The Application of the Generalized Regression Neural Network Model Based on Information Granulation for Short-Term Temperature Prediction

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Abstract: This paper proposes the Generalized Regression Neural Network (GRNN) model based on information granularity and using MATLAB programming for short-term temperature prediction. In this respect, it focuses on the daily average temperature data for the months of July and August for a period of ten years (from 2006 to 2015) for the Jiuhua Mountain scenic spot of Chizhou, in the Anhui Province. The performance of the proposed method is compared with that of the Back Propagation (BP) neural network and with that of the Gauss function for data fitting. This method not only improves the accuracy of short-term prediction, but it also overcomes the disadvantage of inaccurate data fitting. It can slightly improve the effectiveness and practicability of short-term prediction, and it can more effectively analyze short-term data on the Internet.

Keywords: Information Granulation, GRNN neural network, BP neural network, Fourier function, Gauss function.

1. Introduction

Temperature changes affect physical comfort, and the consequences are obvious. Through the prediction of temperature, it is possible to make judgments on the activities and travel of personnel. In the short-term climate prediction, the prediction of precipitation and air temperature is both important and difficult. While studying the methods of weather climatology and climate statistics, it was found that the principle and mechanism of temperature change and precipitation are quite complex. Therefore, meteorologists began to choose to use the method of general circulation model (GCM) (Yan et al., 2008), but this method has disadvantages and is difficult to analyze. Ensemble Canonical Correlation (ECC) is a set of prediction methods based on the Canonical Correlation Analysis (CCA) method, which uses multiple prediction factor fields for the same forecast object (Wu & Wu, 2005), When the forecast factor is employed too much, it may reduce the accuracy of weather forecast. Certain foreign scholars use the Ensemble Canonical Correlation (ECC) analysis as a temperature prediction method. ECC method was also employed in the research on domestic climate prediction, Wang et al. (2013) employed the ECC method to forecast the daily precipitation in Sichuan Basin, and the prediction results were very good. As regards the study of summer temperature, less research has been conducted using ECC method, and Ruan et al. (2016) believe that it is necessary to carry out further research based on this method.

In the context of statistical prediction, Chen (2013) predicted the extreme precipitation events in Huaihe basin by employing the method of interannual increment prediction and multiple linear regression analysis. The model is very effective for extreme weather conditions. It can amplify interannual signal, but also reproduce interdecadal variation trend (Fan et al., 2007). Ortiz-García et al. (2012) employed support vector machine model for short-term prediction of surface air temperature. The method can accurately predict the hourly temperature in Barcelona international airport, the method of temperature prediction using intelligent computing method is gradually carried out.

With the rise of machine learning in recent years, some scholars began to optimize the weather prediction methods. The prediction model of Jin et al. (2011) was validated by simulation and the independent trials data. This method is more accurate than the stepwise regression model. Some scholars (Wang et al., 2016; Zhou et al., 2016) began to use different types of models for data prediction: CART predictive model based on decision tree, Fusion model of LSVM and Elman neural network, Grey-Markov temperature prediction model based on seasonal index, etc. These models provide a variety of reference

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methods for the study of weather forecasting, which can effectively improve the prediction accuracy for daily air temperature, and identify the more accurate temperature prediction methods. For temperature prediction, Back Propagation (BP) neural network model (Wu et al., 2006) and method was employed.

The remainder of this paper is organized as follows. Section 2 presents the model knowledge, showing that GRNN neural network is characterized by fast learning speed and needs few parameter adjustment actions. Section 3 describes the model framework. Section 4 sets forth the model framework and describes the implementation of the proposed model. First, the data is selected and the method of information granulation is employed in order to process the data, then a neural network model is built for predicting the data, and finally data analogy is performed and the original data is used for testing the prediction error. Section 5 focuses on the comparison of simulation results, two different functions for data fitting are employed and the obtained results are compared, which again shows the advantages of the model employed in this paper, which is applied for short-term temperature prediction. Finally, section 6 includes the conclusion of this paper.

2. Model Knowledge

2.1 GRNN Neural Network

Generalized Regression Neural Network (GRNN) is a parallel radial basis function neural network (Qian and Cui, 2012). It is a feedforward neural network. It is based on nonlinear regression theory and approximates functions by activating neurons. In terms of topology, GRNN is divided into four layers. These are the Input layer, Model layer, Summation layer and Output layer. The network input is $X=[x_1,x_2,\cdots,x_n]^T$, and the network output is $Y=[y_1,y_2,\cdots,y_k]^T$.

