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The prediction of air pollution by using Neuro-fuzzy GMDH

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Abstract

Air pollution is one of today modern life phenomena. It is resulted to create round-the-clock human begin activities. Control of environment pollution is complicated scientific process that enters policy, economy, technology and sociology.

GMDH (Group Method of Data Handling) has been used for the identification of a mathematical model that has many input variables but limited data needs by using a hierarchical structure. This paper proposes a Neuro-fuzzy GMDH model, adopting Gaussian radial basis functions (GRBF) as partial descriptions of GMDH. GRBF is reinterpreted as both a simplified fuzzy reasoning model and as a three-layered neural network. In this paper, is used Neuro-fuzzy GMDH algorithm for predicting air pollution data and then were compared the results of predicting air pollution data by using Neuro-fuzzy GMDH and Multi Layer Perceptron (MLP).

Keyword: Air pollution data, Neuro-fuzzy GMDH, Gaussian radial basis functions, gradient descent.

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1. Introduction

According to Andres S.wigend, application of neural network in this prediction of time series is based on capability of neural network in approximation of nonlinear function. Neural network is a set of connection of neurons that have input and output number. Multi layer perceptron analyses in these multi neurons. The first layer for inputting variable and the last layer for outputting variable that there is at least a hidden layer between two layers.

in this paper Each neuron of network is used intelligent prediction system by Neuro-fuzzy network with high capability named neuro-fuzzy (NF-)GMDH that in this network for learning low level and fuzzy systems are used to consider linguistic variable such as high capability calculations and combination of both with GMDH algorithm.

2. Structure of proposed network

NF-GMDH proposed network for predicting time series data contain one input layer with six input layers and one output layer with one output layer and four hidden layers. Because of in each hidden layer is three neurons each neuron contain two input and one output. because of each neuron is equation RBF (Radial Base Function) network.

Fig.1 shown a Network in the first hidden layer receive inputs and in the next layers of each neuron receive out neurons in the previous layer. Finally output layer neuron receives outputs of all the neurons in last hidden layer. As a result, output layer neuron provides output variable amount. Let the number of neurons in each layer be *M* and the number of layers be *P*. The final output *y* is the average of outputs in the last layer.

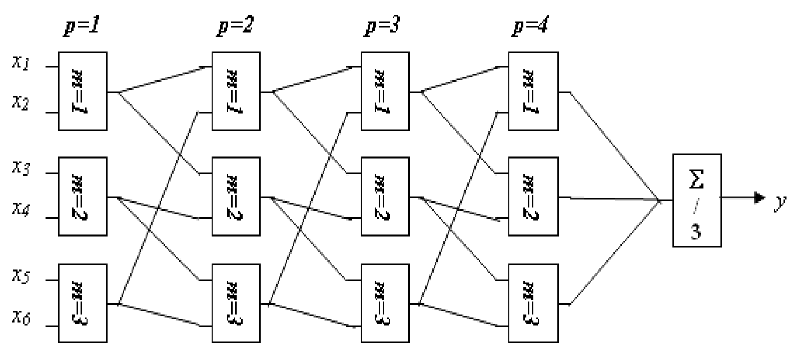

Figure 1. Structure of proposed neurofuzzy GMDH with six input variables.

In this network for diagnostic error amount network of learning considers from mean squared error (MSE) criterion such that output criterion. until error a mount network clears back propagation error that calculates in this equation.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(y^{*}(t) - y(t) \right)^{2} \qquad (1)$$

In equation 1, $\mathbf{y}^*$ output value of network and $\mathbf{y}$ expected output value of network is in certain time $\mathbf{t}$.

3. Inter structure of each neuron

Each neuron in network NF-GMDH is equation RBF neuron. The RBF network is a technique for interpolating data in multidimensional spaces. The networks have the architecture that uses a single internal layer of locally tuned processing units and are called localized receptive fields. Brown and Harris demon started in their book entitled Neurofuzzy adaptive modeling and control that there exists an invertible relationship between fuzzy logic systems and RBF networks, with each inheriting the properties of the other.

