



REVIEW ARTICLE

COMBINATION AIR TEMPERATURE FORECASTING MODEL BASED ON TRIANGULAR FUZZY NUMBER

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ABSTRACT

Scientific and accurate temperature prediction is a key link in realizing meteorological disaster early warning and efficient use of climate resources, and it is also an important prerequisite for promoting smart meteorological construction and refined meteorological services. Due to the complex characteristics of temperature series such as non-linearity, time-varying, and seasonality, and the comprehensive influence of various uncertain factors such as atmospheric circulation, topography, humidity, and wind speed, the data obtained through various data collection methods are often uncertain. These uncertainties may affect the information presented by the quantitative results, which limits the accuracy of the prediction model to a certain extent. In this paper, the monthly average minimum temperature, monthly average temperature and monthly average maximum temperature in Chengdu from 2008 to 2018 are used as three boundary points to construct a triangular fuzzy number sequence, and to convert the triangular fuzzy number sequence into three index number sequences with equal information for the sake of data integrity. For the three index number sequences, the time series Autoregressive Integrated Moving Average (ARIMA) model and the gated recurrent unit (GRU) neural network are constructed respectively. Finally, on the basis of the prediction results of a single model, the induced order weighting (IOWA) operator are introduced. A triangular fuzzy combination prediction model of ARIMA-GRU integrating IOWA operators is established, and the temperature prediction value is obtained by de-fuzzification. The new model is applied to the temperature series prediction of Chengdu from 2008 to 2018, and compared with ARIMA model and GRU neural network, the results show that the performance of the new model in terms of mean square error (MSE) and average accuracy is better than that of other models, significantly improving the prediction accuracy of air temperature.

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INTRODUCTION

Temperature is an important meteorological element reflecting climate change, and its accurate prediction is of great significance in the fields of meteorological disaster early warning, agricultural production scheduling, and refined urban management. Temperature prediction methods usually use accurate values to describe temperature. In temperature prediction research, original observation data usually have high-frequency fluctuations and uncertainties. Therefore, reconstruction and aggregation on the time scale are often required before modeling to improve the smoothness and predictability of the sequence. Existing studies mostly use daily or average temperature as the basic unit of time series modeling, and use it to predict future temperature changes. For example, Oleg Makarynskyy et al. built an artificial neural network model based on the daily average temperature series, and realized the effective prediction of daily temperature (1); Murat et al. used daily air temperature data to establish ARIMA model and regression model to model and predict air temperature time series (2). In addition, the method based on LSTM network has been gradually applied to the prediction of mean temperature series in recent years, and has achieved good results (3). Transforming the original observation series into mean temperatureseries is a common pretreatment in air temperature time series modeling. However, the temperature change process itself has obvious stage and trend characteristics. For example, intraday temperature typically exhibits a diurnal pattern, gradually increasing from early morning to the afternoon and then decreasing toward nighttime. It is easy to ignore the dynamic information in the process of temperature change if only the mean value or extreme value statistics are used to express it, resulting in the loss of part of the characteristic information. To address the uncertainty inherent in time-series data, Song and Chissom (4, 5) proposed the fuzzy time series (FTS) forecasting method and

successfully applied it to university enrollment forecasting. At present, the research on fuzzy numbers includes interval fuzzy numbers, triangular fuzzy numbers, rectangular fuzzy numbers and so on. Among them, the triangular fuzzy number describes the data through the lower bound, the center value and the upper bound. The monthly temperature can be described by the monthly average minimum temperature, monthly mean temperature and maximum temperatures. Thus, the monthly average temperature can be described by triangular fuzzy numbers, which can express its uncertainty while retaining the main characteristics of the data. Therefore, expressing the temperature series as a triangular fuzzy number series is helpful to reflect the interval characteristics and internal structure of temperature changes more comprehensively. On the other hand, a single prediction model often has certain limitations in modeling complex time series. The ARIMA model has advantages in describing linear relationships, such as small amount of data required, simple calculation, and high accuracy; The GRU neural network has advantages in capturing nonlinear dynamic characteristics and temporal dependencies, but its performance may be limited when the available training data are insufficient. In 1969, Bates and Granger proposed a combined forecasting method (6), showing that appropriately combining forecasts from multiple models can improve forecasting performance. Due to the limitations of each model, how to determine the weight ratio of each model in the combined model has become an important issue. Among them, Wang et al. introduced the Induced Ordered Weighted Averaging (IOWA) operator, and obtained the coefficients of each individual method by introducing inducing variables to dynamically modify the weights, which played an important role in determining the weights of the combined model (7). Most of the combined models are directly weighted and averaged by each single model when they are established. Aiming at the data uncertainty and the limitation of single model in air temperature series forecasting, this paper proposes an ARIMA-GRU combined forecasting model combining triangular fuzzy number and IOWA operator. Specifically, the monthly minimum temperature, mean temperature and maximum temperatures are constructed as triangular fuzzy numbers, and further transformed into equivalent information index sequences. On this basis, individual ARIMA and GRU forecasting models are developed, and the IOWA operator is subsequently employed to perform weighted aggregation of their forecasting results, thereby improving the forecasting accuracy of the air temperature series. Compared with a single model, the method used in this paper has higher prediction accuracy.

