

# AN HOURLY FORECAST MODEL FOR THE DAYTIME PARTS OF OUTSIDE DRY-BULB TEMPERATURE

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## ABSTRACT

Due to a variety of influence factors, outside dry-bulb temperature takes on a systematic and random fluctuation. If a deterministic model is used to forecast the dry-bulb temperature, the predicted result often has a rough accuracy. Neural network can learn the internal regularity of the sample data by sample training; therefore it has very much adaptability and advantage in the aspects of forecast.

The influence factors of outside dry-bulb temperature exist difference in the daytime and the nighttime, which makes the fluctuant regularity of outside dry-bulb temperature inconsistent. Therefore, in this paper, daily dry-bulb temperature was divided into the daytime parts and the nighttime parts in terms of a certain principle based on sunshine duration. Through updating the recurrent back propagation network and combined with the characteristic of daytime parts of outside dry-bulb temperature, an hourly forecast model for the daytime parts of outside dry-bulb temperature was put forward in according to the dry-bulb temperature historic data of four records each day in meteorological station.

## KEYWORDS

daytime parts, dry-bulb temperature, forecast model, neural network

## INTRODUCTION

The data of hourly outside dry-bulb temperature are often indispensable to the calculations and applications in many areas, such as, the load calculation and energy consumption analysis of air-conditioning system. In general, the outside dry-bulb temperature is made four records each day in a meteorological station, viz. 2, 8, 14 and 20 (GMT+8) respectively. At the same time, the extreme values are recorded, including the maximum and the minimum dry-bulb temperature.

At present, there are some calculation or simulation methods for hourly outside dry-bulb temperature in a few of papers published, such as the Lagrangian quadratic interpolation model (Ji and Fang 1998), Fourier series fitting model (Yan et al. 2002), sine-exponential function model (Ephrath et al. 1996) and other models (Gelegenis 1999). These methods attempt to use a deterministic mathematical model to characterize hourly outside temperatures of the whole year, which give little consideration to the random fluctuations in the daily temperature. Therefore, these models are more effective on the data simulation of hourly dry-bulb temperature with general characteristics, such as typical annual data (Lang 2002), standard annual data (Ji and Fang 1998), rather than being used to predict the actual hourly outside dry-bulb temperature.

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Neural networks coming forth recently have more advantages in the aspect of forecasting, but it is important to take account of the actual situation of the forecasting objects. The factors of outside dry-bulb temperature have differences during daytime and nighttime, which cause the mechanism of the outside temperature change inconsistent correspondingly. Therefore, according to the sunshine duration, the hourly outside dry-bulb temperatures could be divided into daytime parts and nighttime parts, and the forecast model could be established respectively. Based on the historical data of four records each day for outside dry-bulb temperature in a meteorological station and the factors of dry-bulb temperature, neural network would be adopted to present a forecast model for hourly outside dry-bulb temperature. Taking paper length into account, the modeling of the daytime parts was discussed in this paper, and that of the nighttime parts would be discussed in the other.

## DAYTIME PARTS OF OUTSIDE DRY-BULB TEMPERATURE

Relative motion between Sun and Earth makes the daily sunshine durations different in the whole year. However research shows it is not significant between each of daily sunshine durations a month and the mean value of the same month that is usually less than half an hour. Therefore, based on the mean sunshine duration each month, the outside dry-bulb temperature could be separated under a certain principle.

Taking Shanghai as an example, at north latitude  $31^{\circ}14'$  and east longitude  $121^{\circ}29'$ , the mean sunshine duration each month (MSD)  $\bar{h}^s$  was calculated according to the location, consequently it could be worked out for the mean-times each month(GMT+8) of both sunrise  $\bar{\tau}^s$  and sunset time  $\bar{\tau}^d$  (Cao and Cao 2006), as shown in table 1.