RBF network

Let A_{ki} denote the membership function of the k-th fuzzy rule*(k=1,2,…,K)* in the domain of the i-th input variables $x_i(i=1,2,…,I)$. The k-th fuzzy rule is written as:

“ **if** x_1 is A_{k1} and x_2 is A_{k2} **…** and x_I is A_{kI} **then** y is w_k ”

The conclusion part of the fuzzy inference rule which infer output y is simplified as a real number w_k. The compatibility degree of the premise part of the k-th fuzzy rule for an observed system state $\boldsymbol{x}$ is computed with the algebraic product operation of the compatibility degree as:

$$\mu_k = \prod_{i=1}^{I} A_{ki}(x_i) \qquad (2)$$

where, $\boldsymbol{x} \in R^I$, and I is 1 or 2 for the partial descriptions of the GMDH. The conclusion part of the fuzzy inference rule which infers output y is simplified as a real number w_k .

$$y = \sum_{k=1}^{K} \mu_k w_k \qquad (3)$$

This model is called the simplified fuzzy reasoning. When Gaussian membership function:

$$A_{ki}(x_i) = \exp\left(-\frac{(x_i - a_{ki})^2}{b_{ki}}\right) \qquad (4)$$

Where the parameters a_{ki} and b_{kj} are given for each rule and are changed in the training procedure. μ_k are products of Gaussian functions each of which is a function of x. since exponential function can be factored, μ_k have the form of Gaussian functions, and the function y is its linear combination Gaussian RBF networks.

The simplified fuzzy model of Eq.(3) is equivalent to the network of Gaussian RBFs. While the initial values of weights $\boldsymbol{w}$ are chosen from random numbers in the artificial neural networks, those of unknown parameters in the networks of RBFs are usually given a priori, that is, the basis functions are uniformly spaced and their weight coefficients are set to zero.

The network type NF-GMDH have been proposed , whose partial descriptions are represented by the

RBF networks. The NF-GMDH model we adopt here is a kind of adaptive learning network (i.e., a network type of GMDH) in the hierarchical structure. In the net, two input variables are introduced in each partial description. Figure 1 shows the model structure and figure 2 showns Inter structure of each neuron.

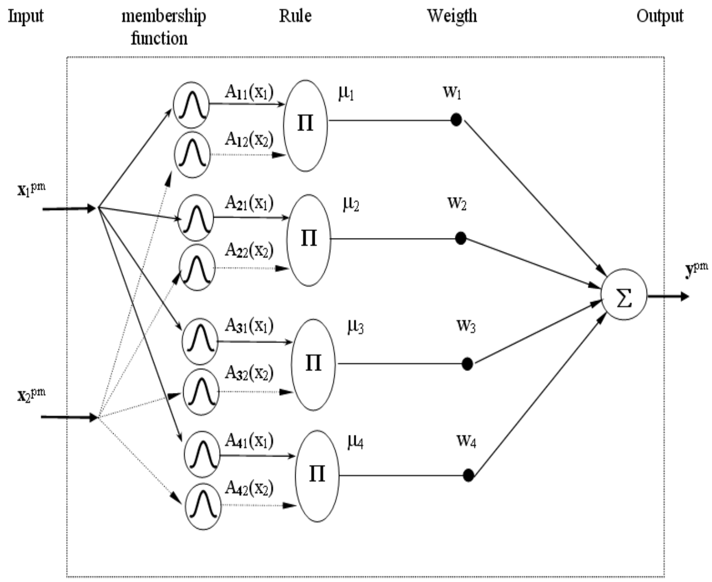

Figure2. Inter structure of each neuron

4. Learning rules of back propagation

In neurofuzzy GMDH network parameters learning is gradient descent method that one of the most efficient learning method network and in this error output network is returned more called backup propagation error. In mooted proposed network and by considering inter structure each neuron learning capability parameters of Gaussian function parameters contain central function(a) and variance function(b) and also weight(w) in each neuron.

