

## Analysis of Using a Hybrid Neural Network Forecast Model to Study Wire Ice-covering

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### Abstract

*When applied to wire ice-covering forecasting, the back propagation (BP) neural network is a lack of guidance for selecting the neural network initial connection weight and network structure, which contributes to the problem of a high degree of randomness and poses a difficulty for selecting an initial node with global properties. Combination traditional forecasting methods of Mean Generating Function-optimal subset regression (MGF-OSR), this paper proposes a new hybrid MGF-OSR-BP model based on Genetic Algorithm (GA) evolution BP. This paper uses the hybrid MGF-OSR-BP model based on GA evolution BP to analyze 108-ten days of ice thickness data from Erlang Mountain glacial stage, China, from 2001 to 2009. The results show that the model has a better forecast accuracy and high convergence. This paper can serve as a reference for similar middle-and long-term forecast research based on elements of time series data.*

**Keywords:** *Wire ice-covering, Neural Network, Genetic Algorithm (GA), Mean Generating Function (MGF), Optimal Subset Regression (OSR)*

### 1. Introduction

Cold weather has the greatest effect on power department, and excessive ice-covering can bring severe influence to the power equipment. The accident of transmission line emerges frequently in China [1]. As a result, analysis the characteristics and the regularity of the wire ice-covering, it is of important significance to secure and stable operation of the power system [2].

Study wire ice-covering thickness by the neural network, which is becoming a matter of concern for more and more people. But it utilizes the neural network alone and not tries to improve neural network in wire ice-covering prediction. Xu and Chen used L-M neural network to build a new model and conducted a forecast experiment on annual extreme ice thickness, and their results show that this forecast method is better than the back propagation (BP) neural network [3]. Lan and Zhen put forward a new forecast method named Generalized Regression Neural Network (GRNN) to study the wire ice-covering thickness, and their results show that this model is better than BP neural network forecast model [4]. Wang and Cai (2010) used optimal subset regression (OSR) to build the mathematical model and recover the ice-covering thickness from Erlang Mountain, from 1951 to 2001, their results provided a method of analyzing the ice accumulation on transmission line [2].

## 2. Data and Methods

This paper uses 108-ten days of ice thickness data from 2001-2009 (there is no ice thickness for 27-ten days, length of samples are 108, direction is WE ) from Erlang Mountain glacial stage(11-3 month),and its related meteorological factor(ice cover thickness, the daily maximum temperature, minimum temperature, daily average temperature, relative humidity, average wind speed, precipitation) as the training sample and the 8-ten days, which are 6-ten days of January-February and 2-ten days of March of 2009 and are not to participate in learning and the direction is NS, are used as the verification sample for forecast verification.

This paper uses a combination of Mean Generating Function (MGF), optimal subset regression (OSR), and neural networks to build a new hybrid MGF-OSR-BP forecast model based on Genetic Algorithm (GA) evolution BP, which uses a MGF to extend original data, an OSR to select the best series as the BP neural network input node and learning matrix, and the original series as the network output. Then, GA optimizes the weights of BP neural network model, and BP algorithm further revises it until the smallest error.

Below is a detailed analysis.

### 2.1. MGF Extension

In this section, the paper selects 6 related Meteorological Pre-forecasting factors (ice cover thickness, the daily maximum temperature, minimum temperature, daily average temperature, relative humidity, average wind speed) from Erlang Mountain as candidate prediction factors of exogenous variables, which related significantly level is above 0.02. Then, the paper uses MGF to consider the data itself significant periodic variation .The calculation process of MGF is as follows [8]:

Suppose that the standard-deviation-normalized time series is as follows:

$$x^{(0)}(t) = \{x(1), x(2), \dots, x(N)\} \quad (1)$$

A first-order differential operation is applied to the series:

$$\Delta x(t) = x(t+1) - x(t), t = 1, 2, \dots, N-1$$

Thus, the following first-order differential series is obtained:

$$x^{(1)}(t) = \{\Delta x(1), \Delta x(2), \dots, \Delta x(N-1)\} \quad (2)$$

Next, a second-order differential operation is applied:

$$\Delta \Delta x(t) = \Delta^2 x(t) = \Delta x(t+1) - \Delta x(t), t = 1, 2, \dots, N-2$$

Thus, the following second-order differential series is obtained:

$$x^{(2)}(t) = \{\Delta^2 x(1), \Delta^2 x(2), \dots, \Delta^2 x(N-2)\} \quad (3)$$

We use the following formula,

$$\bar{x}_i(i) = \frac{1}{n_i} \sum_{j=0}^{n_i-1} x(i+j) \quad (4)$$

to perform a MGF calculation on the original series, first-order differential series, and second-order differential series, in which  $i=1, 2, \dots, 1 \leq i \leq M$  and  $n_i = INT(N/i)$  and  $M$  can be  $INT(N/2)$  or  $INT(N/3)$  depending on the sample size, where  $INT$  indicates the integer part. In this example, suppose that the sample series maximum period length  $M_{\max} = INT(N/3) = 36$ , the paper selects  $m=35$ , the MGF at time interval 35 is shown in Table 1:

Similarly, a periodic extension formula (5) is used to perform a periodic extension calculation on series MGF.