Table 1 The MSD and the mean-times of both sunrise and sunset time each month

MONTH	1	2	3	4	5	6	7	8	9	10	11	12
$\bar{h}^s$	10.2	10.8	11.8	12.7	13.5	13.9	13.8	13.1	12.2	11.2	10.4	10.0
$\bar{\tau}^s$	7:39	7:23	6:50	6:13	5:45	5:36	5:46	6:05	6:25	6:44	7:06	7:29
$\bar{\tau}^d$	17:51	18:11	18:38	18:55	19:15	19:30	19:34	19:11	18:37	17:56	17:30	17:29
Daytime	8~18	8~19	7~19	7~19	6~20	6~20	6~20	6~20	7~19	7~18	8~18	8~18

If the mean-times each month of both sunrise and sunset were integers, the time interval of daytime parts of outside dry-bulb temperature could be defined from the sunrise time to the sunset. Otherwise, the time interval of daytime parts could be assigned from the whole point after the mean sunrise time to that of the mean sunset time. The daytime interval shows in table 1.

## FORECAST MODEL FOR DAYTIME PARTS

### Choice of input data for forecast model

The following data should be adopted as the input items of the forecast model for daytime parts of hourly outside dry-bulb temperature: Hourly historical data of total solar irradiance and diffusion irradiance, historical data of the outside dry-bulb temperature, geographic latitude, the day number of a year and the time corresponding to outputs of the model.

Through correlation analysis between dry-bulb temperature and total solar irradiance or diffusion solar irradiance, the data of solar irradiance with higher correlation coefficients could be sorted out as the input data for dry-bulb temperature forecasting.

Generally, the daytime parts of hourly outside temperatures typically included the two records of 8 and 14 o'clock among four records each day in a meteorological station value. To study the mechanism of change could find out the maximum dry-bulb temperature to be one of the daytime parts which in general appears during 14 to 15 o'clock in many cities in China, such as Shanghai. By analysing the relationship between the moment of the maximum dry-bulb temperature and that of the maximum solar irradiance in many different regions, it was known that the former appearing moment lagged two to three hours behind the latter. Hence, as long as the moment of the maximum solar irradiance was figured out (corresponding to 12 o'clock of apparent solar time), the moment of maximum outside temperature could approximately be known. Therefore, the data of outside dry-bulb temperatures at 8, 14 o'clock and the maximum temperature appearing moment could be used to training the forecast neural network model for the daytime parts of outside temperatures.

While forecasting the daytime parts of hourly outside dry-bulb temperature based on the sample data of outside dry-bulb temperatures at 8, 14 o'clock and the maximum temperature appearing moment, it was very important how to determine the neural network structure and the neural network training scheme.

### Determination of neural network model and training scheme

As for the determination of neural networks, it is easy to think of multilayer perceptron, BP network, RBF network, and the recurrent BP network(RBPN), etc. However, if taking into account the consistency of the input data in the process of training and of forecasting, the nowadays training methods are difficult to meet the requirements that add the historical data of outside dry-bulb temperature in the input data because of lacking hourly temperature data. In order to solve this problem, this paper adopted the RBPN (Cao and Cao 2005) and presented a training method to updating the weights and biases.