The *m-th* model in the *p-th* layer is the output variables of the *(m-1)-th* and the *m-th* models in the *(p-1)-th* layer, the number of rules begin K, then

$$y^{pm} = F(y^{p-1,m-1}, y^{p-1,m}) = \sum_{k=1}^{4} \mu_k^{pm} \, w_k^{pm} \tag{5}$$

$$\mu_k^{pm} = \prod_{i=1}^{2} \exp\left(- \frac{(s_i^{pm})^T x^p - a_{ki}^{pm}}{b_{ki}^{pm}} \right) \tag{6}$$

Where μ_k^{pm} and w_k^{pm} are the degree of compatibility of the premise part and the real number of the conclusion part, respectively, of the m-th neuron and the k-th rule in the p-th layer. As the final output y is the average of outputs in the final layer, let the number of neuron in each layer be M(= 3) and the number of layers be P(=4), then

$$y = \frac{1}{M} \sum_{m=1}^{M} y^{Pm} \tag{7}$$

Then the learning rule, based on the Least Mean Square approach (gradient descent method) is derived as follows:

$$\begin{aligned} w_{ki}^{pmNEW} &= w_{ki}^{pmOLD} - \tau.\frac{\partial E}{\partial w_{ki}^{pm}} \\ &= w_{ki}^{pmOLD} - \tau.\frac{\partial E}{\partial y}.\frac{\partial y}{\partial y^{pm}}.\frac{\partial y^{pm}}{\partial w_{ki}^{pm}} \\ &= w_{ki}^{pmOLD} + \tau.(y^* - y).\nabla y^{pm}.\frac{\partial y^{pm}}{\partial w_{ki}^{pm}} \end{aligned} \quad (8)$$

$$a_{ki}^{pmNEW} = a_{ki}^{pmOLD} + \tau.(y^* - y).\nabla y^{pm}.\frac{\partial y^{pm}}{\partial a_{ki}^{pm}} \quad (9)$$

$$b_{ki}^{pmNEW} = b_{ki}^{pmOLD} + \tau.(y^* - y).\nabla y^{pm}.\frac{\partial y^{pm}}{\partial b_{ki}^{pm}} \quad (10)$$

Where, τ is the learning rate (positive small number) and $\nabla y^{pm}=\partial y/\partial y^{pm}$. ∇y^{pm} is $\nabla y^{Pm}=1/M$ for the P-th layer, and

$$y^{p+1,q} = \sum_{k=1}^{4}\sum_{i=1}^{2}\exp\left[-\frac{(s_i^{p+1,q})^T x^{p+1,q} - a_{ki}^{p+1,q}}{b_{ki}^{p+1,q}}\right].w_{ki}^{p+1,q} \quad (11)$$

Furthetmore.

$$\begin{aligned} (s^{p+1,q})^T.x^{p+1} &= s_{i1}^{p+1,q}.x_1^{p+1} + s_{i2}^{p+1,q}.x_2^{p+1} + ... + s_{im}^{p+1,q}.x_m^{p+1} + ... \\ &= s_{i1}^{p+1,q}.y^{p,m} + s_{i2}^{p+1,q}.y^{p,m} + ... + s_{im}^{p+1,q}.y^{p,m} + ... \end{aligned} \quad (12)$$

In the intermediate layer ($p \neq P$)

5. Simulations and Results

Air pollution is phenomenon that produces the combination of air, material and special particles in certain time. If it is continuing, it will cause diseases of human beings, animals and plans. It remarkably endangers human life. Considerate of air pollution of nature dates is dynamic and variable by passing the time. Data in the air pollution stations are shown in each day from 6 to 16 and from 16 hours to 24 hours is in each hour twice during the day.

Number of 300 co sample data are shown for predicting of NF-GMDH fuzzy neural network that 200 0f them learning and 100 of sample data is used for test and measuring credit or predicting capability network.