Input Layer: the number of input layer neurons is equal to the dimension of the input vector in the learning samples. Each neuron is a simple distribution unit, which directly passes input variables to the model layer.

Model Layer: The number of neurons in the model layer is equal to the number of learning samples n, each neuron corresponds to different samples. The transfer function of the model layer neuron is

$$P_\mathrm{i}=\exp\left[-\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}\right]\quad i=1,2,\cdots,n \tag{1}$$

In this formula, X is the input variable of the network, X_i is a learning sample corresponding to the i-th neurons, σ is Smoothing Factor. The distance between the input variable and the corresponding sample is Euclidean distance, and the exponential form of the Euclidean distance squared is $D_i^2=(x-x_i)^T(x-x_i)$ which is the output of the i-th neurons.

Summation Layer: Summation of two types of neurons.

The first formula is:

$$\sum_{i=1}^{n}\exp\left[-\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}\right] \tag{2}$$

The output of all the neurons in the model layer is summed up, and the weight of the connection between the model layer and each neuron is 1.

The transfer function is:

$$S_D=\sum_{i=1}^{n}P_i \tag{3}$$

The second formula is：

$$\sum_{i=1}^{n}y_{ij}\exp\left[-\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}\right] \tag{4}$$

It is the weighted sum of all the neurons. There is a connection value between the i-th neuron in the mode layer and the j-th neuron in the summation layer. This connection value is the j-th element in the i-th output sample.

The transfer function is：

$$S_{Nj}=\sum_{i=1}^{n}y_{ij}P_i \quad j=1,2,\cdots,k \tag{5}$$

Output Layer: The number of neurons in the output layer is equal to the dimension (j) of the output vector in the learning sample. Divide the first type of data in the summation layer by another type of data.

$$y_i=\frac{S_{Nj}}{S_D}\quad j=1,2,\cdots,k \tag{6}$$

2.2 Information Granulation

Professor Lotfi A. Zadeh put forward the concept of information granulation, the whole is divided into many parts, each part will make up a informofer. This paper introduces the framework of granular computing based on fuzzy set theory, and the model of domain system construction (Zadeh, 1997).

In this paper, Witold Pedrycz fuzzy granulation model is used. By fuzzifying the fixed time series data, a fuzzy information particle P is established on X. There is also a fuzzy concept, namely G, which can be described reasonably.

$$P \triangleq X \ \text{ is } \ G \tag{7}$$

Its function is to determine function A, the process is

$P = A(X)$. A is the membership function of the fuzzy concept. Here, fuzzy graining is used for data processing.

(1) Fuzzy particles can represent the original data reasonably.

(2) Fuzzy particles should have a certain particularity.

In order to meet the two requirements above, to find the best balance between the two ideas, the establishment of a function on A can be considered.

$$Q_A = \frac{M_A}{N_A} \tag{8}$$

In the above formula M_A satisfies the basic idea (1) for establishing fuzzy particles. N_A satisfies the basic idea (2) for establishing fuzzy particles.

The membership function used in this paper is:

$$A(x,a,m,b) = \begin{cases} 0, x < a \\ \dfrac{x-a}{m-a}, a \le x \le m \\ \dfrac{b-x}{b-m}, m < x \le b \\ 0, x > b \end{cases} \tag{9}$$

3. Model Construction

Step 1: Based on the data collected from 2006 to 2015 for Jiuhua Mountain scenic spot of Chizhou, Anhui Province, the average daily temperature in the area was selected for the months of July and August.

Step 2: In this paper, data from the months of July and August is listed. For the 31 data groups collected per month, this paper considers the information granulation. Thus, the average value of the original data is obtained, and 10 datasets are generated.

Step 3: The processed data in step 2 shall be used, the first 8 data groups shall be used as data input, and the remaining two data groups as the network output, so as to construct the GRNN neural network.

Step 4: For this training data, cross-validation method is used to train the GRNN neural network, and the optimal SPREAD value is found through the loop calculation. The Forecast flow chart is shown in Figure 1.

