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A Novel Prediction Model using Neural and Fuzzy Temperature Forecasting

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ABSTRACT

The soft computing techniques especially fuzzy logic has been used by many researchers for temperature prediction in recent years. Artificial neural networks (ANN) have been popular due to their capabilities in handling complex, nonlinear problems in a better way when compared to traditional techniques. In this paper, the theory of ANN with radial basis function (RBF) is presented, and the RBF model is used to predict the daily average temperature for Taipei, Taiwan. The historical data of the daily average temperature and daily cloud density from June 2012 to September 2012 collected from central weather bureau were fed into the RBF model for training and testing. The results were compared with those of previous studies and the performance of the RBF model is found to be prominently better. The expensive experimental result shown, we can conclude that ANN models are more applicable and accurate than fuzzy models to deal with temperature prediction.
KEYWORDS: Temperature prediction, Fuzzy forecasting, Neural forecasting, Radial basis function.

1. INTRODUCTION

Forecasting play an important role in our daily life, including stock market forecasting, traffic flow fore-casting, weather forecasting, economic growth rate forecasting, enrollments forecasting, etc. If we can make a forecast as precise as possible, we can pre-vent damages from potential disasters, such as economic recession, company loss, traffic jams, storms and typhoons [1]. Weather is a continuous, data-intensive, dynamic and chaotic process. The parameters required to predict weather are enormously complex such that there is uncertainty in prediction even for a short period [2]. In recent years, some fuzzy forecasting methods have been presented for dealing with forecasting problems [3, 4, 5, 6, and 7].

In [1] and [2], Chen and Chang presented a method to deal with temperature prediction based on fuzzy clustering and fuzzy rules interpolation techniques. The authors in [8], also is applied the forecasting software DTREG [9] to obtain the forecasting results of the radial basis function neural network (RBFNN) for different orders from June 2012 to September 2012. In [10], authors presented a method for temperature prediction based on fuzzy time series. In [11], authors presented a method for temperature prediction based on two-factor high-order fuzzy time series. In [12], authors reviewed the first-order time-variant fuzzy time series model and the first-order time-invariant fuzzy time series model proposed by Song and Chissom, where these models are com-pared with each other and with a time-variant Markov model using linguistic labels with probability distributions [13].

In this work, we examined the prediction of daily average temperature using RBF neural networks. One of the most popular training algorithms in the domain of neural networks used so far, for weather forecasting is the back propagation algorithm. It is a gradient descent method. The algorithm suffers from many problems [4]. When RBF is used to approximate any functions, it has better capacity of approximation, identification and learning speed than back propagation networks. So, we chose RBF for the model to forecast weather. The property of artificial neural networks that they not only analyze the data but also learn from it for future predictions makes them suitable for weather forecasting. Neural networks provide a methodology for solving many types of nonlinear problems that are difficult to be solved through traditional techniques. Furthermore neural networks are capable of extracting the relationship between inputs and outputs of a process without the physics being explicitly provided [6]. Hence these characteristics of neural networks guided us to use them for the temperature prediction problem. We proposed a complete survey on these models in [20].

The motivation of this work is firstly, to increase the accuracy of the average forecasting results and secondly, to perform comparison between the two main approaches- ANN techniques and fuzzy techniques to deal with temperature prediction. The rest of this paper is organized as follows. In Section 2, the definition of radial basis networks has been briefly reviewed.

An overview of the sample data is carried out, in section 3. The experimental results and the discussion of them have been given in Section 4. The comparison between RBF model and the existing fuzzy methods was also made. Finally, the conclusions are discussed in Section 5.

2. Radial Basis Function Neural Networks

The RBFNN is a universal approximator, with a solid foundation in the conventional approximation theory. The generic topology of the RBFNNs consists of three layers as shown in Fig. 1. Each node in the hidden layer uses an RBF denoted by $\varphi(r)$, as its nonlinear activation function. The hidden layer per-forms a nonlinear transform of the input, and the out-put layer is a linear combiner mapping the nonlinearity into a new space. The biases of the output layer neurons can be modeled by an additional neuron in the hidden layer, which has a constant activation function $\varphi 0(r) = 1$ [14].

F or an input pattern x, the output of the network is given by:

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$$y_j(x) = \sum_{k=1}^{p} w_{kj}\varphi_k(x) \quad (1)$$

For $j = 1,...,m$, where $y_j(x)$ is the *j*th output of the RBFNN, and w_{ki} is the connection weight from the *k*th hidden unit to the *j*th output unit. In the case of the Gaussian type of RBFs, we have:

$$\varphi_k(x) = e^{-(\frac{\|x-\mu_k\|^2}{2\sigma_k^2})} \quad (2)$$

Where μ_k is the prototype or center of the *k*th hidden unit, σ_k is the spread of the corresponding Gaussian function and ||.|| denotes the Euclidean norm. The activation of an RBF unit is determined by the distance between the input and prototype vectors. Thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units.