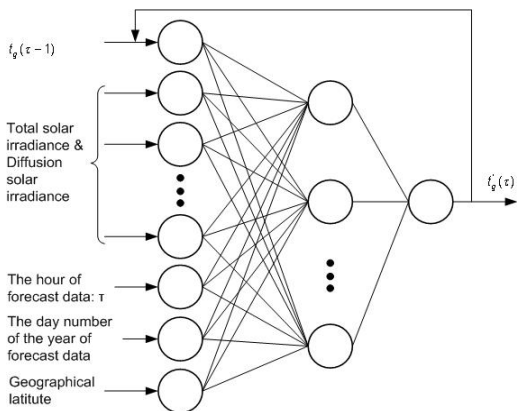


Figure 1. RBPN for forecasting daytime parts

In view of the time interval of six hours between adjacent two records of four records each day for outside temperature, a RBPN with six expected training time-steps was presented for daytime parts of outside temperature, the structure is shown in Figure 1. Where  $\tau$ ,  $\tau-1$  were the forecasting time and the contiguous whole time ahead of the forecasting time respectively, and  $t'_g(\tau)$  represented the forecasted outside dry-bulb temperature at the  $\tau$  moment. Obviously, conventional RBPN's training methods were unlikely to be used to train the RBPN by the input items shown in figure 1. Therefore, an improved training method was put up to train the RBPN, that is, the weights and biases were updated using the calculated increments in the 6<sup>th</sup> time-step instead of the calculated mean increments in all time-steps, namely :

$$\Delta \mathbf{W} = \Delta \mathbf{W}^{(6)}, \quad \Delta \boldsymbol{\theta} = \Delta \boldsymbol{\theta}^{(6)} \quad (1)$$

Where  $\Delta \mathbf{W}^{(6)}$ ,  $\Delta \boldsymbol{\theta}^{(6)}$  denoted the calculated increments of the weights and biases in the 6<sup>th</sup> time-step respectively, and  $\Delta \mathbf{W}$ ,  $\Delta \boldsymbol{\theta}$  were the increments of the weights and biases, respectively.

The selected training data sets were divided into three groups, as follows :

- The data of outside temperatures of 8-14 o'clock as the first training group
- The data of outside temperatures of 14-20 o'clock as the second training group
- The data of outside temperatures of the successive 5 hours before and including the maximum temperature appearing moment as the third training group

In the training process of RBPN, the first and second groups were rearranged as input data of RBPN according to the table2 and table3 respectively. As for the third group, provided that the moment of maximum temperature was at 15 o'clock, it was reorganized in accordance with table 4.  $\{e_{g1}\}^{(\tau)}$ ,  $\{e_{g2}\}^{(\tau)}$  ( $\tau=0,10,\dots,23$ ) (see table2, 3, 4) denoted the sequence data of hourly total solar irradiance and hourly diffusion solar irradiance which had higher correlation coefficients to the outside dry-bulb temperature at  $\tau$  o'clock respectively, and  $t'_g(\tau)$  represented the forecast value of outside dry-bulb temperature at  $\tau$  o'clock.  $\varphi_w$ ,  $d_n$  were the geographic latitude and the day number of a year of forecast data, respectively.  $t_{g,max}$  denoted the maximum temperature on the forecasting day.

Table 2 Input and output data of the RBPN in each time-step for the first group data

TIME-STEP NO.	INPUT DATA	OUTPUT DATA	EXPECTED OUTPUT
1	9, $\varphi_w$ , $\{e_{g1}\}^{(9)}$ , $\{e_{g2}\}^{(9)}$ , $d_n$ , $t_g(8)$	$t'_g(9)$	/
2	10, $\varphi_w$ , $\{e_{g1}\}^{(10)}$ , $\{e_{g2}\}^{(10)}$ , $d_n$ , $t'_g(9)$	$t'_g(10)$	/
3	11, $\varphi_w$ , $\{e_{g1}\}^{(11)}$ , $\{e_{g2}\}^{(11)}$ , $d_n$ , $t'_g(10)$	$t'_g(11)$	/
4	12, $\varphi_w$ , $\{e_{g1}\}^{(12)}$ , $\{e_{g2}\}^{(12)}$ , $d_n$ , $t'_g(11)$	$t'_g(12)$	/
5	13, $\varphi_w$ , $\{e_{g1}\}^{(13)}$ , $\{e_{g2}\}^{(13)}$ , $d_n$ , $t'_g(12)$	$t'_g(13)$	/
6	14, $\varphi_w$ , $\{e_{g1}\}^{(14)}$ , $\{e_{g2}\}^{(14)}$ , $d_n$ , $t'_g(13)$	$t'_g(14)$	$t_g(14)$

Table 3 Input and output data of the RBPN in each time-step for the second group data