Basic concepts

Definition 1 (8). Let $x_t = (a_t, b_t, c_t), (t = 1, 2, 3 \dots)$, If it satisfies $a_t \leq b_t \leq c_t$, then it is called a triangular fuzzy number (TFN). The general form of a triangular fuzzy number is given in Eq. (1):

$$\tilde{y}_t^\Delta = [(y_t - \Delta), y_t, (y_t + \Delta)]. \quad (1)$$

where $\tilde{y}_t^\Delta$ denotes the fuzzy time series data, y_t represents the time series data at time $t (t = 1, 2, \dots, n)$, Δ denotes the left and right spreads of the triangular fuzzy number. The value of Δ depends on the fuzzification method, as shown in the figure:

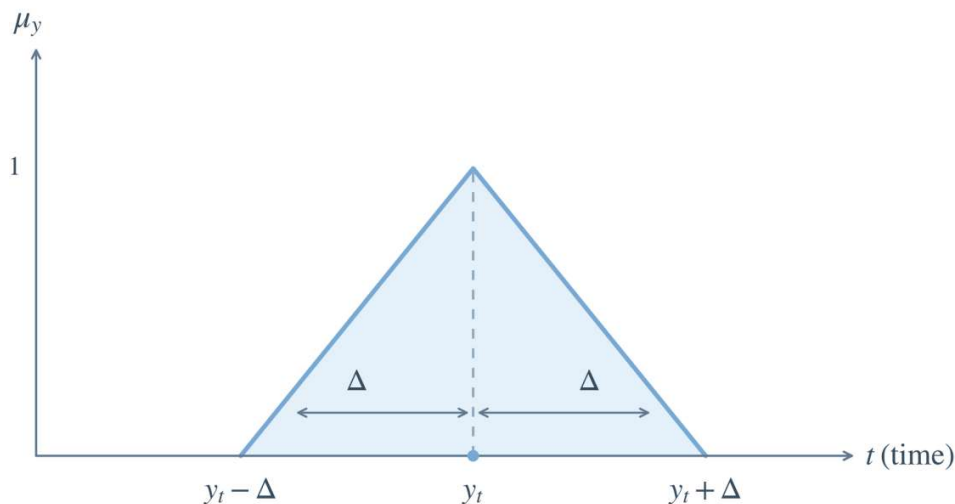


Fig. 1. Schematic Diagram of a Triangular Fuzzy Number

Furthermore, if $b_t - a_t = c_t - b_t$ holds, it is called a symmetric triangular fuzzy number. If $a_t = b_t = c_t$ holds, it reduces to an ordinary real number. Let $x_i = (a_i, b_i, c_i)$ and $x_j = (a_j, b_j, c_j) (i \neq j)$, be two triangular fuzzy numbers. Then, the following operational properties hold:

$$(1) x_i = x_j \Leftrightarrow a_i = a_j, b_i = b_j, c_i = c_j;$$

$$(2) x_i \mp x_j \Leftrightarrow (a_i, b_i, c_i) \mp (a_j, b_j, c_j) \Leftrightarrow (a_i \mp a_j, b_i \mp b_j, c_i \mp c_j);$$

$$(3) kx_i = (ka_i, kb_i, kc_i).$$

Definition 2(9). Triangular fuzzy number (TFN) $x_t = (a_t, b_t, c_t)$ is equivalent to TFN $y_t = (s_t, b_t, g_t)$, where $s_t = (c_t - a_t)/2$, $g_t = (a_t + b_t + c_t)/3$. s_t, b_t, g_t are referred to as the area, midpoint, and centroid indices of the TFN x_t , respectively. Based on these three index sequences, the lower and upper bounds of the original triangular fuzzy time series can be reconstructed using Eq. (2)

$$a_t = (3g_t - b_t - 2s_t)/2, b_t = b_t, c_t = (3g_t - b_t + 2s_t)/2. \quad (2)$$

Definition 3 Error! Reference source not found.. Let $IOWA_w: R^n \rightarrow R$ be an m-ary function, and $W = (w_1, w_2, \dots, w_m)^T$ be a weight coefficient vector satisfying $\sum_{i=1}^m w_i = 1, w_i \geq 0$, if

$$IOWA_w(u_1, a_1, u_2, a_2, \dots, u_n, a_n) = \sum_{i=1}^n w_i a_{u-index(i)}$$

holds, then $IOWA_w$ is called an n-dimensional generalized induced ordered weighted averaging operator constructed by $u_1, u_2, \dots, u_n$, which is briefly denoted as the $IOWA$ operator.

Definition 4 Error! Reference source not found.. Let

$$\begin{aligned} \delta_t &= \alpha(1 - |s_t - \hat{s}_t|/s_t) + \beta(1 - |b_t - \hat{b}_t|/b_t) + \gamma(1 - |g_t - \hat{g}_t|/g_t) \\ &= \alpha \left(1 - \left| \sum_{i=1}^m w_i |s_{\mu-index(i)} - s_t| / s_t \right| \right) + \beta \left(1 - \left| \sum_{i=1}^m w_i |b_{\mu-index(i)} - b_t| / b_t \right| \right) \\ &\quad + \gamma \left(1 - \left| \sum_{i=1}^m w_i |g_{\mu-index(i)} - g_t| / g_t \right| \right). \end{aligned} \quad (3)$$

Then, δ_t , as defined in Eq. (3), is called the comprehensive forecasting accuracy of the combined model at time t , where $\alpha \geq 0, \beta \geq 0, \gamma \geq 0, \alpha + \beta + \gamma = 1$. It can be seen that a larger comprehensive forecasting accuracy indicates better forecasting performance. Therefore, the optimal weight coefficients of the combination forecasting model can be determined using Eq. (4).

$$\max F(W) = \frac{1}{N} \sum_{t=1}^N \left[\alpha \left(1 - \frac{\sum_{i=1}^m w_i |s_{\mu-index(i)} - s_t|}{s_t} \right) + \beta \left(1 - \frac{\sum_{i=1}^m w_i |b_{\mu-index(i)} - b_t|}{b_t} \right) + \gamma \left(1 - \frac{\sum_{i=1}^m w_i |g_{\mu-index(i)} - g_t|}{g_t} \right) \right] \quad s.t. \begin{cases} \sum_{i=1}^m w_i = 1, \\ w_i \geq 0, i = 1, 2, \dots, m. \end{cases} \quad (4)$$

Construction and Transformation of Triangular Fuzzy Sequences: The temperature data used in this study are derived from the China Meteorological Forcing Dataset (CMFD) version 1.6 Error! Reference source not found.. This dataset was developed by Yang Kun et al. and released by the National Tibetan Plateau Data Center (<https://data.tpdc.ac.cn/home>). It has a spatial resolution of 0.1° and a temporal resolution of 3 hours, which can effectively characterize the spatiotemporal variation characteristics of meteorological elements in China. The construction method and data characteristics of this dataset are described in He et al. Error! Reference source not found.. The monthly average minimum temperature a_t , average temperature b_t and maximum temperature c_t are used to construct the three parameters of the triangular fuzzy number, as defined in Eq. (5).

$$\tilde{T}_t^\Delta = [a_t, b_t, c_t]. \quad (5)$$

including the area, midpoint, and centroid index sequences. $S, B, G, S=(s_t), B=(b_t), G=(g_t), t=1, 2, 3, \dots$. Separate forecasting models are developed for S, B, G , respectively, based on a total of 132 data samples. The original data are shown in **Table 1**.