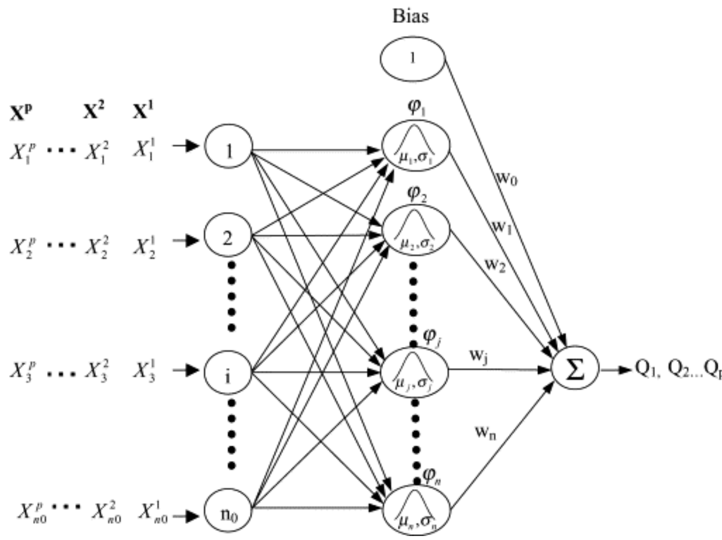

Fig. 1. Architecture of the RBFNN. The input layer has n nodes, the hidden and output layers have p and m neurons, respectively.

The training of RBF is done in three sequential stages. The first stage of the learning consists of determining the unit centers μ_k by the *k*-means clustering algorithm. Next, the unit widths σ_k is determined using a heuristic approach that ensures the smooth-ness and the continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least squares objective function [15].

RBFs may require more neurons than standard feed forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed forward networks. They work best when many training vectors are available [18].

3. Sample Data Explanation

In order to compare the performance of the RBF method with some fuzzy forecasting methods in literature, we apply the RBF model to forecast the daily average temperature from sampled database in Tehran, where the historical data set consists of the daily average temperature and the daily average cloud density, respectively shown in Table 1. If we want to forecast the daily average temperature of day *i*, then we use the RBF model to get the forecasted variation (i.e., the inferred output) of day *i*, and the forecasted daily average temperature of day *i* is equal to the daily average temperature of day *i* –1 plus the fore-casted variation of day *i*. Similar to the best common method [20], we partition each data set into four groups, i.e., June 2012, July 2012, August 2012 and September 2012, and apply the RBF model to each group by using the variation of the daily average temperature and the daily average cloud density be-tween any two adjacent days. Table 2 shows the variation of the daily average temperature and the daily average cloud density in June 2012, respectively.

In our research, a window basis *w* using the historical data of the past *w* days is considered to predict the forecasted data of the day being considered, where *w* is a positive integer. That is, the historical variation T_{i-w}, . . . , T_{i-2} and T_{i-1} of the daily average temperature and the historical variation D_{i-w}, . . . , D_{i-2}, and D_{i-1} of the daily average cloud density are used to predict the variation T_i of the daily average temperature of day *i*, where T_{i-w}, . . . ,T_{i-2}, T_{i-1}, D_{i-w},. . . , D_{i-2}, D_{i-1} and T_i form a training pattern (T_{i-w}, D_{i-w}, . . . , T_{i-2}, D_{i-2}, T_{i-1}, D_{i-1}, T_i). Table 3 shows the 27 training patterns (including input training vector and target output pair *s*: *t* [33]) of June 2012 based on the window basis *w* = 2.

4. Experimental Result

4.1. Simulation of RBF

In order to train, validate and test the RBF prediction model, we used neural network toolbox provided by MATLAB. The network consists of three-layer structure. The first layer is input layer, which contains four nodes to input training vectors $S_j^{(1)}$, $S_j^{(2)}$, $S_j^{(3)}$ and $S_j^{(4)}$, based on the window basis $w = 2$. The second layer is hidden layer. The number of hidden nodes is optimized using a trial and error approach, so that are added neurons to this layer of the radial basis network until it meets the specified mean squared error goal. For training patterns of June 2012, shown in Table 3, the hidden layer contains 27 nodes. The last layer is the output layer, which consists of the target of the forecasting model, T_j. The structure of RBF for training patterns of June 2012 can be shown in Fig. 2.

