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A New Model of Fuzzy Neural Networks and its Application*

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***Abstract* - In this paper, We summarize fuzzy neural network's research actuality, development tide and application field. expound basic conception of fuzzy logic system, artificial neural and fuzzy neural network; set up a normal fuzzy neural network model and study algorithm aim at actual problem, the node number of fuzzy layer, normal layer and rule layer is computable if the model has assured input and output pattern and fuzzy layer's subject function, and the model has good applicability to export express and pattern identification. The combination model is applied to synthetic integration of forecasted rainfall data produced by gradual regression method, periodic analysis plus multi-layer method and model output statistics method. The model is trained by short-term rainfall data of Zhejiang province from 1980 to 1997. The synthetic integration (forecast) results from 1998 to 2000 show that the presented model can obtain satisfactory forecast performance.**

Index Terms* - *Neural network, Fuzzy logic, fuzzy neural network, Synthetic integration , Meteorological forecast.

I. INTRODUCTION

The increasing demand for more exact and in time meteorological forecast and growing dependency of the economy and population life upon the weather and natural environment conditions necessitate continuous improvement of meteorological forecasting technologies. Meteorological forecast is a very complicated task with characteristics of fuzziness and non-linearity and is a complex learning process. In order to improve forecast performance, neural networks and fuzzy logic technology are introduced to meteorological forecast [1,2], and have widely been adopted in the research of rainfall forecast[3-9]. In this paper, based on neural networks and fuzzy logic, a new kind of combination model is presented for the synthetic integration of rainfall forecasted data produced by gradual regression method, periodic analysis plus multi-layer method and MOS (Model Output Statistics) method. Synthetic integration experiment results show that the presented combination model can effectively integrate forecasted data to obtain more exact rainfall forecast.

II. COMBINATION METHODS OF NEURAL NETWORK AND FUZZY LOGIC

Neural networks are in nature fuzzy and differ from traditional information process methods in two aspects: first, neural networks are adaptable and trainable, secondly, the neural networks are in nature large-scale and parallel. The weights attached to data play an important role in the operation of a neural network. It is, however, very difficult to understand a behavior of a neural network. Fuzzy logic is mainly concerned with imprecision and can express knowledge of field experts. Since fuzzy logic rules are constituted by human intuitions, Fuzzy logic has no adaptable and trainable properties. In a complex system, the more rules, the more complex the calculation is, the longer it will take to identify and set up this rules. These properties limit the applicability of fuzzy logic. A brief comparison of neural networks and fuzzy logic systems is given in *Table 1*.

Both neural networks and fuzzy logic systems are estimators without mathematical models. Many scholars have testified the mapping competence of neural networks. B.Kosko, *et al* have also proven that fuzzy logic systems can also approach real continuum functions in compact sets with any precision [8]. Fuzzy logic systems manage unknown models or imprecise control by imitating some human thinking logic, while neural networks works as a function estimator imitating the working process of human nerve cells.

Neural networks and fuzzy systems have a lot of similar properties in some aspects and many different properties in other aspects. It is obvious that neural networks and fuzzy logic systems have complementary property. There are a lot of combination schemes to

TABLE 1 COMPARISON OF NEURAL NETWORK AND FUZZY SYSTEM

	Neural Networks	Fuzzy System
Components	Nerve cells	Fuzzy rules Fuzzy inference
Advantages	Learning Adaptation Error toleration	Processing imprecision information Expressing expert's knowledge
Disadvantages	Trouble to describe Slow learning rate	No learning Inference ambiguity
Applications	Function mapping Modeling Estimation	Control systems without precise model but can be controlled with experience

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combine neural networks and fuzzy logic systems. The followings are some popular combination methods:

(1) Using fuzzy logic operations "and" and "or" to replace Sigmoid function in neural networks;
(2) Adopting fuzzy weights in the neural networks;
(3) Using fuzzy input data in the neural networks input layer;
(4) Using both fuzzy weights and fuzzy input data.
(5) Combination of above methods.

Researches on combination of neural networks and fuzzy logic systems have led to the emergence of so-called neurofuzzy systems.