Table 1. Monthly Temperature Data

t	Original Data			Transformed Data		
	a_t	b_t	c_t	s_t	b_t	g_t
200801	-2.66	3.82	14.17	8.41	3.82	5.11
200802	-3.11	5.67	17.75	10.43	5.67	6.77
200803	1.47	13.71	24.26	11.4	13.71	13.15
200804	10.02	17.44	29.66	9.82	17.44	19.04
...	...	...	...	...	...	...
201809	16.43	22.03	33.17	8.37	22.03	23.88
201810	9.35	16.39	24.22	7.44	16.39	16.65
201811	3.47	11.56	23.03	9.78	11.56	12.69
201812	-1.25	7.23	16.29	8.77	7.23	7.42

Construction of ARIMA Models for Triangular Fuzzy Time Series: The autoregressive moving average (ARMA) model combines an autoregressive AR(p) component and a moving average MA(q) component. For a non-stationary time series, differencing can be applied to achieve stationarity. An ARIMA(p, d, q) model is obtained by applying d-order differencing to the original series and then fitting an ARMA(p, q) model to the differenced series. The general form of the ARIMA model is given in **Eq. (6)**.

$$\begin{cases} \Phi(B)\nabla^d X_t = \Theta(B)\varepsilon_t, \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \delta_t^2, E(\varepsilon_t \varepsilon_s) = 0, s \neq t, \\ E(x_s \varepsilon_t) = 0, \forall s < t, \end{cases} \tag{6}$$

where $\nabla^d=(1-B)^d$, $\Phi(B)=1-\phi_1B-\dots-\phi_pB^p$ represents the autoregressive coefficient polynomial of the stationary and invertible ARIMA(p,q) model, and p is the order of the autoregressive model. $\Theta(B)=1-\theta_1B-\dots-\theta_qB^q$, $\{\varepsilon_t\}$ is the white noise sequence, and B is the lag operator. The basic process of ARIMA modeling is illustrated in the following **Figure 2**.

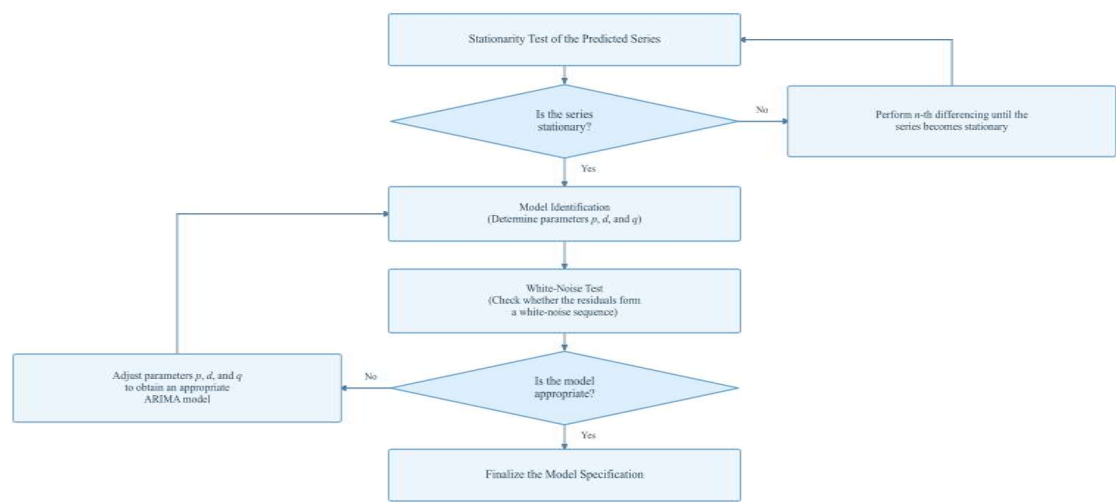


Fig. 2. Flowchart of ARIMA Modeling Process

The historical data of S, B , and G from 2008 to 2018 in **Table 1** are used to construct ARIMA models. According to the basic procedure of ARIMA modeling, ARIMA(2,0,2), ARIMA(2,1,3), and ARIMA(1,1,1) models are established for S, B and G , respectively. The specific model formulations are given in **Eqs. (7)–(9)**.

$$s_t = 8.76 + 1.72s_{t-1} - 0.98s_{t-2} + \varepsilon_t - 1.67\varepsilon_{t-1} + 0.89\varepsilon_{t-2}, \tag{7}$$

$$g_t = 2.73g_{t-1} - 2.73g_{t-2} + g_{t-3} + \varepsilon_t - 2.6\varepsilon_{t-1} + 2.45\varepsilon_{t-2} - 0.81\varepsilon_{t-3}. \quad (9)$$

Using the above models (7)-(9), the S , B , and G values from 2008 to 2018 are back-tested, yielding an MSE of 2.26°C^2 and an RMSE of 1.50°C . The corresponding data are presented in the **Table 2**.