After determining the structure of RBF, the training patterns of June, July, August and September 2012 were fed into the network for training, respectively. Through the network training for training patterns of June 2012, the performance of RBF is shown in Fig. 3. From this figure, we can see that the network can meet forecasting model requirements and it is also converged at 27 epochs.

4.2. Results and Discussion

In this section, the forecasting results are calculated based on the window basis $w = 2$. Table 4 shows the forecasted variations and the forecasted daily average temperature from June 4 to June 30. From Table 4, we can see that the accuracy of prediction is fairly good.

4.3. Comparative Evaluation

In this paper, we use the average error rate (AER) to evaluate the forecasting results for temperature prediction, where,

$$AER = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{T_{Forcasted}(i) - T_{Actual}(i)}{T_{Actual}(i)}\right| \times 100\% \qquad (3)$$

$T_{Forecasted}(i)$ and $T_{Actual}(i)$ denote the forecasted temperature and the actual temperature of day i, respectively, and n denotes the number of forecasted days.

To evaluate the performance of the presented model, five best existing fuzzy methods, [12, 26, 3, 11 and 2], are selected for comparison. A comparison of the average error rates is listed in Table 5 where all forecasting models are based on the window basis $w = 2$.

Table 1. The historical data of the daily average temperature (°C) and the daily average cloud density (%) from June 1, 2012, to September 30, 2012, in Tehran

Day	June	July	August	September
1	26.1°C, 36%	29.9°C, 15%	27.1°C, 100%	27.5°C, 29%
2	27.6°C, 23%	28.4°C, 31%	28.9°C, 78%	26.8°C, 53%
3	29.0°C, 23%	29.2°C, 26%	28.9°C, 68%	26.4°C, 66%
4	30.5°C, 10%	29.4°C, 34%	29.3°C, 44%	27.5°C, 50%
5	30.0°C, 13%	29.9°C, 24%	28.8°C, 56%	26.6°C, 53%
6	29.5°C, 30%	29.6°C, 28%	28.7°C, 89%	28.2°C, 63%
7	29.7°C, 45%	30.1°C, 50%	29.0°C, 71%	29.2°C, 36%
8	29.4°C, 35%	29.3°C, 34%	28.2°C, 28%	29.0°C, 76%
9	28.8°C, 26%	28.1°C, 15%	27.0°C, 70%	30.3°C, 55%
10	29.4°C, 21%	28.9°C, 8%	28.3°C, 44%	29.9°C, 31%
11	29.3°C, 43%	28.4°C, 36%	28.9°C, 48%	29.9°C, 31%
12	28.5°C, 40%	29.6°C, 13%	28.1°C, 76%	30.5°C, 25%
13	28.7°C, 30%	27.8°C, 26%	29.9°C, 50%	30.2°C, 14%
14	27.5°C, 29%	29.1°C, 44%	27.6°C, 84%	30.3°C, 45%
15	29.5°C, 30%	27.7°C, 25%	26.8°C, 69%	29.5°C, 38%
16	28.8°C, 46%	28.1°C, 24%	27.6°C, 78%	28.3°C, 24%
17	29.0°C, 55%	28.7°C, 26%	27.9°C, 39%	28.6°C, 19%
18	30.3°C, 19%	29.9°C, 25%	29.0°C, 20%	28.1°C, 39%
19	30.2°C, 15%	30.8°C, 21%	29.2°C, 24%	28.4°C, 14%
20	30.9°C, 56%	31.6°C, 35%	29.8°C, 25%	28.3°C, 3%
21	30.8°C, 60%	31.4°C, 29%	29.6°C, 19%	26.4°C, 38%
22	28.7°C, 96%	31.3°C, 48%	29.3°C, 46%	25.7°C, 70%
23	27.8°C, 63%	31.3°C, 53%	28.0°C, 41%	25.0°C, 71%
24	27.4°C, 28%	31.3°C, 44%	28.3°C, 34%	27.0°C, 70%
25	27.7°C, 14%	28.9°C, 100%	28.6°C, 29%	25.8°C, 40%
26	27.1°C, 25%	28.0°C, 100%	28.7°C, 31%	26.4°C, 30%
27	28.4°C, 29%	28.6°C, 91%	29.0°C, 41%	25.6°C, 34%
28	27.8°C, 55%	28.0°C, 84%	27.7°C, 14%	24.2°C, 59%
29	29.0°C, 29%	29.3°C, 38%	26.2°C, 28%	23.3°C, 83%
30	30.2°C, 19%	27.9°C, 46%	26.0°C, 33%	23.5°C, 38%
31		26.9°C, 95%	27.7°C, 26%	