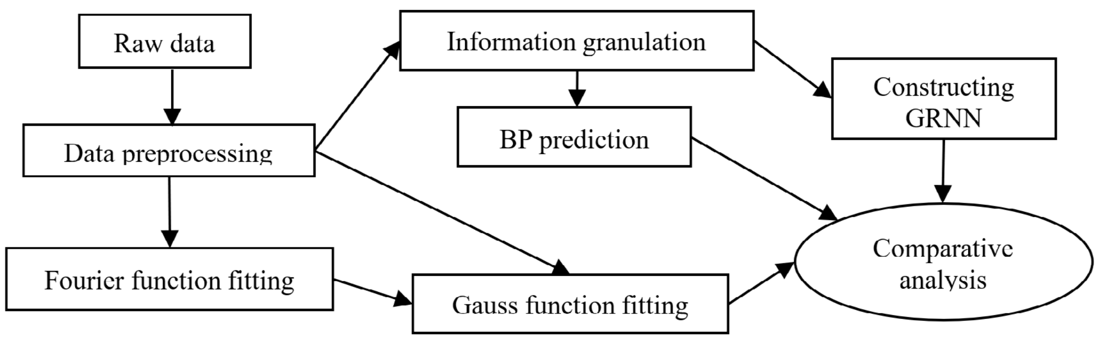

Figure 1. The forecast flow chart

4. Model Application

4.1 Model Framework

4.2 Data Information Granulation

It can be seen from the model framework in Figure 2 that the first step is data processing. In this paper, 620 groups of temperature data from 2006 to 2015 are used, which are from Anhui Meteorological Bureau. The pieces of data for July and August are combined for each year, and two sets of 10*31 pieces of data are obtained. Then, the information granulation method is employed to preprocess the two sets of data.

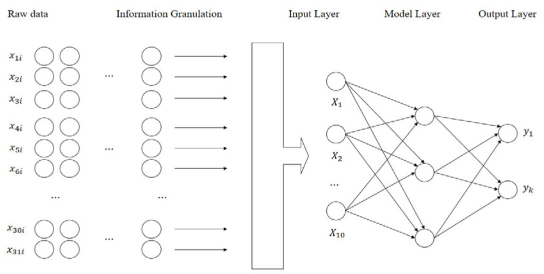

Figure 2. Prediction model structure

Then, two groups of 10*10 samples of data are obtained. They include the R parameters generated after granulating the original information. The fluctuation of the R parameter describes the change of the average value of the data. The daily average temperature data for July 2016 was taken as an example, the raw data is shown in Table 1. The temperature fluctuations for July 2006 are shown in Figure 3. The data peculiar to information granulation is illustrated in Table 2.

The temperature-related information granulation is shown in Figure 4. The LOW in Figure 4 represents the minimum value of each window, R represents the average value, and UP represents the maximum value.