**Table1. The MGF at Time Interval 35**

X <sub>1</sub> (1)	X <sub>2</sub> (1)	X <sub>2</sub> (2)	X <sub>2</sub> (1)	X <sub>3</sub> (2)	X <sub>3</sub> (3)	...	X <sub>35</sub> (1)	...	X <sub>35</sub> (35)
23.92	24.02	23.83	23.85	21.13	26.78	...	34.6	...	30.77

$$f_l(t) = \bar{x}_l \left[ t - \text{LIN} \left( \frac{t-1}{l} \right) \right] \quad (5)$$

Where  $t=1,2,\dots,N$ ,  $l=1,2,\dots,M$ , and the constructed MGF extension matrix is as follows:

$$H_{108 \times 35} = \begin{bmatrix} 23.92 & 24.02 & 23.85 & 23.2 & \dots & 34.6 \\ 23.92 & 23.83 & 21.13 & 23.14 & \dots & 24.87 \\ 23.92 & 24.02 & 26.78 & 24.83 & \dots & 19.57 \\ 23.92 & 23.83 & 23.85 & 24.51 & \dots & 15.2 \\ 23.92 & 24.02 & 21.13 & 23.2 & \dots & 31.07 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 23.92 & 23.83 & 26.78 & 24.51 & \dots & 19.57 \end{bmatrix}$$

Similarly, a periodic extension calculation is performed on the first-and second-order differential MGF series. Finally, we derive the X1, X2, X3, X4, X5, X6, Yn, ..., Y1 time series from the MGF extension and external variable factors.

### 2.2. Stepwise Regression Model

The higher correlation series selected from MGF extension series represent the factors influencing the periodic variation of predictions themselves. The higher correlation series and the external variable factors, which are 47 hybrid predictors, are used to establish the stepwise regression equation, which is as follows:

$$Y = -85.486 + 0.238X_{21} + 0.287X_{19} + 0.301X_{23} + 0.227X_7 + 0.216X_{14} + 0.41X_{15} + 0.156X_{18} - 0.25X_{39} + 0.356X_{46} + 0.314X_{17} + 0.27X_8 + 0.348X_4 + 0.28X_9 + 0.196X_{20}$$

Substituting each factor with its value in the regression equation yields the fitting results shown in Figure 1 and the forecast results shown in Table 3.

### 2.3. Establishment of an MGF-OSR-BP Model Forecast

Currently, although MGF is the subject of much research, MGF has some intrinsic weaknesses when selects the subset, which is not always the global optimum, while the advantage of OSR is the ability to select the globally optimal subset. So we can combine MGF with OSR and pick out prediction variables, which are used to construct a BP neural network training set, and the training set was loaded into a 3-layer neural network input.

Based on the above method, 105 MGF extension series were generated as independent variables for screening. A simple regression for the time of each extension series and original series was established, and the couple score criterion (CSC) value was calculated. Selecting series satisfying  $CSC > \chi^2_\alpha$  as initial forecast factors, it was assumed that all P extension series had been selected. Next, all possible  $2^P$  regression subsets were calculated [9]. In the paper, 20 extension series had been selected and  $2^{20}$  regression subsets were calculated. According to the couple score variable selection criterion, one optimal subset was selected as the forecast equation.

Table 2 shows the optimal subset for different numbers of independent variables, CSC values, and root mean square error (RMSE) values. According to the optimal subset

combination of a different number of independent variables and the CSC and RMSE values, one optimal regression subset was selected as the forecast equation. The forecast equation is as follows:

$$Y = -47.080 + 0.423X_1 + 0.172X_4 + 0.141X_6 + 0.204X_7 + 0.274X_8 + 0.373X_9 + 0.215X_{10} + 0.339X_{11} + 0.226X_{12} + 0.367X_{13} + 0.272X_{14} - 0.173X_{15}$$

Meanwhile, the selected MGF extension series with 12 independent variables and the exogenous variables were used to construct a BP neural network training set, and the training set was loaded into a 3-layer feed forward network input end. In the example, we obtain 10 hidden layer nodes and 1 output layer, establish a MGF-OSR-BP neural network model, which is 18-10-1, and use it for training and solving and learning is complete when the convergence error reaches 0.0001. The results of fitting the MGF-OSR-BP neural network model with the 108-ten days samples is shown in Figure 1 and the forecast results is shown in Table 3.