TIME-STEP NO.	INPUT DATA	OUTPUT DATA	EXPECTED OUTPUT
1	15, $\varphi_w$ , $\{e_{g1}\}^{(15)}$ , $\{e_{g2}\}^{(15)}$ , $d_n$ , $t_g(14)$	$t'_g(15)$	/
2	16, $\varphi_w$ , $\{e_{g1}\}^{(16)}$ , $\{e_{g2}\}^{(16)}$ , $d_n$ , $t'_g(15)$	$t'_g(16)$	/
3	17, $\varphi_w$ , $\{e_{g1}\}^{(17)}$ , $\{e_{g2}\}^{(17)}$ , $d_n$ , $t'_g(16)$	$t'_g(17)$	/
4	18, $\varphi_w$ , $\{e_{g1}\}^{(18)}$ , $\{e_{g2}\}^{(18)}$ , $d_n$ , $t'_g(17)$	$t'_g(18)$	/
5	19, $\varphi_w$ , $\{e_{g1}\}^{(19)}$ , $\{e_{g2}\}^{(19)}$ , $d_n$ , $t'_g(18)$	$t'_g(19)$	/
6	20, $\varphi_w$ , $\{e_{g1}\}^{(20)}$ , $\{e_{g2}\}^{(20)}$ , $d_n$ , $t'_g(19)$	$t'_g(20)$	$t_g(20)$

Table 4 Input and output data of the RBPN in each time-step for the third group data

TIME-STEP NO.	INPUT DATA	OUTPUT DATA	EXPECTED OUTPUT
1	10, $\varphi_w$ , $\{e_{g_j}\}^{(10)}$ , $\{e_{d_j}\}^{(10)}$ , $d_n$ , $t'_g(9)$	$t'_g(10)$	/
2	11, $\varphi_w$ , $\{e_{g_j}\}^{(11)}$ , $\{e_{d_j}\}^{(11)}$ , $d_n$ , $t'_g(10)$	$t'_g(11)$	/
3	12, $\varphi_w$ , $\{e_{g_j}\}^{(12)}$ , $\{e_{d_j}\}^{(12)}$ , $d_n$ , $t'_g(11)$	$t'_g(12)$	/
4	13, $\varphi_w$ , $\{e_{g_j}\}^{(13)}$ , $\{e_{d_j}\}^{(13)}$ , $d_n$ , $t'_g(12)$	$t'_g(13)$	/
5	14, $\varphi_w$ , $\{e_{g_j}\}^{(14)}$ , $\{e_{d_j}\}^{(14)}$ , $d_n$ , $t'_g(13)$	$t'_g(14)$	/
6	15, $\varphi_w$ , $\{e_{g_j}\}^{(15)}$ , $\{e_{d_j}\}^{(15)}$ , $d_n$ , $t'_g(14)$	$t'_g(15)$	$t_{g,max}$

After been trained using the data of the three group data, the RBPN could be used to forecast the daytime parts of hourly outside dry-bulb temperature.

## TRAINING OF IMPROVED RBPN AND FORECASTING

In order to check out the feasibility of above-decribed RBPN model, taking the meteorological data sequences recorded by Baoshan Meteorological Station in Shanghai from January 2001 to January 2002 as the object of study, a RBPN was to be established to forecast the daytime parts of outside temperature in accordance with above method of modeling. The meteorologic data sequences from January 2001 to January 2002, included the data of hourly total solar irradiance and diffusion solar irradiance, the data of four records each day and the extreme values of outside dry-bulb temperature.

The mean transit times (GMT+8) each month were easily calculated from the sunrise time and the sunset time in Shanghai (see Table 1), all of which appeared between 12 o'clock and 13 o'clock; hence the moment of the maximum outside temperature could be obtained to be between 14 o'clock and 15 o'clock by the mean transit time of the same month plus 2. Therefore, the moment of the maximum temperature was fixed on 15 o'clock.