Table 2. Monthly Forecast Values of Each Indicator Using ARIMA

t	Forecast Indicator			Indicators converted back according to the formula		
	s_t	b_t	g_t	a_t	b_t	c_t
200801	8.7688	0	0	-2.65	3.82	14.16
200802	8.6714	3.82	5.11	-3.11	5.67	17.75
200803	9.1661	6.7593	7.0607	1.47	13.71	24.27
...						
201809	7.9387	22.4535	23.2266	16.44	22.03	33.17
201810	8.411	17.6527	18.1636	9.34	16.39	24.22
201811	8.8782	12.6911	12.7653	3.47	11.56	23.03
201812	9.4479	9.234	9.0207	-1.26	7.23	16.28

Construction of a Triangular Fuzzy GRU Forecasting Model: The Gated Recurrent Unit (GRU) neural network introduces a gate mechanism based on the traditional Recurrent Neural Network (RNN) to alleviate the problems of gradient explosion and gradient vanishing, thereby addressing the long-term dependency issue. GRU is a gated recurrent neural network variant proposed based on the Long Short-Term Memory (LSTM) architecture. By combining the cell state and hidden state, GRU simplifies the state transmission mechanism and reduces the complexity of the gating structure. It merges the input gate and forget gate into a single update gate, which simultaneously achieves selective forgetting of the previous hidden state and selective retention of the current candidate state. In addition, GRU introduces a reset gate to control the influence of the previous hidden state on the current candidate state. Despite simplifying the structure, GRU achieves performance comparable to LSTM in most tasks. The network structure of the GRU model is shown in **Figure 3**, and its calculation process is presented in Equations (10)-(13).

The reset gate is calculated using **Eq. (10)**.

$$r_t = \sigma(W_R[h_{t-1} \boxtimes x_t]). \quad (10)$$

The update gate is calculated using **Eq. (11)**.

$$z_t = \sigma(W_z[h_{t-1} \boxtimes x_t]). \quad (11)$$

The calculation formula for the candidate state $\tilde{h}_t$ is given in **Eq. (12)**.

$$\tilde{h}_t = \tanh(W_r[r_t \boxtimes h_{t-1}, x_t]). \quad (12)$$

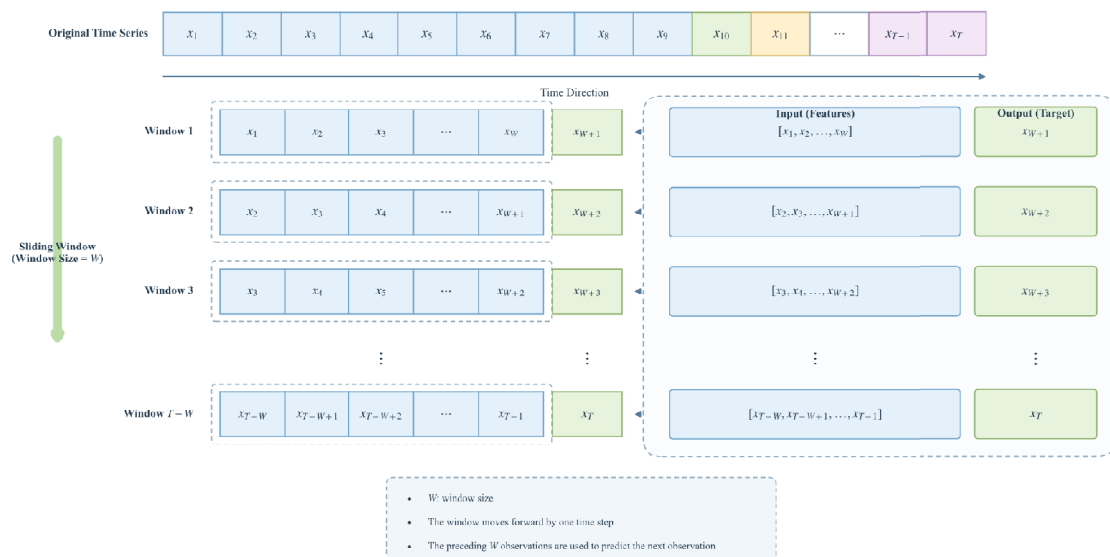
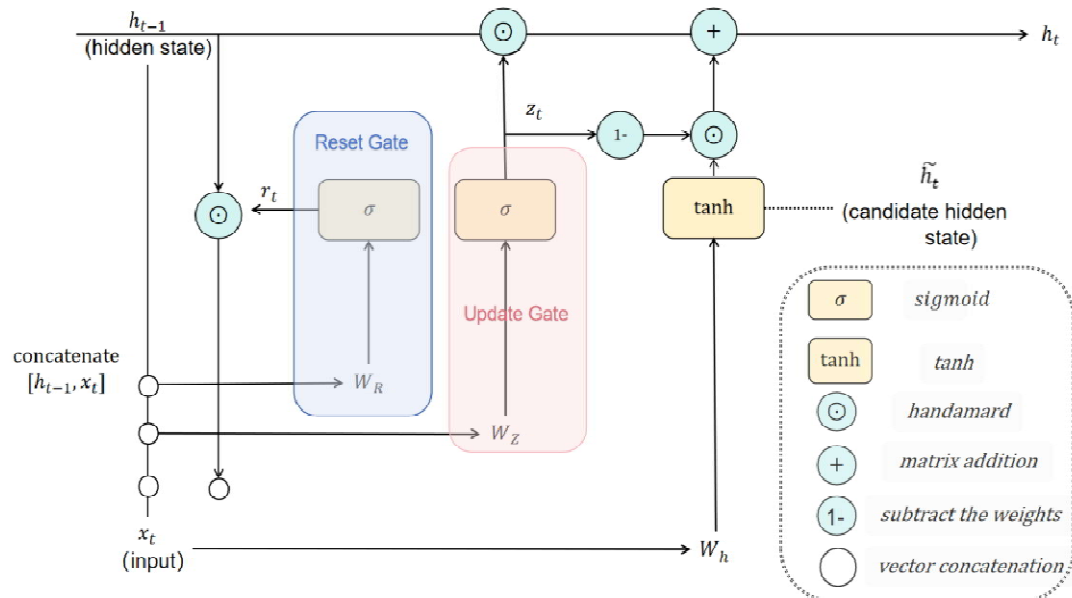
The calculation formula for the hidden layer output is given in **Eq. (13)**:

