*=0.629, and R^2=0.731) produced the worst predictive performance, and the GA-ELM (*MRE*=0.336, *MAE*=0.219, *RMSE*=0.273, *MSE*=0.074, and R^2=0.834) had better predictive performance than the PSO-ELM (*MRE*=0.453, *MAE*=0.443, *RMSE*=0.503, *MSE*=0.253, and R^2=0.795). The above results show that the use of a biologically inspired algorithm can improve the prediction accuracy of the ELM; and the improved accuracy of the biologically inspired algorithms is ranked from high to low as the MA, the GA and PSO.

Table III. The prediction evaluation results of the air speed and air temperature.

Prediction object	Method	*MRE*	*MAE*	*RMSE*	*MSE*	R^2
Air speed	ELM	0.106	0.422	0.613	0.376	0.608
	GA-ELM	0.082	0.292	0.355	0.126	0.843
	PSO-ELM	0.089	0.332	0.417	0.174	0.812
	MA-ELM	0.053	0.186	0.217	0.047	0.881
Air temperature	ELM	0.833	0.705	0.793	0.629	0.731
	GA-ELM	0.336	0.219	0.273	0.074	0.834
	PSO-ELM	0.453	0.443	0.503	0.253	0.795
	MA-ELM	0.197	0.142	0.169	0.289	0.920

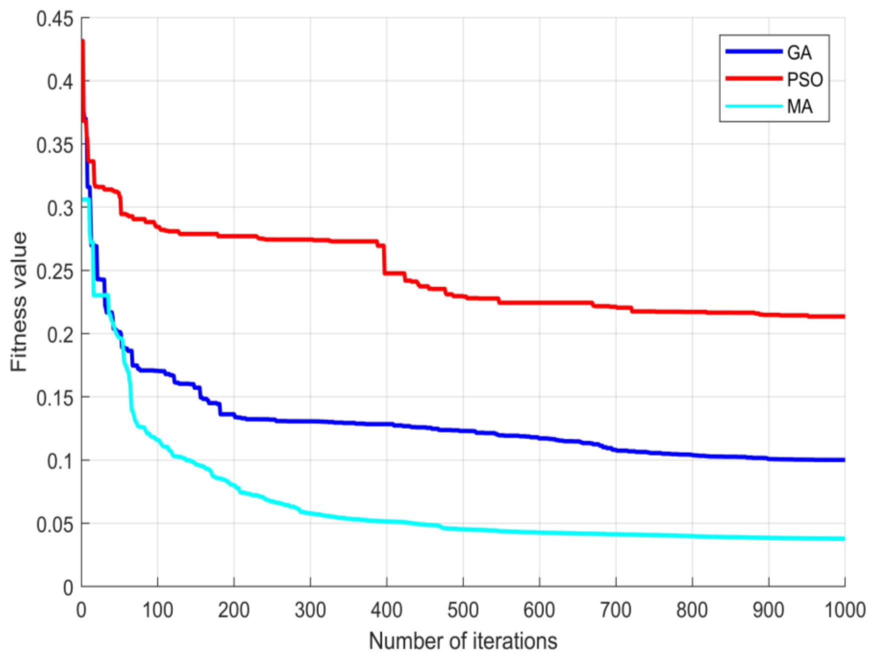


Figure IX. The fitness convergence curve of the GA, PSO and the MA for air conditioner status prediction.

5.3 Discussion

As reported by Li et al. (2019), the temperature in cold chain logistics is the main factor affecting the quality of fresh food. Although previous studies have discussed temperature monitoring in cold chain logistics, the potential risks of temperature change cannot be identified. To address this research gap, the MA-ELM hybrid method proposed in this research will accurately predict the temperature of cold chain logistics, thereby improving the precision of temperature control. In terms of prediction accuracy, Table II and Table III show that the hybrid MA-ELM method is superior to the traditional ELM and the ELM optimized by classical biologically inspired algorithms, including the GA and PSO. This research has brought three theoretical contributions. First, this research establishes a multifactor prediction model for the refrigerated truck temperature. In a previous study, Konovalenko et al. (2021) did not consider the key factors affecting temperature, in which only the temperature data were used to train the model, resulting in the limited accuracy of the prediction model. This research collected data on five factors that affect the refrigerated truck temperature including the outside temperature, air conditioning speed, air conditioning temperature, load and whether the door is opened, to make it more realistic, which help to improve the accuracy of temperature prediction for refrigerated trucks. Second, this research develops multiple prediction methods, including the ELM, GA-ELM, PSO-ELM and MA-ELM, to assess the prediction accuracy. In previous studies, the ELM was widely used in fuel consumption prediction (Khan et al., 2021), evapotranspiration prediction (Wu et al., 2019), traffic flow prediction (Cai et al., 2020), and copper spot price prediction (Wang et al., 2019). To the best of our knowledge, this research is the first study using the ELM to predict the temperature of refrigerated truck. In addition, some studies have proposed biologically inspired algorithms to optimize the ELM to improve the prediction accuracy, including the GA-ELM (Zhou et al., 2020) and PSO-ELM (Kumar et al., 2019). This research further proposes using the MA-ELM for prediction; and the results show that the MA-ELM can maximize the prediction accuracy compared with the ELM, GA-ELM and PSO-ELM. Third, this research innovatively proposes two prediction models: temperature prediction and air conditioner status prediction. Based on the temperature prediction, the prediction of the air conditioner state can achieve precise temperature control. Hence, it is believed that this is the first study on air conditioning state prediction.

6. Conclusion

To ensure the product fresh, this research uses the ELM to predict the temperature and air conditioning status (air speed and air temperature). However, the input weight and hidden bias of the ELM are randomly generated, which easily reduces the algorithm performance and causes unstable results. In response to this shortcoming, biologically inspired algorithms, which have a good global search ability, are proposed to optimize the ELM parameters. Therefore, four prediction methods are proposed to make predictions: the ELM, GA-ELM, PSO-ELM and MA-ELM. In the temperature prediction model, the prediction effects ranked from good to bad are MA-ELM > GA-ELM > PSO-ELM > ELM. The conclusions of the research on the prediction of the air conditioning status are consistent with those for the temperature. That is, the prediction effects are also ranked as MA-ELM > GA-ELM > PSO-ELM > ELM. The above results show the following: (1) The biologically inspired algorithms (the GA, PSO and the MA) with the ELM can improve the prediction accuracy. (2) The MA has better global search ability to maximize the prediction accuracy. This research has made two contributions to theory and practice. In theory, the MA-ELM is proposed for the first time to predict the temperature and air conditioning status of refrigerated truck, which provides a reference for future research. In practice, this research has achieved accurate temperature prediction, which ensures food quality and reduces energy waste. However, this research has some limitations. The ELM and its variants considered in this research, including the GA-ELM, PSO-ELM and MA-ELM, are limited. In future research, other new biologically inspired algorithms, including the whale optimization algorithm (WOA), seagull optimization algorithm (SOA) and spotted hyena optimization (SHO), can be used to optimize ELM and compared with the method proposed in this research. On the other hand, other factors that affect product quality can be considered in subsequent research, such as humidity, vibration, oxygen and sunlight. Finally, numerical experiments are worthy of being carried out to analyze the specific changes that temperature predictions bring to improve food quality and reduce energy.

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