Table 2. The variation of the daily average temperature and the daily average cloud density in June 2012

Day	Daily average temperature (°C)	Variation of the daily average temperature	Daily average cloud density (%)	Variation of the daily average cloud density
1	26.1		36	
2	27.6	1.5	23	-13
3	29.0	1.4	23	0
4	30.5	1.5	10	-13
5	30.0	-0.5	13	3
6	29.5	-0.5	30	17
7	29.7	0.2	45	15
8	29.4	-0.3	35	-10
9	28.8	-0.6	26	-9
10	29.4	0.6	21	-5
11	29.3	-0.1	43	22
12	28.5	-0.8	40	-3
13	28.7	0.2	30	-10
14	27.5	-1.2	29	-1
15	29.5	2	30	1
16	28.8	-0.7	46	16
17	29.0	0.2	55	9
18	30.3	1.3	19	-36
19	30.2	-0.1	15	-4
20	30.9	0.7	56	41
21	30.8	-0.1	60	4
22	28.7	-2.1	96	36
23	27.8	-0.9	63	-33
24	27.4	-0.4	28	-35
25	27.7	0.3	14	-14
26	27.1	-0.6	25	11
27	28.4	1.3	29	4
28	27.8	-0.6	55	26
29	29.0	1.2	29	-26
30	30.2	1.2	19	-10

According to Table 5, it is clear that the presented model forecasts more accurate than the existing fuzzy methods. That is, the presented method gets higher average forecasting accuracy rates than the best method in the literature. From this comparison, it is easy to observe that the neural network technique is more suitable to predict temperature than the fuzzy techniques because the RBF model is more close to the desired output than the existing methods.

Table 3. The training patterns for June based on the window basis w = 2

Training patterns	$(S_j^{(1)}, S_j^{(2)}, S_j^{(3)}, S_j^{(4)}, T_j)$	Training patterns	$(S_j^{(1)}, S_j^{(2)}, S_j^{(3)}, S_j^{(4)}, T_j)$
P_1	(1.5, -13, 1.4, 0, 1.5)	P_{15}	(-0.7, 16, 0.2, 9, 1.3)
P_2	(1.4, 0, 1.5, -13, -0.5)	P_{16}	(0.2, 9, 1.3, -36, -0.1)
P_3	(1.5, -13, -0.5, 3, -0.5)	P_{17}	(0.2, 9, 1.3, -36, -0.1)
P_4	(-0.5, 3, -0.5, 17, 0.2)	P_{18}	(-0.1, -4, 0.7, 41, -0.1)
P_5	(-0.5, 17, 0.2, 15, -0.3)	P_{19}	(0.7, 41, -0.1, 4, -2.1)
P_6	(0.2, 15, -0.3, -10, -0.6)	P_{20}	(-0.1, 4, -2.1, 36, -0.9)
P_7	(-0.3, -10, -0.6, 9, -0.6)	P_{21}	(-2.1, 36, -0.9, -33, -0.4)
P_8	(-0.6, -9, 0.6, -5, -0.1)	P_{22}	(-0.9, -33, -0.4, -35, 0.3)
P_9	(0.6, -5, -0.1, 22, -0.8)	P_{23}	(-0.4, -35, 0.3, -14, -0.6)
P_{10}	(-0.1, 22, -0.8, -3, 0.2)	P_{24}	(0.3, -14, -0.6, 11, 1.3)
P_{11}	(-0.8, -3, 0.2, -10, -1.2)	P_{25}	(-0.6, 11, 1.3, 4, -0.6)
P_{12}	(0.2, -10, -1.2, -1, 2)	P_{26}	(1.3, 4, -0.6, 26, 1.2)
P_{13}	(-1.2, -1, 2, 1, -0.7)	P_{27}	(-0.6, 26, 1.2, -26, 1.2)
P_{14}	(2, 1, -0.7, 16, 0.2)		

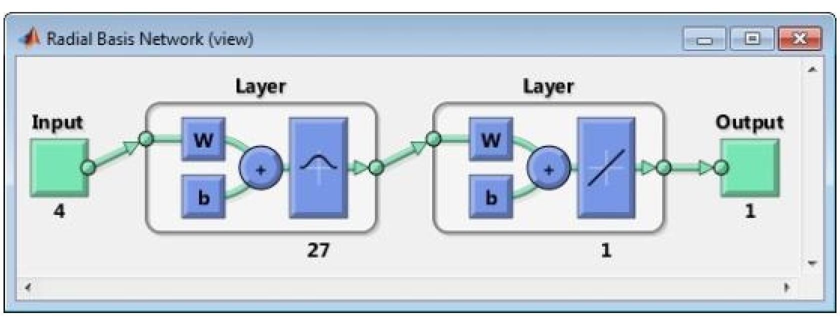

Fig. 2. The structure of RBF for training patterns of June.