$$h_t = (1 - z_t) \boxtimes h_{t-1} + z_t \boxtimes \tilde{h}_t. \quad (13)$$

In (10)-(13), σ and $\tanh$ denote the Sigmoid activation function and the hyperbolic tangent activation function, respectively; $\boxtimes$ represents the Hadamard product; r_t indicate the reset gate state and update gate state at time t , z_t denotes the update gate state at time t ; x_t denotes the input sample at time t ; h_{t-1} and h_t denotes the hidden state at time $t-1$ and the hidden state output at time t , respectively; $\tilde{h}_t$ denotes the candidate state at the current time step; W_r , W_z , W_h denote the weight matrices corresponding to the reset gate, update gate, and candidate state, respectively. After constructing the triangular fuzzy sequence from the original sequence, the sub-membership sequences S , B , and G can be obtained. Based on this, a GRU-based prediction model for the sub-membership sequences is constructed by referring to the modeling approach in Reference **Error! Reference source not found.** Two different strategies are adopted for modeling. Strategy 1 considers the three sub-membership sequences as a three-

dimensional sequence and performs prediction using a single GRU neural network model. Strategy 2 applies separate GRU neural network models to predict the S , B , and G sub-membership sequences individually. Both strategies have certain applicability, but their prediction performances differ under different application scenarios. Due to the limited length of the original monthly

window length is set to 12 months, with a stride of one month. Each input sample consists of the observations from the preceding 12 months, while the corresponding output is the observation of the subsequent month. Consequently, 120 input-output pairs are constructed from the original series. It should be noted that the sliding-window transformation reorganizes the original sequence for supervised learning rather than increasing the number of independent observations. The specific procedure is illustrated in **Figure 4**.



The original data are fitted and learned by the model. The number of hidden layers is set to 2, with 128 neurons in the GRU layer and 64 neurons in the fully connected layer. The batch size is set to 8, and the number of training iterations is set to 100. The mean squared error (MSE) between the normalized data values and the model prediction values is adopted as the loss function during training, and the Adam optimization algorithm is employed to update the model parameters. Following the strategy proposed in this study, the TFN are incorporated into the GRU model for training. The two strategies employed in this paper are as follows:

comparison between the predicted and actual values of S , B , and G is presented in Figure 6. The model achieved an MSE of 1.0896°C^2 and an RMSE of 1.0438°C on the test set.

can be observed that the loss decreased steadily throughout the training process. The feature S tended to converge after the 5th epoch, while the features B and G tended to converge after the 20th and 30th epochs, respectively. The feature S achieved an MSE of 1.3113°C^2 and an RMSE of 1.1451°C on the test set; the feature B achieved an MSE of 1.5204°C^2 and an RMSE of 1.2331°C ; and the feature G achieved an MSE of 1.5634°C^2 and an RMSE of 1.2504°C . The average MSE and RMSE were 1.4651°C^2 and 1.2095°C , respectively. The comparison between the predicted and actual values of S , B , and G is presented in Figure8.