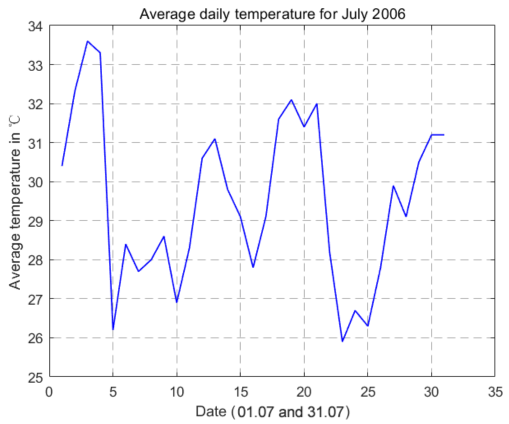

Figure 3. The fluctuations of average daily temperatures for July 2006

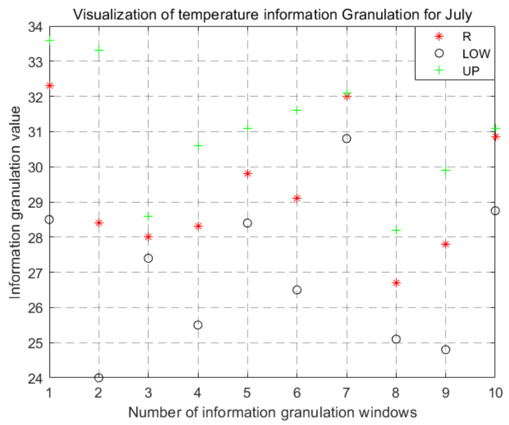

Figure 4. The temperature-related information granulation for July 2006

Table 1. Daily average temperature data for July 2016

Date	1	2	3	4	5	6	7	8
Average temperature in °C	30.4	32.3	33.6	33.3	26.2	28.4	27.7	28
Date	9	10	11	12	13	14	15	16
Average temperature in °C	28.6	26.9	28.3	30.6	31.1	29.8	29.1	27.8
Date	17	18	19	20	21	22	23	24
Average temperature in °C	29.1	31.6	32.1	31.4	32	28.2	25.9	26.7
Date	25	26	27	28	29	30	31	
Average temperature in °C	26.3	27.8	29.9	29.1	30.5	31.2	31.2	

Table 2. Information granulation data

window	1	2	3	4	5	6	7	8	9	10
R	32.30	28.40	28	28.30	29.80	29.10	32	26.70	27.80	30.85
LOW	28.5	24	27.40	25.50	28.40	26.50	30.80	25.10	24.80	28.75
UP	33.60	33.30	28.60	30.60	31.1000	31.6000	32.100	28.200	29.90	31.08

4.3 Temperature Prediction Based on the GRNN Neural Network

First, in the context of the annual temperature change for July and August, the R value for the original data information granulation for the months of July and August is illustrated in Table 3 and Table 4, respectively. The items in windows 1 to 8 are considered as training data and the items in windows 9 and 10 as predicted data. Then the premnmx function and tramnmx functions are used for the normalization of data, and the processed data is concentrated in the (-1, 1) interval.

The next step is to find the optimal smoothing factor (SPREAD). Take the number between 0.1 and 2 as the smoothing factor, and each number is 0.01 apart, and the optimal solution is obtained by training the smoothing factor. In this paper, the neural network is trained by cross-validation method, and the best SPREAD is found by circulation. According to the program calculation, when SPREAD = 0.7, the results for the July data show that the average error rate is the smallest. When SPREAD = 2, the results for the August data show that the average error rate is the smallest.

GRNN neural network is employed for temperature forecasting, and the predicted data is anti-normalized to get the prediction results. The training data is compared with the extrapolated prediction samples. The results are shown in Table 5.

Table 3. R value for original data information granulation for July (the years 2006 to 2015)

	Network training samples								Extrapolated prediction samples	
	1	2	3	4	5	6	7	8	9	10
2006	29.5	29.2	28.3	30.8	32.7	29.6	27.5	27.8	28.7	31.2
2007	31.8	29.2	31.6	29.7	28.7	29.5	28.8	29.1	28.9	27.45
2008	26.9	30.3	30.1	30.2	28	27	31.1	27.6	26.7	24.35
2009	26.8	27.8	27.9	26.3	28.5	29.7	31.2	29.2	31.3	23.2
2010	33	31.9	31.2	32.7	33.7	29.6	28.8	29.2	23.2	26.45
2011	27.9	28.5	28.8	28	30.2	32.3	29	23.8	24	26.35
2012	29.4	30	27.3	26.3	29.3	29.1	29.7	23.5	27	27.9
2013	31.4	33.2	33.4	31.2	32.4	31.7	30	29.3	28.4	29.75
2014	28.3	30.8	26	24.5	22.5	22.3	24.1	26.6	25.4	25.25
2015	30.5	30.3	28.3	25.9	26.9	27.1	25.8	25.6	25.7	26.55

Table 4. R value for original data information granulation for August (the years 2006 to 2015)

	Network training samples								Extrapolated prediction samples	
	1	2	3	4	5	6	7	8	9	10
2006	32.3	28.4	28	28.3	29.8	29.1	32	26.7	27.8	30.85
2007	28.1	31.6	31.7	29.5	26.8	30	32.4	27.1	29.8	31.45
2008	29.6	31.9	28.3	28.7	30.2	31.6	28.1	30.5	31.9	27.35
2009	25.5	27.5	31.4	31.6	30.2	33.2	33.2	31	27.8	24.05
2010	32.1	28.2	26.7	25.8	25.4	28.2	29.2	28.8	29.4	30.2
2011	30.9	32.2	28.2	26.8	23.7	24.8	27.1	30.5	33	31.8
2012	31	32.4	31.4	31.9	25.6	27.3	29.8	32	31.4	31.95
2013	30.4	29.9	30.5	30.9	28.5	30	30.1	30.8	30.9	32.1
2014	24.1	24.3	27.1	28	25.6	26.8	29.8	31.9	26.7	28.9
2015	26.3	21.1	20.2	25.6	29.1	25.4	25.7	26	28.7	30.15