**Table 2. Optimal Subset of Different Numbers of Independent Variable**

k	Optimal subset	CSC	RMSE
1	X12	84.61	9.24
2	X11X12	118.46	7.79
...	...	...	...
11	X1X6X7X8X9X10X11X12X13X14X15	181.16	4.82
12	X1X4X6X7X8X9X10X11X12X13X14X15	192.75	4.77
13	X1X3X4X6X7X8X9X10X11X12X13X14X15	183.15	4.75
14	X1X3X4X5X6X7X8X9X10X11X12X13X14X15	186.74	4.74
...	...	...	...
20	X1X2X3X4X5X6X7X8X9X10X11X12X13X14X15X16X17X18X19X20	190.25	4.7

#### 2.4. Hybrid MGF-OSR-BP Forecast Model based on GA Evolution BP

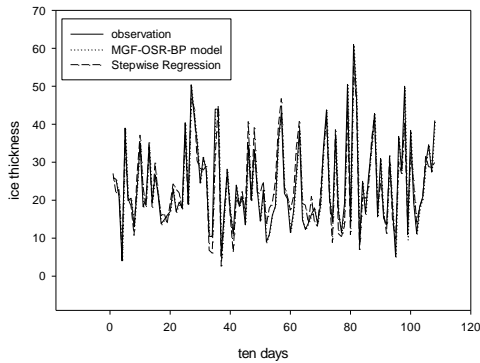
The BP algorithm is an efficient neural network learning algorithm; however, in practice, BP neural networks have some intrinsic weaknesses, such as slow convergence and very easy convergence to local extreme values. In addition, there is a lack of guidance for selecting the neural network initial connection weight and network structure, which contributes to the problem of a high degree of randomness and poses a difficulty for selecting an initial node with global properties. However, GA has strong global searching capacity, which overcomes the disadvantages of the BP neural network. Therefore, the paper propose that GA optimizes the initial connection weight and threshold of BP neural network, avoid local extreme values and gain global values, then, utilize BP algorithm further modification until the smallest error.

There has been divided into three parts for GA evolution BP neural network: the structure of BP neural network was obtained; optimization based on Genetic Algorithm; prediction with BP neural network [10].

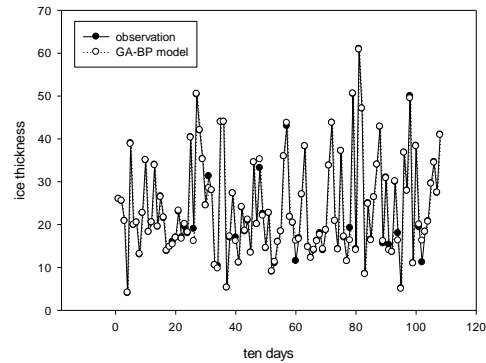
Based on the above analysis, 18 independent variables were selected as the 3-layer BP neural network input and the original series as the network output. There are various methods for network hidden layer node number determination, such as an empirical method and an equation method. In this example, we utilize empirical method to obtain 8 hidden layer nodes, establish a MGF-OSR-BP neural network model based on GA evolution BP, which is 18-8-1, and use it for training and solving. The evolutionary parameter of GA settings is as follows: 10 were selected as the initial population of GA in the evolutionary process, 50 were selected as the total evolution algebra, 0.35 was selected as the crossover probability, and 0.02 was selected as mutation probability. The total of absolute error was predicted by training data, which were selected as individual fitness value. The smaller the individual fitness value, the more excellent is the individual. The results of fitting the MGF-OSR-BP neural network model based on GA evolution BP, with the 108-ten days samples, is shown in Figure 2 and the forecast results is shown in Table 4.

### 3. Comparison and Analysis of Three Models

Figure 1 shows the variation curves of the actual values and the fitted values from the stepwise regression model and the MGF-OSR-BP model. This figure shows that the two models yield good fitting results, with the MGF-OSR-BP model having better fitting than the stepwise regression model. This result is not surprising because the MGF-OSR-BP model uses OSR for modeling factor selection and extracts the global optimal subset variables to establish the model. As a result, its model fitting accuracy is better than that of the regression model. The stepwise regression model for sample fitting, the mean relative error is 16.86%, while MGF-OSR-BP neural network for sample fitting, the mean relative error is 0.85%, which dropped by 16.01% over the previous model. The results show that the MGF-OSR-BP model is more close to the actual values.



**Figure 1. Fittings of the MGF-OSR-BP model and Stepwise Regression model.**



**Figure 2. Fittings of the MGF-OSR-BP model based on GA evolution BP.**

Figure 2 shows the variation curves of the actual values and the fitted values from the hybrid MGF-OSR-BP neural network model based on GA evolution BP. It is clear that the MGF-OSR-BP neural network model based on GA evolution BP has better fitting than the other two models in Figure 1. The MGF-OSR-BP neural network model based on GA evolution BP for sample fitting, the mean relative error is 0.68%.