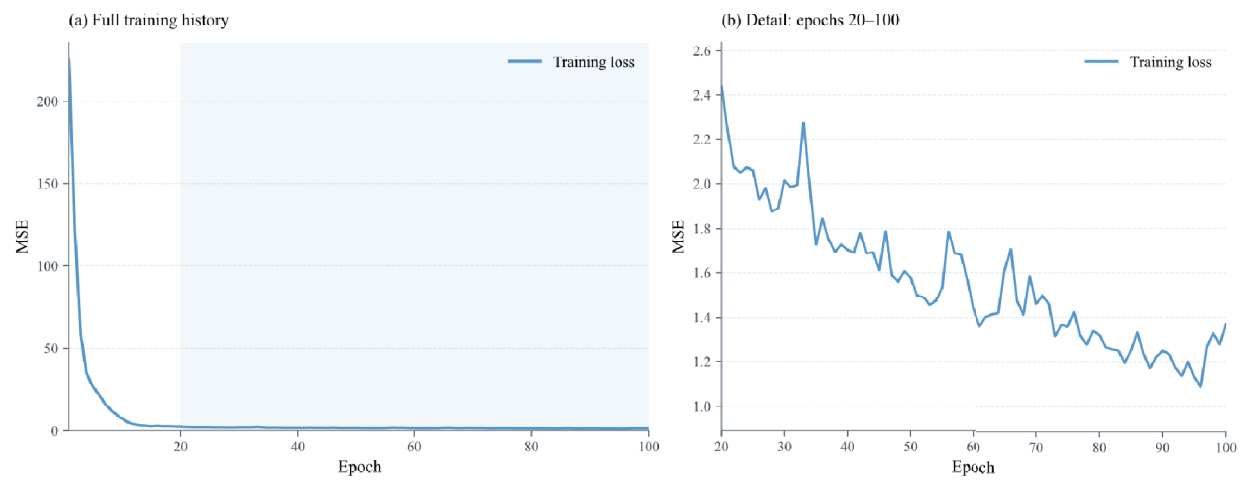


Fig. 5. Loss Curve During Training

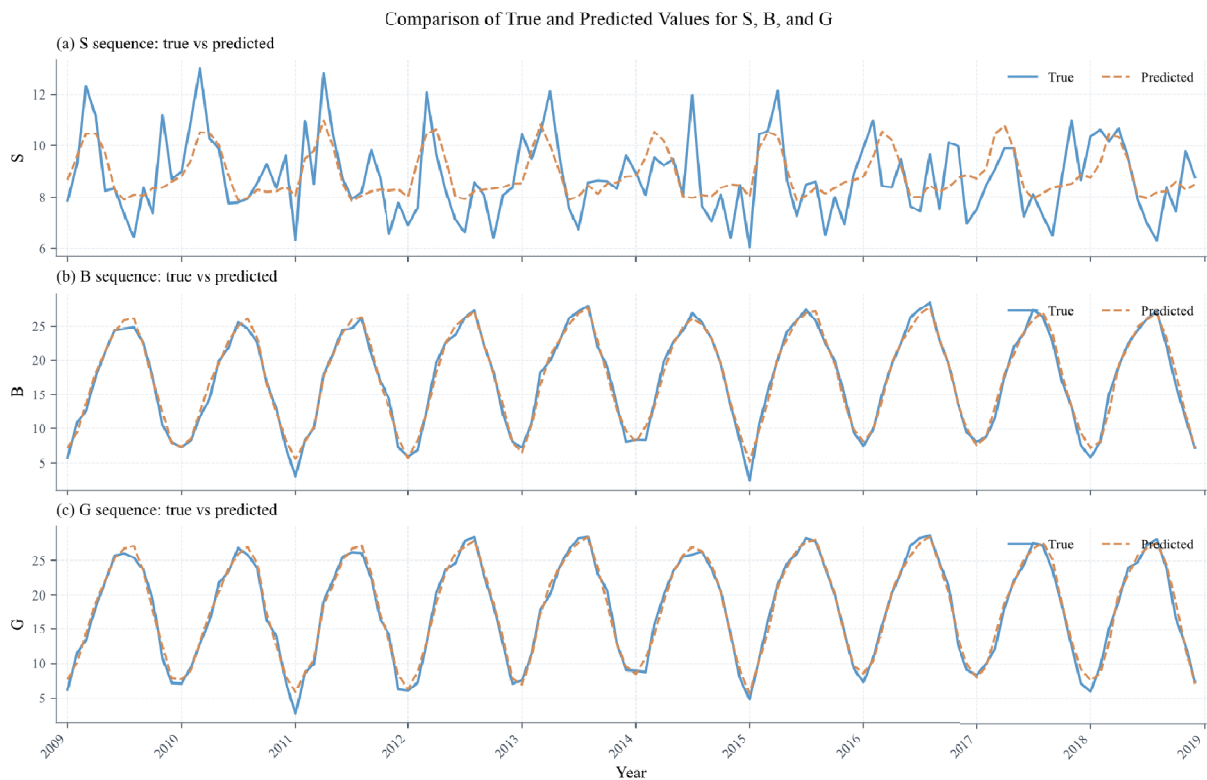


Fig. 6. Comparison of GRU Prediction Results and Actual Values Using S , B , and G as a Three-Dimensional Input Vector

The results of the two strategies are presented in Table3.

Table 3. Monthly Prediction Results of Each Indicator Using GRU

t	Prediction Indicators of Strategy 1			Prediction Indicators of Strategy 2		
	s_t	b_t	g_t	s_t	b_t	g_t
200901	8.67	7.13	7.67	8.21	6.34	7.21
200902	9.59	9.49	10.24	9.65	9.03	10.2

200903	10.49	13.77	14.36	10.73	15.6	16.42
...	...	...	...	...	...	...
201809	8.23	23.21	24.44	7.99	22.67	23.94
201810	8.6	18.16	18.95	8.16	17.63	18.51
201811	8.29	12.17	12.18	8.32	11.75	11.56