Table 5. Prediction results for the GRNN neural network based on information granulation

GRNN	July		August	
window	9	10	9	10
actual	28.70	30.15	25.70	27.25
forecast	28.62	29.98	25.68	26.55
deviation	0.08	0.17	0.02	0.60

5. Comparison of Simulation Results

5.1 Gauss and Fourier Function Fitting

For the purpose of data, the analysis is carried out further and the Gauss function and Fourier function is employed to fit the original data.

The Gaussian function is widely used in many fields. This paper uses MATLAB software to accomplish the fast, efficient and accurate fitting of Gauss function curve. The fitting of Fourier function to the data is quite similar to the Gauss function fitting.

In this paper, the days of July and August are digitally arranged to obtain a set of Data, which includes items from 1 to 62. Figure 5 illustrates the fluctuations of the original data, and Figure 6 shows the scatter diagram for the original data. The mean value of the original data for 10 years is taken to obtain Figure 7, while Figure 8 illustrates the historical mean daily temperature scatter map for the months of July and August. The expression of the Gauss function fitting is:

$$G(x) = \sum_{i=1}^{8} a_i \exp\left(-(\frac{x-b_i}{c_i})^2\right) \tag{10}$$

The shape of the Gauss function is like an upside down clock. Parameter a_i refers to the peak of the Gaussian curve, b_i is its corresponding abscissa, and c_i is the standard deviation.

The expression of the Fourier function fitting is:

$$F(x) = a_0 + \sum_{i=1}^{8}\left(a_i \cos(i\omega x) + b_i \sin(i\omega x)\right) \tag{11}$$

$$i = 1, 2, \cdots, n$$

ω is the angular frequency and a_i and b_i are the Fourier Coefficients.

In the process of data fitting, the dimension of the function is gradually changed, and the obtained results are illustrated in Figure 9 and Figure 10, which were obtained through step-by-step optimization analysis.