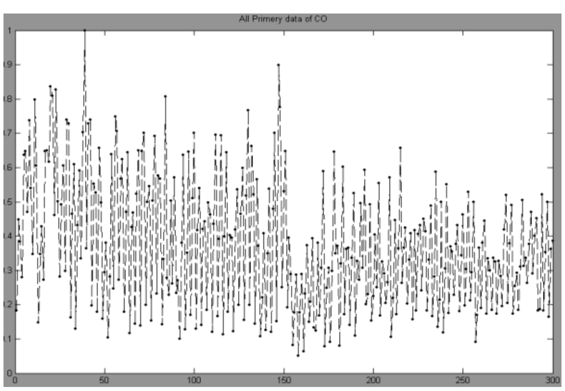

Figure3. real data curve of CO

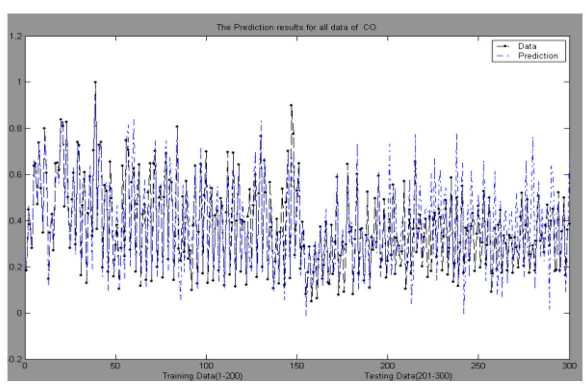

Figure4. prediction curve of CO

The all data of CO are shown in Fig.3 and the predictive errors of NF-GMDH real and predicated value are shown in Fig.4.

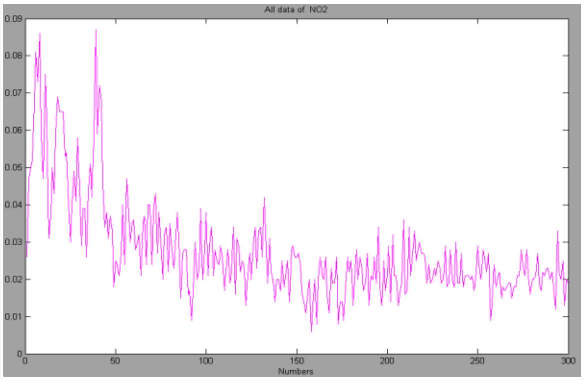

Figure5.real data curve of NO2

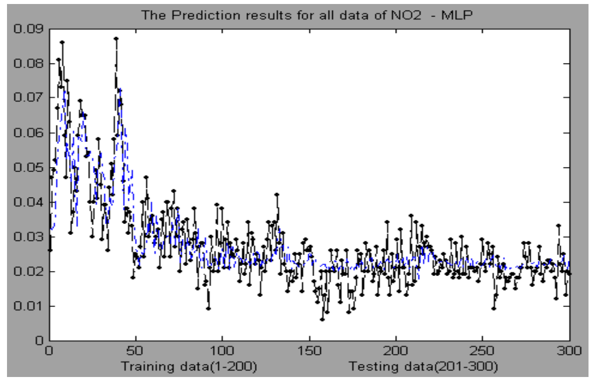

Figure6.prediction curve of NO2

The all data of NO2 are shown in Fig.5 and the predictive errors of NF-GMDH real and predicated value are shown in Fig.6.

The comparison of prediction capability for data of time series of air pollution is listed in table 1.

		MSE	Training Time(s)
CO	***NF-GMDH***	0.000078	62360
	MLP	0.04341	50000
NO2	***NF-GMDH***	0.000023	998820
	MLP	0.000169	100000

Table1. The results comparison for NF-GMDH and MLP networks for prediction capability

6. Conclusion

As observed, it appears to use neuro-fuzzy GMDH network is useful strategy for diagnostic data of time series of air pollution encounter such as dynamic world nature. The conclusions show that we can get better results to compare with less concentration on the structure network and meddle with some air pollution data train. Work for future, in this paper RBF neural network considers such as fuzzy method. Main changes can consider to make for prediction of neural network with neural network and combination RBF network and polynomial of A. G. Ivakhnenko.

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