Above is a comparison of the fitting results of the different models. The MGF-OSR-BP neural network model based on GA evolution BP has a better fitting accuracy than the other two models; however, having a strong forecast model fitting capability does not necessarily indicate a better practical forecast capability. Although the fitting results are one aspect of model evaluation, the forecast results are more important.

**Table 3. Comparison of the Predicting Accuracy of Independent Samples of the Two Models**

Month day	Actual values	stepwise regression model			MGF-OSR-BP model		
		prediction	absolute error	relative error/%	prediction	absolute error	relative error/%
1.5	15.1	19.05	3.95	26.19	25.88	10.78	71.36
1.15	7.9	28.29	20.39	258.13	11.30	3.40	43.07
1.25	19	21.97	2.97	15.64	23.35	4.35	22.87
2.8	3.6	22.95	19.35	537.57	26.12	22.52	625.66
2.18	11.2	24.09	12.89	115.07	20.55	9.35	83.51
2.28	40.7	26.49	14.21	34.92	23.36	17.34	42.61
3.3	10.6	26.27	15.67	147.79	30.73	20.13	189.92
3.13	35.3	27.13	8.17	23.16	26.59	8.71	24.67
AVA			12.20	144.81		12.07	137.96

**Table 4. Comparison of the Predicting Accuracy of Independent Samples of the MGF-OSR-BP Model based on GA Evolution BP and the Actual Values**

Month day	Observation	GA-BP model		
		prediction	absolute error	relative error/%
1.5	15.1	6.24	8.86	58.696
1.15	7.9	9.64	1.74	22.043
1.25	19	45.08	26.08	137.263
2.8	3.6	26.36	22.76	632.231
2.18	11.2	11.55	0.35	3.098
2.28	40.7	30.66	10.05	24.681
3.3	10.6	19.15	8.55	80.617
3.13	35.3	38.91	3.61	10.229
AVA			10.25	121.11

The results in Table 3 and in Table 4 show that, using an stepwise regression model for the 8-ten days independent sample forecast, the mean absolute error is 12.20 and the mean relative error is 144.81% .When using the MGF-OSR-BP model for the forecast of 8-ten days independent samples, the error is moderate, and the mean absolute error is 12.07 and the mean relative error is 137.96%. The MGF-OSR-BP neural network model based on GA evolution BP forecast yields markedly better results than the other two models, and its forecast for 8-ten days independent samples has a mean absolute error of 10.25, which dropped by1.95, 1.82, respectively, over the stepwise regression model and MGF-OSR-BP model. And the model has a mean relative error of 121.11%, which dropped by23.7%, 16.85%, respectively, over the stepwise regression model and MGF-OSR-BP model. It indicates a better forecast capability.

#### 4. Conclusions

This paper uses a MGF for data extension, based on an OSR to select the optimal data series as BP neural network input factors, and establishes a new hybrid MGF-OSR-BP neural network model based on GA evolution BP. This model has a better fitting accuracy and forecast result than the other two models. It fully utilizes the advantages of MGF and OSR in global optimal learning matrix selection, and in modeling, it properly utilizes GA selects initial weights and thresholds of BP neural network. The improvement in forecast capability provides a new method to extend the application of neural networks in future wire ice-covering forecast research areas and provides a reference for similar middle- and long-term forecast research based on elements of time series data. It also has promising potential future applications.

#### References

- [1] S. Yin, S. Zhao, Z. Wang, Q. Zhang and W. Tan, Journal of applied Meteorological Science. 20,722 ( 2009).
- [2] W. Wang and X. Cai, Journal of Arid Meteorology, 28, 26 (2010).
- [3] L. Xu and G. Chen, China Offshore Platform.4, 7 (2002).
- [4] D. lan and Z. Zheng, Research and Development, 12, 27 (2010).
- [5] C. Liu and J. Liu, High Voltage Engineering, 37, 241 (2011).
- [6] M. Farzaneh and K. Savadjiev, IEEE Trans Power Deliv, 20, 1080 (2005).
- [7] Y. Shi, X. Jiang and J. Yuan, High Voltage Engineering, 35,591 (2009).
- [8] Q. Wen, G. Sun and C. Zhang, Journal of catastrophology, 15, 11 (2000).
- [9] F. Wei, Editor, Modern climate statistic diagnostics prediction technology, China Meteorological Publishers, Beijing (1999).
- [10] X. Wang, L. Yu and Y. Li, Edited Feng Shi, Analysis of 30 cases by matlab neural network, Beijing University of Aerospace Publishers, Beijing (2010).