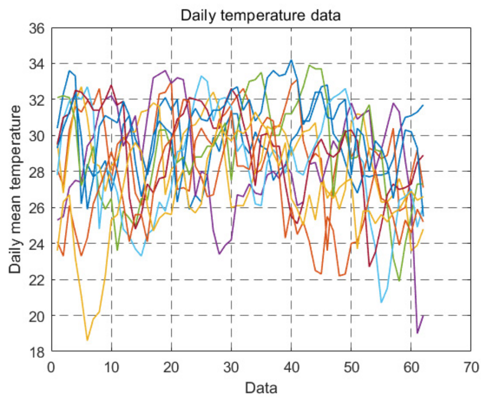

Figure 5. Daily temperature fluctuations for July and for August

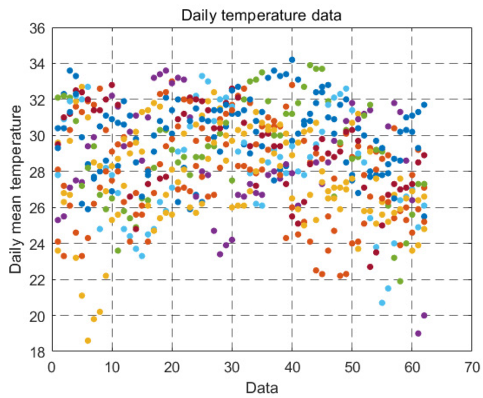

Figure 6. Daily air temperature scatter map for July and for August

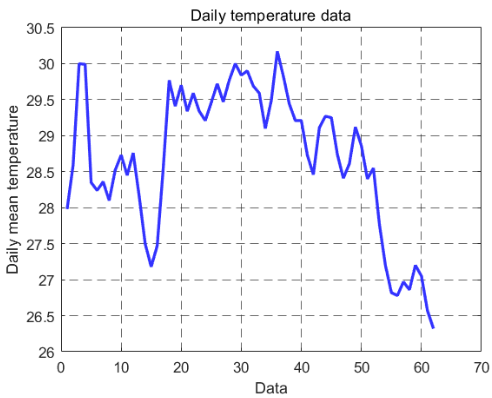

Figure 7. Historical mean daily temperature fluctuations for July and for August

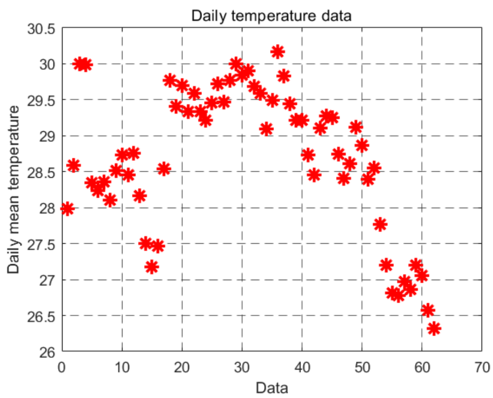

Figure 8. Historical mean daily temperature scatter map for July and for August

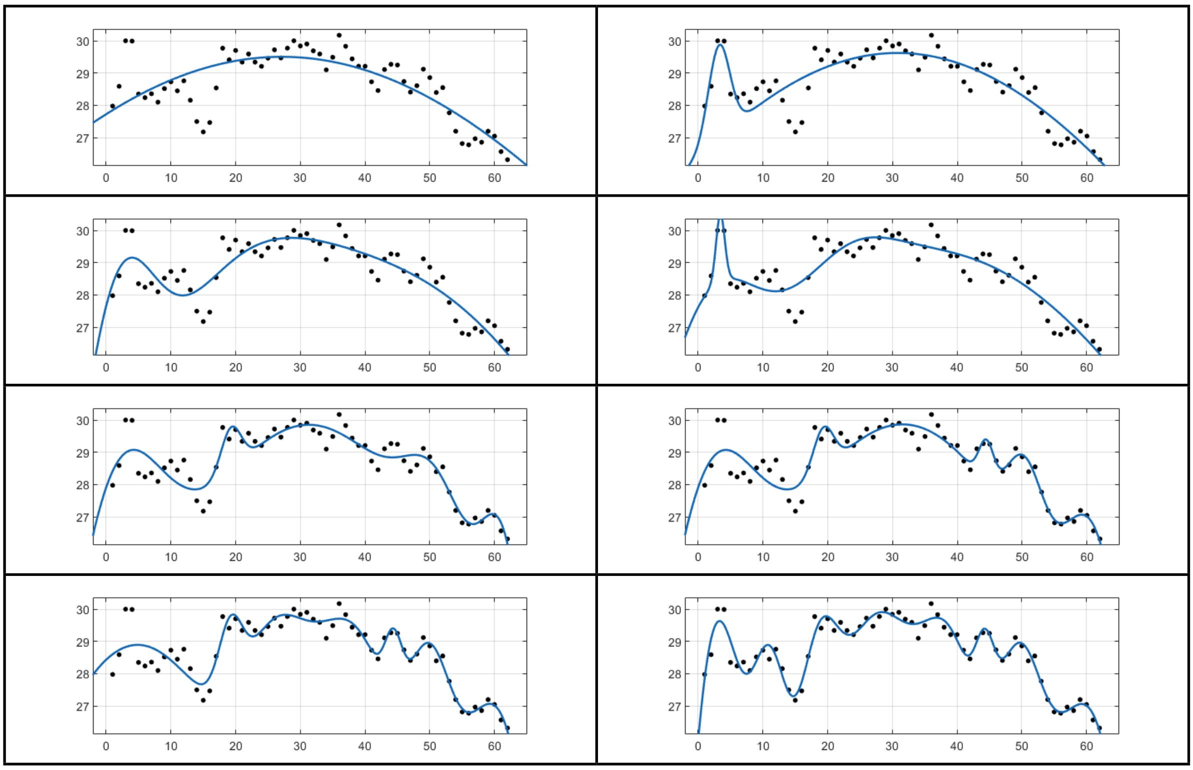

Figure 9. Gauss function fitting gradient image

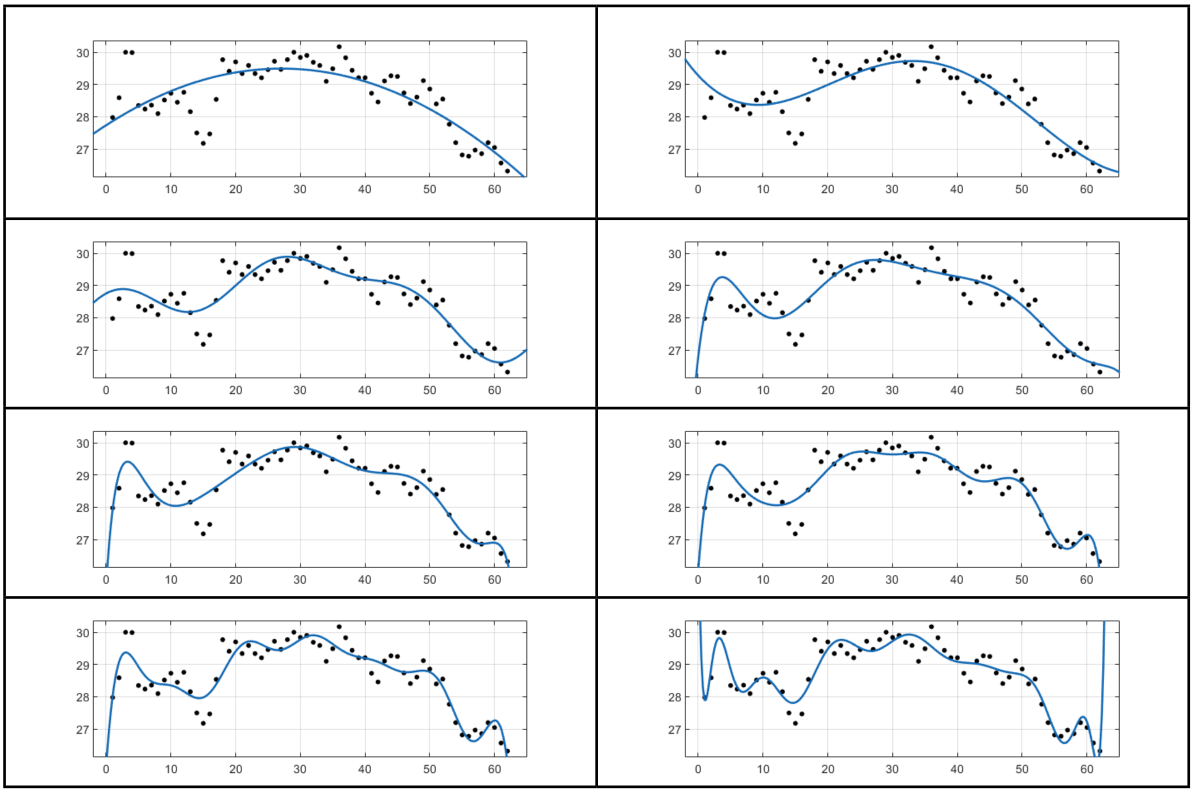

Figure 10. Fourier function fitting gradient image

First, the values of SSE (Sum of Squares due to Error), R-squared (Coefficient of Determination), Adjusted R-squared (Degree-of-freedom Adjusted Coefficient of Determination) and RMSE (Root Mean Squared Error) should be calculated. Through the comparative analysis of the employed data (Table 6), it was found that the fitting results obtained by Gauss function are better than the results obtained by the Fourier function, the total number of coefficients was 8. So, the coefficient of Gauss function could be obtained for the 95% confidence bounds, as it is shown in Table 7.

The data in Table 7 was introduced into the Gauss function to calculate the weather data for the last six days of July and August. By comparing the calculated data with the actual data, the data in Table 8 was obtained.

5.2 The BP Neural Network

For the above data prediction samples, the use of the BP neural network is considered further. Finally, two sets of predicted values are obtained (Table 9), and the error is calculated.