According to table1, the daytime parts could be separated from the historical data of four records each day of outside dry-bulb temperature. Through correlation analysis between dry-bulb temperature and total solar irradiance or diffusion solar irradiance, the data of solar irradiance at the forecasting time and at prior continuous two hours were sorted out as the input data for dry-bulb temperature forecasting. So the neuron numbers of input layer and output of the network were equal to 10 and 1 respectively. Suppose that the initial number of the neuron of hidden layer was given a value of 3, the initial structure of the RBPN could be expressed as 10-3-1.

Before training of the model, the meteorological data were divided into three groups according to table 2, table3 and table 4, and the meteorological data each day should be prepared and some should be preprocessed as follows:

- Prepare the data of outside dry-bulb temperature at 8, 14 and 20 o'clock and the maximum temperature.
- Prepare the data of hourly total and diffusion solar irradiance from 7 to 20 o'clock. If the time was beyond the sunshine duration, zero was given to the corresponding data of solar irradiance.
- Normalize the data of the three groups between 0.1 and 0.9.

Using the data sets of the first and second groups to train the RBPN, the optimum neuron number of hidden layer was 8 by cut and trial method. At last, the structure of the RBPN could be expressed as

10-8-1. The three groups were used separately to train the network, that is, in the first, using the first and second groups, and then using the third groups.

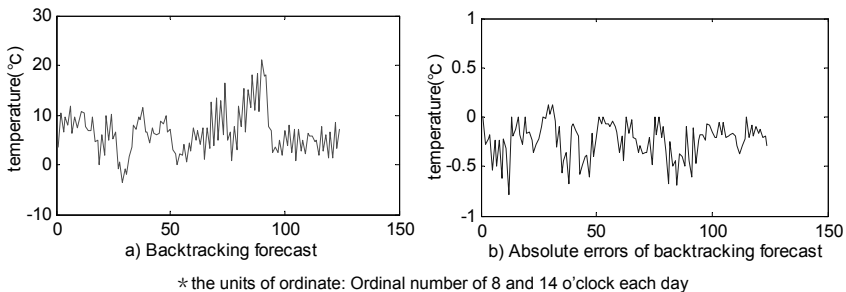


Figure 2 Backtracking forecast of RBPN

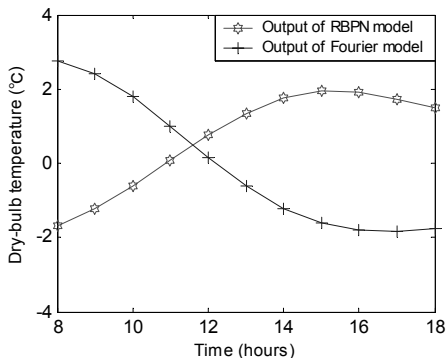
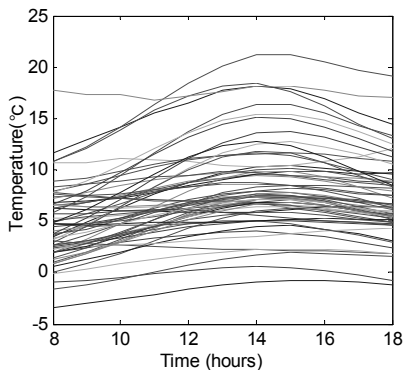
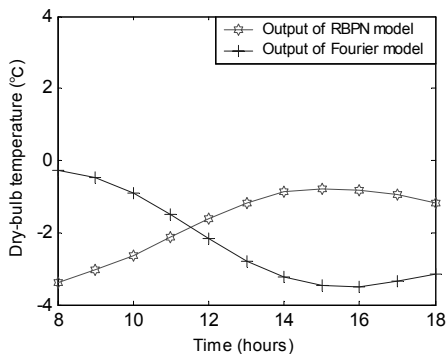
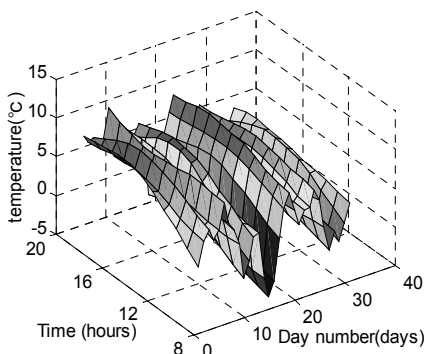