III. A Combination Model of Neural Networks and Fuzzy Systems

In this section, a novel combination model of neural network and fuzzy logic system is presented. Where the fuzzy logic function is fused with node function of neural network. The presented combination model is shown in Fig.1, which is composed of four layers: input layer, membership function constructing layer, inference layer, and defuzzification layer. The structure of the model is a standard multi-layered feed forward network, but nodes of the model work according to fuzzy logic function.

A. Fuzzy inference of the Model

The membership function of each node in the fuzzy neural network combination model is constructed as:

$$\mu_{ij} = \exp\left(-\left(\frac{x_i - m_{ij}}{\delta_{ij}}\right)^2\right), \quad (1 \le i \le n; 1 \le j \le m) \qquad (1)$$

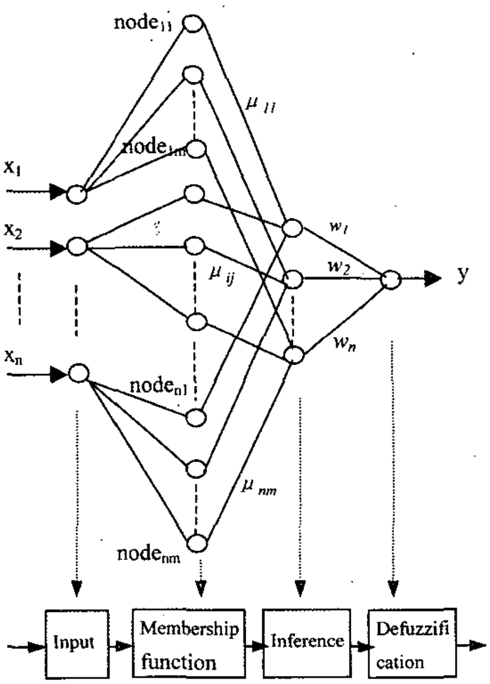

Fig.1 Fuzzy neural network combination model

where, μ_{ij} is the degree of membership function corresponding node ij, m_{ij}, and δ_{ij} are parameters that can be trained, respectively.

Inference results, outputs of the inference nodes, are a product of all inputs into this node. That is:

$$\pi_i = \mu_{1i} \bullet \mu_{2i} \cdots \bullet \mu_{ni} = \prod_{j=1}^{n} \mu_{ji} \qquad (2)$$

The output of the combination model output layer node, defuzzification result, is defined as a linear weighted sum of all inputs to this node:

$$y = \sum_{i=1}^{m} w_i \pi_i \qquad (3)$$

where w_{ij} is the weight that will be trained in the neural network training process.

B. Neural network learning scheme

The popular error back-propagation training algorithm is adopted as the learning strategy to train and adjust the proposed combination model with making cost function $E_p = \frac{1}{2}(Y - \overline{Y})^2$ minimum, the adjusting scheme of m_{ij}, δ_{ij} and w_i are obtained:

$$\Delta m_{ij} = -\eta \bullet \frac{\partial E_p}{\partial m_{ij}} = -\eta \bullet \frac{\partial E_p}{\partial Y} \bullet \frac{\partial Y}{\partial m_{ij}} = -\eta(Y - \overline{Y}) \bullet \frac{\partial Y}{\partial m_{ij}}$$

$$= -\eta(Y - \overline{Y}) \bullet w_j \bullet \prod_{l=1, l \ne i}^{n} \mu_{lj} \bullet 2\exp\left(-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}\right) \bullet \frac{(x_i - m_{ij})}{\sigma_{ij}^2} \qquad (4)$$

$$\Delta \delta_{ij} = -\eta \bullet \frac{\partial E_p}{\partial \delta_{ij}} = -\eta(Y - \overline{Y}) \bullet w_j$$

$$\bullet \prod_{l=1, l \ne i}^{n} \mu_{lj} \bullet 2\exp\left(-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}\right) \bullet \frac{(x_i - m_{ij})^2}{\sigma_{ij}^2} \qquad (5)$$

$$\Delta w_i = -\eta \bullet \frac{\partial E_p}{\partial w_i} = -\eta \bullet (Y - \overline{Y}) \bullet \pi_i \qquad (6)$$

where η is the learning rate, Y is the real output of the neural network and $\overline{Y}$ is the desired value, i.e. teacher signal.