Table 9. Prediction results for temperature data by using the BP model

BP	July		August	
window	9	10	9	10
actual	28.70	30.15	25.70	27.25
forecast	27.46	29.44	25.46	23.71
deviation	1.24	0.71	0.24	2.84

Table 6. Analysis of fitting results for the Gauss and Fourier functions

Gauss Function					Fourier Function				
Coefficients	SSE	R-square	Adjusted R-squared	RMSE	Coefficients	SSE	R-square	Adjusted R-squared	RMSE
1	25.09	0.6009	0.5874	0.6521	1	25	0.6023	0.5817	0.6566
2	13.59	0.7839	0.7646	0.4926	2	16.73	0.7338	0.7101	0.5466
3	13.32	0.7882	0.7562	0.5012	3	13.72	0.7818	0.7535	0.5041
4	10.53	0.8325	0.7957	0.4589	4	12.32	0.804	0.77	0.4868
5	9.08	0.8556	0.8125	0.4395	5	11.43	0.8183	0.7783	0.478
6	8.083	0.8714	0.8218	0.4286	6	10.25	0.8369	0.7928	0.4621
7	7.488	0.8809	0.8228	0.4274	7	8.787	0.8602	0.8147	0.4371
8	3.301	0.9475	0.9157	0.2947	8	6.662	0.894	0.8531	0.3891

Table 7. The coefficient of Gauss function for the 95% confidence bounds

	Value	confidence interval		Value	confidence interval
	17.87	(-118.4, 154.2)	a_5	26.71	(24.92, 28.5)
	40.40	(30.62, 50.18)	b_5	60.19	(56.89, 63.5)
	7.884	(-13.54, 29.3)	c_5	12.49	(-1.072, 26.05)
	28.79	(9.029, 48.55)	a_6	28.56	(-0.3932, 57.51)
	2.736	(-2.488, 7.96)	b_6	26.75	(11.33, 42.18)
	8.121	(1.96, 14.28)	c_6	12.13	(-49.27, 73.52)
	10.53	(-59.3, 80.35)	a_7	2.146	(-0.4707, 4.763)
	17.69	(13.57, 21.8)	b_7	44.28	(43.6, 44.95)
	4.783	(-2.487, 12.05)	c_7	2.079	(0.5834, 3.575)
	10.56	(-27.1, 48.23)	a_8	11.96	(-15.55, 39.47)
	49.41	(45.51, 53.31)	b_8	11.33	(10.21, 12.45)
	5.498	(0.6785, 10.32)	c_8	4.187	(2.234, 6.14)

Table 8. Analysis of data fitting based on Gauss function

July						August					
Date	x	G(x)	Date	x	G(x)	Date	x	G(x)	Date	x	G(x)
26	26	29.6242	29	29	29.8949	26	26	29.6242	29	29	29.8949
27	27	29.8072	30	30	29.8098	27	27	29.8072	30	30	29.8098
28	28	29.9019	31	31	29.6916	28	28	29.9019	31	31	29.6916
mean		29.78	mean		29.80	mean		29.78	mean		29.80
actual		29.65	actual		29.91	actual		27.01	actual		26.65
deviation		0.13	deviation		0.11	deviation		2.77	deviation		3.25

5.3 Data comparison

According to the data in Table 10, it was found that there are high-frequency components in the error of BP algorithm and there are local minimum problems. Due to the existence of local minima in the process of computation, the results were not globally optimal. In the process of using the Gauss function to fit the data, there is also a local optimal situation. Therefore, the superiority of the generalized regression neural network is shown indirectly. Through data processing, one can notice the advantage of the GRNN neural network model based on information granulation, which is mainly applied to short-term data processing.

Table 10. Data comparison for GRNN, BP and the Gauss function

	July		August	
GRNN	0.08	0.17	0.02	0.60
BP	1.24	0.71	0.24	2.84
Gauss	0.12	0.11	2.77	3.25

6. Conclusion

The temperature prediction errors obtained by GRNN neural network were 0.1 for July and 0.5 for August in 2015, which are considered insignificant. By comparing the prediction results for the BP neural network and GRNN neural network, it was found that the prediction error for the BP neural network was higher. The results for Gauss and Fourier function fitting show that the accuracy of the calculation was slightly more consistent for July, but fluctuating for August. In this study, the data of several samples was tested by employing the generalized regression neural network model and by using MATLAB programming. Due to the limitation related to small sample sizes, the prediction accuracy was not very high. Considering these factors, the obtained results are acceptable.

This new temperature prediction model can overcome the difficulty of accurate fitting, slightly improve the prediction results for nonlinear temperature fluctuations, and prove advantageous in comparison with linear models. The proposed model features a high robustness, and represents a new method for the prediction of related types of data, which can make one understand the short-term data of the Internet more efficiently.

Acknowledgments

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