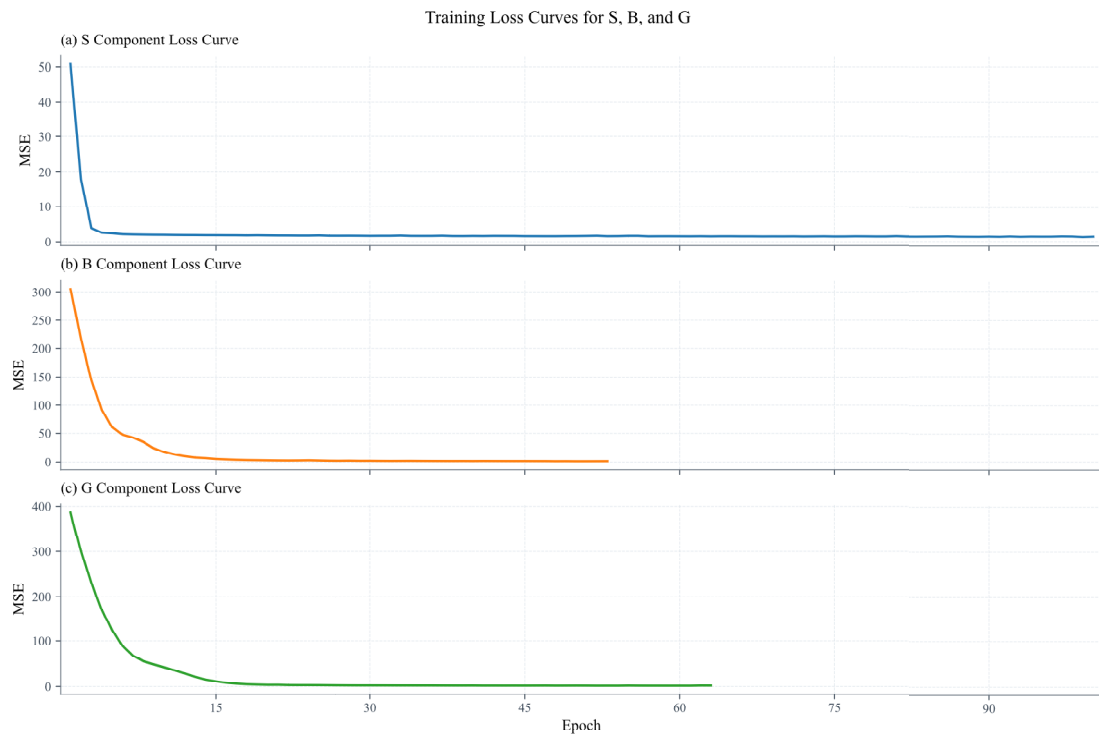


Fig. 7. Loss Curves of S, B, and G

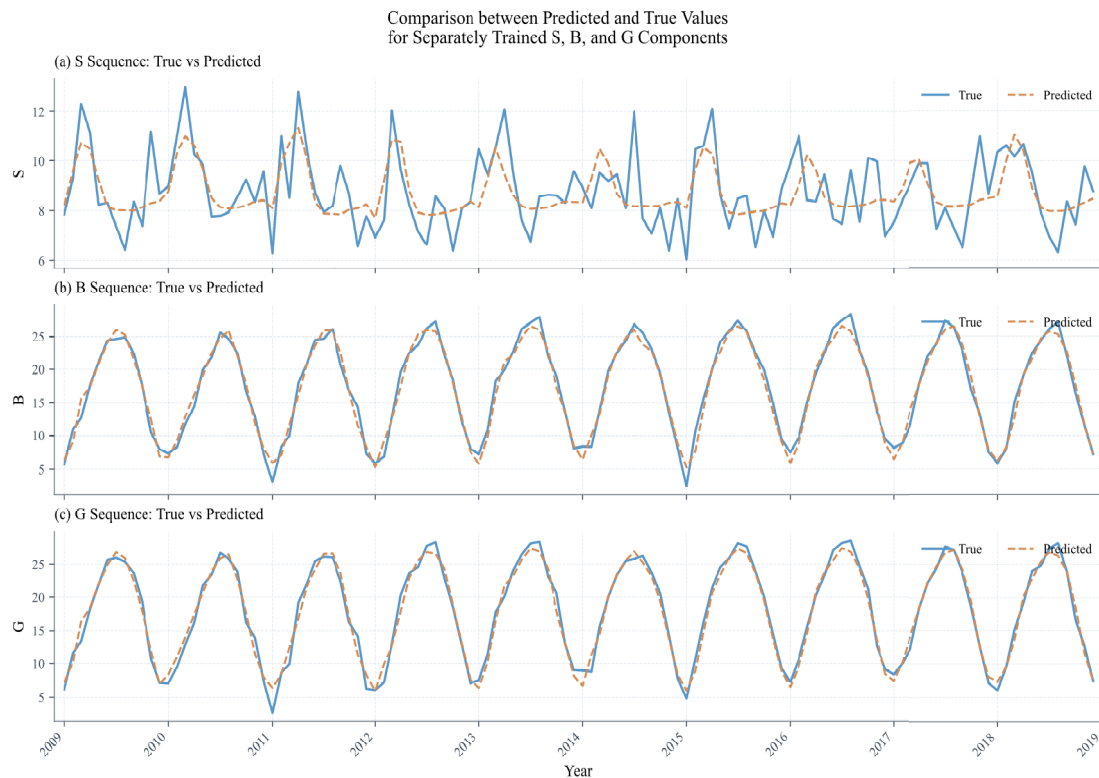


Fig. 8. GRU Predictions vs. Actual Values

The ARIMA-GRU Combination Prediction Model Based on TFN: Let the corresponding sequence obtained after transforming a TFN be denoted as $\{y_t = (s_t, b_t, g_t)\}$. In this study, m methods are adopted to predict y_t . The predicted value of the i -th method at time t is expressed as

where s_{it}, b_{it}, g_{it} represent the prediction results of the i -th method for the area, midpoint, and centroid indicators, respectively. Define

$$\varepsilon_{it} = \begin{cases} 1 - \left| \frac{(s_t - s_{it})}{s_t} \right|, & \left| \frac{(s_t - s_{it})}{s_t} \right| < 1, \\ 0, & \left| \frac{(s_t - s_{it})}{s_t} \right| \geq 1, \end{cases} \quad (14)$$

$$\varphi_{it} = \begin{cases} 1 - \left| \frac{(b_t - b_{it})}{b_t} \right|, & \left| \frac{(b_t - b_{it})}{b_t} \right| < 1, \\ 0, & \left| \frac{(b_t - b_{it})}{b_t} \right| \geq 1, \end{cases} \quad (15)$$

and

$$\phi_{it} = \begin{cases} 1 - \left| \frac{(g_t - g_{it})}{g_t} \right|, & \left| \frac{(g_t - g_{it})}{g_t} \right| < 1, \\ 0, & \left| \frac{(g_t - g_{it})}{g_t} \right| \geq 1. \end{cases} \quad (16)$$

Then, $\varepsilon_{it}, \varphi_{it}$ and ϕ_{it} , as defined in Eqs. (14)-(16), denote the prediction accuracies of the area, midpoint, and centroid indicators produced by the i -th forecasting method at time t , respectively. According to Definition 4, $\varepsilon_{it}, \varphi_{it}$ and ϕ_{it} are taken as the induced values. Subsequently, the *IOWA* operator is employed to aggregate the individual forecasting results and obtain the final predicted values of the area, midpoint, and centroid indicators at time t , that is $\hat{y}_t = (\hat{s}_t, \hat{b}_t, \hat{g}_t)$, as shown in Eq. (17).

$$\begin{cases} \hat{s}_t = IOWA(\langle \mu_{1t}, s_{1t} \rangle, \langle \mu_{2t}, s_{2t} \rangle, \dots, \langle \mu_{mt}, s_{mt} \rangle) = \sum_{i=1}^m w_i (s_{\mu-index(it)}), \\ \hat{b}_t = IOWA(\langle \mu_{1t}, b_{1t} \rangle, \langle \mu_{2t}, b_{2t} \rangle, \dots, \langle \mu_{mt}, b_{mt} \rangle) = \sum_{i=1}^m w_i (b_{\mu-index(it)}), \\ \hat{g}_t = IOWA(\langle \mu_{1t}, g_{1t} \rangle, \langle \mu_{2t}, g_{2t} \rangle, \dots, \langle \mu_{mt}, g_{mt} \rangle) = \sum_{i=1}^m w_i (g_{\mu-index(it)}). \end{cases} \quad (17)$$

Case Study and Effectiveness Analysis: The forecasting accuracies of individual prediction methods are first calculated according to Equations (14)-(16), and then used as the inducing values for the *IOWA* operator. By substituting Equation (17).