Figure 3. Daytime temperature forecast of RBPN for January 2001 and January 2002

Figure 4. Comparison between the forecasted output of the RBPN and that of the Fourier model

The training procedure of the RBPN was as follows:

- Use the data sets of the first and second groups of the meteorological data to train the RBPN until the expected error of network output or the maximum training times was reached, and the procedure turned to next step.
- Use the data sets of the third groups of the meteorological data to train the RBPN until the expected error of network output or the maximum training times was reached. If the error of network output didn't reach the expected, the procedure returned to the above step.

For the training and later for the forecasting, some factors took their values as follows. The expected training error of network output was 0.01. Value of 2000 was assigned to the maximum training times.

After the training, the two records at 8 and 14 o'clock each day of hourly outside dry-bulb temperature in January 2001 and January 2002 could be backtrackingly forecasted by using the trained RBPN, the backtracking forecast and the absolute errors of backtracking forecast shown in Figure 2.

By using the trained RBPN, it was easily to forecast the daytime parts of the hourly outside dry-bulb temperature at intervals January 2001 and January 2002, the forecasted results shown in Figure 3.

From Figure 3(a), it is easy to know the distribution of hourly outside dry-bulb temperature at the daytime intervals each day in January 2001. And each of the curves in Figure 3(b) represents the daytime parts of hourly outside dry-bulb temperature at a corresponding day in January 2001 and January 2002.

In order to have an example to compare with, Fourier series model (Yan et al. 2002) was established for the daytime parts of outside dry-bulb temperature in January 2001 by using the same meteorological data with modeling of RBPN. Then the Fourier series model and the RBPN were used to forecast the daytime parts of dry-bulb temperature, the forecasted on 15 and 16 January 2001 choosed to compare with (see Figure 4).

## RESULTS ANALYSIS AND DISCUSSION

- When the two records at 8 and 14 o'clock each day of hourly outside dry-bulb temperature in January 2001 and January 2002 were backtrackingly forecasted by using the trained RBPN, Figure 2(b) shows that the absolute errors of backtracking forecast are between  $-0.8$  to  $0.2^{\circ}$  C. The mean absolute error of backtracking forecast is  $0.2373^{\circ}$  C, and the mean relative error is 3.73%, the root-mean-square error being  $0.2956^{\circ}$  C correspondingly.
- Figure 3 shows that the maximum temperature each day appears between at 14 to 15 o'clock, which is consistent with the actual situation.
- There is distinct difference in the forecast data of network output by the RBPN and Fourier series model respectively (see Figure 4). As for the forecasted output of Fourier series model, the curve of temperature shows that the maximum temperature reached at 8 o'clock declines to the minimum about 16 o'clock gradually and then has a pickup until the value at 18 o'clock. However, the curve of temperature forecasted by RBPN shows that the temperature has a ascending trend from 8 to 15 o'clock and then a downward trend, the maximum temperature appearing around 15 o'clock. It is evident that the changing trend of the hourly temperature forecasted with the RBPN is reasonable to reflect the actual situation compared with Fourier series model.

## CONCLUSIONS

For the outside dry-bulb temperature is generally composed of four records and the extreme values each day in a meteorological station, the nowadays training methods are difficult to meet the requirements that add the historical data of outside dry-bulb temperature in the input data because of lacking hourly temperature data. Based on the above reasons, this paper had presented a training method to updating the weights and biases of RBPN which made the output of network reasonable. Compared with Fourier series model, the case study shows the forecast data by RBPN is quite in line with the actual situation.

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