IV. Synthetic Integration of Rainfall

The presented combination model now is applied to integrate rainfall forecasted by GRM (Gradual Regression) method, PAM (Periodic Analysis plus Multi-layer) method and MOS (Model Output Statistics) method for short-term rainfall of Zhejiang province, China. Where there are three input data, so the combination model parameter m=n=3. The 18 sets of forecasted data and real data of rainfall from May to September of 1980 to 1997, shown in Table 2, are used to train the presented combination model.

Before training the proposed model, there are two preliminary works. First, data used to train the model are standardized as values between 0 and 1 for accelerating convergence rate of the neural network. So all forecasted data is divided by a historical maximum value among three type forecasted data. Second initial values of m_{ij}, δ_{ij} and w_i have to be assigned before starting the training process. Where initial value of m_{ij} is assigned to the mean of 18 forecast data. Initial values of δ_{ij} and w_i are both assigned as 1. Learning rate η is chosen to be 0.00005. Training ending condition is defined as $\Delta E_p \leqslant 0.0000005$.

After 1000 times training operation the neural network reaches convergence state. The real outputs of the model are shown in the SIM column of Table 2. It indicates that the integrated results are more closed to real rainfall.

The trained combination model is then used to integrate forecasted rainfall data obtained from GRM, PAM and MOS before real rainfall data obtained. Synthetic integration results are demonstrated in Fig.2. It is shown obviously that the accuracy of synthetic integration method exceeds any one's result of GRM, PAM and MOS.

TABLE 2 RAINFALL FROM MAY TO SEPTEMBER
(FORECASTED, REAL AND INTEGRATED RESULTS, UNIT: MM)

	GRM	PAM	MOS	SIM	Real
1980	733.43	841.44	787.44	769.81	745.00
1981	1036.61	975.07	1155.44	1049.35	1080.00
1982	979.58	1140.91	990.58	1023.76	998.00
1983	1180.75	1058.84	1150.65	1140.34	1101.00
1984	1099.47	1145.27	977.25	1051.82	1037.00
1985	1120.71	1160.67	1211.13	1193.27	1209.00
1986	588.72	584.40	634.19	583.35	547.00
1987	1364.35	1078.21	1125.29	1243.59	1358.00
1988	849.61	908.31	820.27	847.30	870.00
1989	1323.68	1374.89	1487.89	1412.16	1480.00
1990	1862.04	1690.84	1651.29	1783.27	1830.00
1991	538.39	612.44	939.55	652.86	563.00
1992	1327.90	1244.87	1299.71	1248.74	1185.00
1993	1203.89	1111.39	1160.66	1216.84	1277.00
1994	1032.17	1106.60	1016.64	1041.65	1013.00
1995	758.05	753.73	884.35	836.29	811.00
1996	718.84	1024.72	709.17	802.45	806.00
1997	1204.73	1215.28	1207.18	1230.89	1247.00

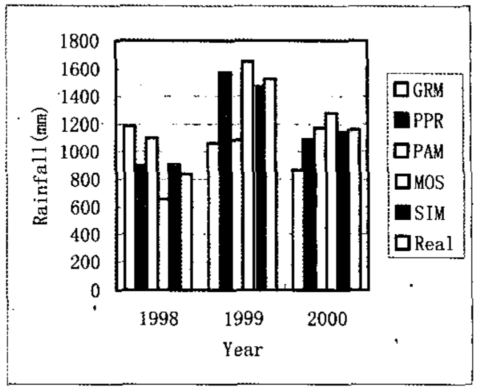

Fig.2 Synthetic integration results

V. CONCLUSION

In this paper, the characteristics of neural networks and fuzzy logic systems have been shortly compared. Some popular combination methods of fuzzy logic and neural networks are briefly described. A new combination model that fuses neural network and fuzzy logic is proposed and it is adopted for synthetic integration of rainfall of forecasted rainfall data produced by gradual regression method, periodic analysis plus multi-layer method and MOS method. The characteristics of the new model are simple in computation and making every layers of the network with physical meaning. Experimental results show that the proposed combination model has more satisfactory forecast performance than traditional forecast methods. The presented combination model is a new try to combine neural networks and fuzzy logic system. The property of this combination model will be discussed in future research.

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