$\hat{y}_{it} = (s_{it}, b_{it}, g_{it})$ into Model(4), and assigning appropriate preference coefficient values α, β, γ , the optimal weight coefficients of the proposed model are obtained, as listed in the Table 4. Subsequently, the prediction results of the S, B , and G sequences generated by different individual forecasting methods are integrated according to the obtained weights, yielding the final forecasting results of the combined model, as listed in the Table 5. To evaluate the effectiveness of the proposed model, the

mean squared errors of the area indicator $MSE_S = \frac{1}{N} \sum_{t=1}^N (s_t - \hat{s}_t)^2$, midpoint indicator $MSE_B = \frac{1}{N} \sum_{t=1}^N (b_t - \hat{b}_t)^2$, and

centroid indicator $MSE_G = \frac{1}{N} \sum_{t=1}^N (g_t - \hat{g}_t)^2$, together with the integrated mean squared error

$MSE_I = MSE_S + MSE_B + MSE_G$, and the average forecasting accuracy, are selected as performance evaluation metrics. The detailed results are provided in the Table 6. It can be seen from Table 4 that, under different values of the preference coefficients with Weight Coefficients α, β, γ , the optimal weight coefficients of the combined model always satisfy $w_2 > w_3 > w_1$. This indicates that the combined model relies more on the information provided by Method 2, namely Strategy 1 GRU, after the

individual forecasting approaches. This finding agrees with the theoretical advantage of GRU networks, which can effectively capture long-term dependencies by selectively retaining useful information and filtering redundant data, thus providing more accurate long-term forecasts than traditional ARIMA models. Moreover, the Strategy 1 GRU model outperforms both the ARIMA

Table 4. Optimal Weight Coefficients of the Combined Model under Different Parameter Settings

Weight Coefficients of the Proposed Model		$\alpha=0.2, \beta=0.5, \gamma=0.3$	$\alpha=0.5, \beta=0.2, \gamma=0.3$	$\alpha=0.1, \beta=0.3, \gamma=0.6$
w_1		0.0016	0.0115	0.0122
w_2		0.9852	0.9759	0.9678
w_3		0.0132	0.0126	0.020
F(W)		0.9886	0.9868	0.9879

Table 5. Forecasting Values of the Proposed Combined Model

t	Raw Data			$\alpha=0.2, \beta=0.5, \gamma=0.3$			$\alpha=0.5, \beta=0.2, \gamma=0.3$			$\alpha=0.1, \beta=0.3, \gamma=0.6$		
	s_t	b_t	g_t	s_{1t}	b_{1t}	g_{1t}	s_{2t}	b_{2t}	g_{2t}	s_{2t}	b_{2t}	g_{2t}
200901	7.86	5.75	6.21	9.08	6.05	6.8	9.07	6.05	6.8	9.08	6.05	6.8
200902	9.32	10.94	11.59	9.71	8.61	9.49	9.71	8.62	9.5	9.71	8.61	9.48
200903	12.32	12.69	13.38	10.2	14.79	15.74	10.2	14.77	15.7	10.2	14.77	15.71
...	...	...	...	...	...	...	...	...	...	...	...	...
201809	8.37	22.03	23.88	7.94	22.65	24.44	7.94	22.65	24.44	7.94	22.65	24.43
201810	7.44	16.39	16.65	8.07	17.65	18.32	8.07	17.65	18.32	8.08	17.65	18.32
201811	9.78	11.56	12.69	8.25	11.71	11.8	8.26	11.71	11.81	8.25	11.72	11.81
201812	8.77	7.23	7.42	8.41	7.21	7.13	8.41	7.2	7.13	8.42	7.22	7.14

Table 6. Evaluation Indicators and Forecasting Accuracy of the Proposed Combined Model and Individual Forecasting Methods

Forecasting Model	MSE _s	MSE _B	MSE _G	MSE _I	Average Forecasting Accuracy
Triangular Fuzzy Number-Based ARIMA Model	1.8166	2.4634	2.5086	6.7886	0.9740
Strategy 1: Integrated GRU Model	1.5467	1.6076	1.5743	4.7286	0.9793
Strategy 2: Separate GRU Models	1.6119	1.7287	1.6594	5.0000	0.9747
Combined Forecasting Model: $\alpha=0.2, \beta=0.5, \gamma=0.3$	1.4232	1.5192	1.5705	4.5130	0.9889
Combined Forecasting Model: $\alpha=0.5, \beta=0.2, \gamma=0.3$	1.5193	1.5075	1.5533	4.5801	0.9884
Combined Forecasting Model: $\alpha=0.1, \beta=0.3, \gamma=0.6$	1.5240	1.5136	1.5589	4.5965	0.9886

model and Strategy 2 GRU model, demonstrating that integrating the *S*, *B*, and *G* variables into a unified three-dimensional input structure yields better forecasting performance than constructing separate models for each variable. The proposed triangular fuzzy ARIMA-GRU combined forecasting model incorporating the *IOWA* operator achieves the lowest values of MSE_s, MSE_B, MSE_G, and MSE_I among all forecasting methods. In addition, the proposed model obtains an average forecasting accuracy of approximately 98.85%, which is superior to all individual forecasting models. These results verify the effectiveness and feasibility of the proposed model for long-term temperature forecasting. Using the forecasting results of individual models as the basis, the proposed framework can be extended to forecast the future *k* periods. For *k*-step-ahead forecasting, the average fitting forecasting accuracy of the latest *k* periods can be selected as the inducing value of the *IOWA* operator, and the optimal weight coefficients can then be obtained by solving the corresponding optimization problem.

CONCLUSION

In this study, the monthly average minimum, mean, and maximum temperature data of Chengdu City from 2008 to 2018 are employed to construct triangular fuzzy number sequences. To avoid discontinuities caused by directly forecasting the boundary points of TFN, the original fuzzy sequences are transformed into three indicator sequences with equivalent information. Based on these transformed sequences, a triangular fuzzy ARIMA model and two GRU models with different modeling strategies are developed. Furthermore, by incorporating the *IOWA* operator and optimizing the comprehensive forecasting accuracy at time *t*, a triangular fuzzy optimal-weight combined forecasting model integrating ARIMA and GRU models is established. The experimental results and comparative analysis indicate that the proposed combined model achieves superior forecasting performance compared with individual forecasting models. Consequently, the proposed model is verified to be effective and applicable for TFN-based forecasting problems.

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