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A Fuzzy Model based on the PNN Structure

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Abstract

In this paper, a fuzzy model based on the Polynomial Neural Network (PNN) structure is proposed to estimate the emission pattern for air pollutant in power plants. The new algorithm uses PNN algorithm based on Group Method of Data Handling (GMDH) algorithm and fuzzy reasoning in order to identify the premise structure and parameter of fuzzy implications rules, and the least square method in order to identify the optimal consequence parameters. Both time series data for the gas furnace and data for the NOx emission process of gas turbine power plants are used for the purpose of evaluating the performance of the fuzzy model. The simulation results show that the proposed technique can produce the optimal fuzzy model with higher accuracy and feasibility than other works achieved previously.

Keywords : Polynomial neural network, Fuzzy model, NOx emission, PNN structure

1. Introduction

Recently, many researchers have had much interest in various methods for system modeling. Among them, mathematical modeling methods such as regression techniques were widely used to identify and to predict the linear systems based on input-output data. However, the mathematical models to express dynamic analysis of nonlinear real system, have had lots of problems in the selection, of variables constructing the model among many input output variables, and of model structure. In general, higher-order equations require too many data against estimating all system parameters in mathematical models. To solve the problem, the PNN based on GMDH was first introduced by A. G. Ivakhnenko[1,2].

The GMDH has been used to synthesize the PNN - the building blocks of modeling methodology. This approximation technique based on the perceptron principle with a neural network-type architecture has been applied to modeling, identification and prediction of the input-output relationship of a nonlinear process system with limited data sets. Fuzzy modeling is another highly skilled technique, using trial and error, to properly describe the statics and dynamics of nonlinear process system.

As known, fuzzy modeling has been widely investigated and successively used for industrial applications. Therefore, two methods have had the advantages in the performance of systems with intense non-linearity. However, they have a little problem against accuracy and feasibility, to some extent.

In this paper, a fuzzy model based on the PNN structure is proposed to estimate the structure and parameters of fuzzy system, using the GMDH algorithms[1,2] and the fuzzy modeling methods [3,4]. The new algorithm fuses the PNN algorithm and fuzzy inference by replacement of each neuron of the PNN with fuzzy implications rules, in order to model the nonlinear process system with limited data sets, namely, to identify the premise structure and parameters of fuzzy implications rules. The premise fuzzy membership of each input variable uses Gaussian functions obtained by heuristic.

The consequence utilizes the simplified inference consisting of constants and the linear inference consisting of regression polynomials. The optimal consequence parameters are obtained by the least square method. The new fuzzy model is applied to both time series data for gas furnace and data for the NOx emission process of gas turbine power plants, for the purpose of evaluating its performance.

2. The Fuzzy Model Based on the PNN Structure

In this section, a fuzzy model is proposed to estimate the fuzzy structure and parameters of the nonlinear process system with limited data sets, using the PNN based on the GMDH algorithm[1,2] and the fuzzy modeling methods[3,4]. The new algorithm fuses the PNN algorithm and fuzzy inference by replacement of each neuron of the PNN with fuzzy implications rules, in order to identify the premise structure and parameters of fuzzy implications rules. The differences between new fuzzy model and conventional PNN are also considered. While the conventional PNN obtains the output using the second order equation of two variables, the new fuzzy model extracts the output from each node of conventional PNN, using fuzzy models with fuzzy implications rules. Each node is operated as a small fuzzy system. Overally, the structure of novel fuzzy model is like Figure 1.

The premise of fuzzy membership function of each node is expressed by Gaussian functions obtained from heuristics. This function is selected by the c-means clustering and simplex methods. The consequence of each node is expressed by constants in proposed model using the simplified inference and by regression polynomials in proposed model using linear inference. If premise input variables and parameters are given, the optimal consequence parameters which minimizes performance index can be determined by least-square method in a similar way of fuzzy systems. The algorithm and structure of new fuzzy model are almost like those of the PNN[1,2] except using the fuzzy system in each node.

In this paper we considered nine types of nodal regression polynomials as shown in Table I.

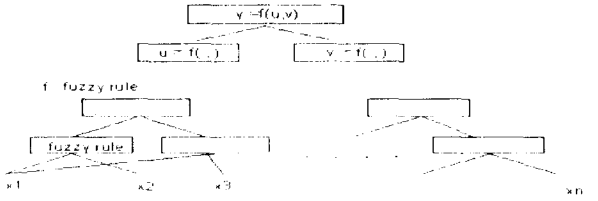


Figure 1. Basic fuzzy PNN configuration

The methodology of new fuzzy model is implemented on the random input-output sets of measured training and testing data obtained from gas furnace and NOx emission process of gas turbine power plants.