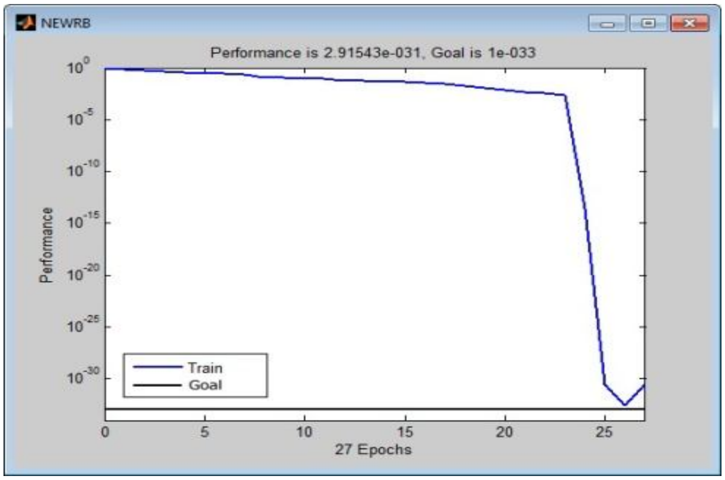

Fig. 3. Training performance function for June 2012 training patterns.

5. Conclusion

The work presented in this paper was aimed to show the suitability of neural networks to perform predictions. An application of radial basis function for temperature prediction is presented in this paper. The performance of RBF model was compared with several fuzzy forecasting methods for window basis $w = 2$ by MATLAB simulation. The experimental results show that the RBF method produces better forecasting results than several existing methods. In summary, neural forecasting was generally more ac-curate than fuzzy forecasting.

This work is an important part of the presentation and implementation of the weather forecasting model at a comparative statement on the performance of neural network and fuzzy techniques. Our efforts included: (1) the study of ANNs, (2) a literature survey in forecasting problems, (3) an extensive study of temperature prediction, (4) the definition of criteria in order to choose a more suitable model for practical application in guiding the design of neural network, (5) the use of RBF as more efficient and accurate model for predicting the daily average temperature and (6) a comparative analysis of neural forecasting and fuzzy forecasting for temperature prediction problem. It was also observed that using ANN for temperature prediction, not only is forecasting method simplified, but also forecasting results are intelligent. So, ANN played a significant role while predicting problems because of its associative memory and distributed parallel capacity, meeting the need of real-time performance.

Table 4. Forecasted variation and forecasted daily average temperature in June 2012

Day	Actual temperature	Forecasted variation	Forecasted daily average temperature
1	26.1		
2	27.6		
3	29.0		
4	30.5	1.500	30.500
5	30.0	-0.500	30.000
6	29.5	-0.500	29.500
7	29.7	0.200	29.700
8	29.4	-0.300	29.400
9	28.8	-0.600	28.800
10	29.4	-0.600	28.200
11	29.3	-0.100	29.300
12	28.5	-0.800	28.500
13	28.7	0.200	28.700
14	27.5	-1.200	27.500
15	29.5	2.000	29.500
16	28.8	-0.700	28.800
17	29.0	0.200	29.000
18	30.3	1.300	30.300
19	30.2	-0.100	30.200
20	30.9	0.700	30.900
21	30.8	-0.100	30.800
22	28.7	-2.100	28.700
23	27.8	0.900	27.800
24	27.4	-0.4	27.400
25	27.7	0.300	27.700
26	27.1	-0.600	27.100
27	28.4	1.300	28.400
28	27.8	-0.600	27.80
29	29.0	1.200	29.000
30	30.2	1.200	30.200

Table 5. A comparison of the average error rates of the RBF model with the existing fuzzy methods, from June to September in Tehran for window basis w =2

Month	RBFNN (1) method [31]	Chen and Hwang's method [12]	Lee et al.'s method [26]	Chen and Chang's method [a] [2]	Chen and Chang's method [a] [1]	Presented RBF model
June	2.67%	2.88%	1.44%	1.70%	1.55%	0.15%
July	2.58%	3.04%	1.59%	1.62%	1.75%	0.00%
August	2.48%	2.75%	1.26%	1.60%	1.47%	0.00%
September	2.65%	3.29%	1.89%	1.44%	1.44%	0.07%

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