Table I. The nodal regression polynomials considered for polynomial neural network synthesis

	1	2	3
1	linear	bilinear	trilinear
2	quadratic	biquadratic	triquadratic
3	cubic	bicubic	tricubic

trilinear $= x_0 + w_1x_1 + w_2x_2 + w_3x_3$

triquadratic $=$ *trilinear* $+ w_4x_1x_2 + w_5x_1x_3 + w_6x_2x_3 + w_7x_1^2 + w_8x_2^2 + w_9x_3^2$

tricubic $=$ *triquadratic* $+ w_{10}x_1x_2x_3 + w_{11}x_1^3 + w_{12}x_2^3 + w_{13}x_3^3$

2.1 The Fuzzy PNN Model by Simplified Inference

The consequence part of the simplified inferences expressed by constants is given as Eq.(1).

$$R^i: If\ x_i\ is\ A_{i1}, \cdots, x_k\ is\ A_{ik},\ Then\ y = a_i$$

$$y^* = \frac{\sum_{i=1}^{n} \mu_i a_i}{\sum_{i=1}^{n} \mu_i} = \sum_{i=1}^{n} \hat{\mu}_i a_i \tag{1}$$

where R^i is the i-th fuzzy rule, is input variable, A_{ik} is a membership function of fuzzy sets, a_i is a constant, n is the number of the fuzzy rules, y^* is the inferred value, μ_i is the premise fitness of R^i and $\hat{\mu}_i$ is the normalized premise fitness of μ_i.

If input variables and parameters of the premise are given, the optimal consequence parameters which minimizes PI can be determined in consequence parameter identification. PI is a criterion which uses the mean squared differences between the output data of original system and the output data model. It can be defined by Eq.(2)

$$PI = \frac{1}{m-1} \sum_{k=1}^{m} [y(k) - y^o(k)]^2 \tag{2}$$

where y^o is output of fuzzy model, k is number of input variables, and m is total number of data.

The consequence parameters can be estimated by least-square method, when the input-output data set is given as $x_{1i}, x_{2i}, \cdots, x_{ki} - y_i$ ($i = 1, 2, \cdots, m$). Eq.(3) provides the minimal estimated values of a by least-square method.

$$\hat{a} = (X^T X)^{-1} X^T Y \tag{3}$$

where $\hat{a} = [a_1, a_2, \cdots, a_n]^T$, $X = [x_1, x_2, \cdots, x_m]^T$, $Y = [y_1, y_2, \cdots, y_m]^T$.

2.2 The Fuzzy PNN Model by Regression Polynomial Inference

The consequence part of the inferences expressed by regression polynomials in the Table I is given as Eq.(4).

$$R^i: If\ x_1\ is\ A_{i1}, \cdots, x_k\ is\ A_{ik},$$
$$Then\ y = f_i(x_1, \cdots, x_k)$$
$$f_i(x_1, \cdots, x_k) = a_{i0} + a_{i1}x_l + \cdots + a_{ik}x_k \tag{4}$$
$$y^* = \frac{\sum_{i=1}^{n} \mu_i}{\sum_{i=1}^{n} \mu_i} = \sum_{i=1}^{n} \hat{\mu}_i f_i(x_1, \cdots, x_k)$$

where R^i is the i-th fuzzy rule, x_k is input variable, A_{ik} is a membership function of fuzzy sets, a_{ij} is coefficients of regression polynomial, n is the number of the fuzzy rules, y^* is the inferred value, μ_i is the premise fitness of R^i and $\hat{\mu}_i$ is the normalized premise fitness of μ_i.

The consequence parameters can be estimated by least-square method in a similar way of Eq.(2) and (3).

3. Simulations and Results

In this section, both time series data for gas furnace and data for the NOx emission process are considered for the purpose of evaluating the performance of the new model. These systems use PI as criterion. Varying the nodal polynomial, the results of new fuzzy model are analyzed. Triquadratic type shows the best performance among the nine nodal polynomials in Table I.

As shown in two systems, new fuzzy model gives a very sophisticated model from a very limited data set and/or a system with intense non-linearity. New fuzzy model also has more performance in regression polynomial reasoning method than simplified reasoning method. Therefore, this model provide very good results in performance, when the number of membership function is properly chosen in modeling system.

3.1 Gas Furnace

The density of burned carbon dioxide is modeled using the time series data of gas furnace[6]. While the delayed terms of gas flow rate, u(t) and burned CO_2 density, y(t) are input variables such as u(t-1), u(t-2), u(t), y(t-3), y(t-2) and y(t-1), y(t) is the output variable. Gaussian is used as the premise membership function of new fuzzy model. In this process, though we use all the inputs, the optimal model chooses only 4 inputs such as u(t), y(t-3), y(t-2) and y(t-1).

The output of identified model using new fuzzy model was compared with real measured data[7]. The identification error of new fuzzy model is also compared with other fuzzy modeling methods in Table II.

Table II. Comparison of identification error with conventional fuzzy modeling method

Model	PI
Tong's model	0.469
Pedrycz's model	0.320
Xu's model	0.328
sugeno's model	0.355
Oh's model	0.098
PNN	0.054
FPNN(Our model)	0.014

3.2 NOx Emission Process of Gas Turbine Power Plant

The density of NOx emissions is also modeled using the data of gas turbine power plants[7]. Till now, almost NOx emission process use mathematical model in order to obtain regulation data from control process. However, a mathematical model does not design the relationships between variables of the NOx emission process and parameters of its model, accurately and effectively. The accurate modeling of the NOx emission process should be required vigorously. The accurate model can provide control information for the control operators so that they should treat and predict NOx emission efficiently.

A NOx emission process of GE gas turbine power plant in Virginia, U.S.A., is chosen as a model. The modeling by new fuzzy model is done in the model, using the measured real data, NOx[PPMVD] of gas turbine power plant. at 15 % oxygen

We really measured input variables such as Tamb(Ambient Temperature at site), Com (Compressor Speed), LPT(Low Pressure Turbine Speed) and Pcd(Compressor Discharge Pressure) and Texh (Turbine Exhaust Temperature), and output variable such as NOx. Gaussian is used as the premise membership function of new fuzzy model. In this process, we use all the inputs.

The new fuzzy model's structure of modeling for NOx emission process is shown in Figure 2, as a figure for the cases of linear, biquadratic and trilinear polynomials, respectively. For each structure, the PIs are calculated under the change of the number of membership functions in Table III and Figure 3.

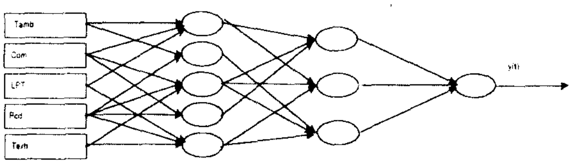


Figure 2. New fuzzy model's structure for gas turbine emmisions in the cases of (a) linear, (b) biquadratic and (c) trilinear polynomials.

Table III. PIs of NOx emission process model in new fuzzy model's structure in the cases of (a) simplified (b) linear and (c) regression polynomials.

no. of x_1 MF / no. of x_2 MF	2	3	4	5
2	32.7117	25.72016	13.76321	9.45963
3	18.22881	17.47180	6.31693	2.85677
4	11.31882	8.05596	8.36299	2.71943
5	8.64925	3.42258	1.81934	0.61192

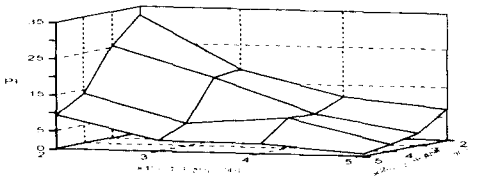
(a)

no. of x_1 MF / no. of x_2 MF	2	3	4	5
2	3.37044	1.41596	0.30468	0.03083
3	0.68505	0.21629	0.00778	0.00176
4	0.02400	0.00454	0.00228	0.00176
5	0.01784	0.00213	0.00136	0.00050

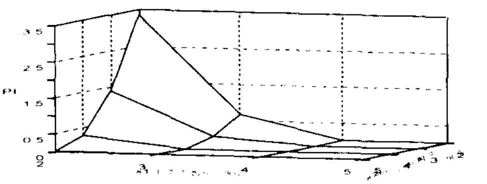
(b)

no. of x_2 MF \ no. of x_1 MF	2	3	4	5
2	0.34217	0.00814	0.00226	0.00164
3	0.00419	0.00201	0.00051	0.00066
4	0.00177	0.00094	0.00073	0.00066
5	0.00099	0.00065	0.00078	0.00015

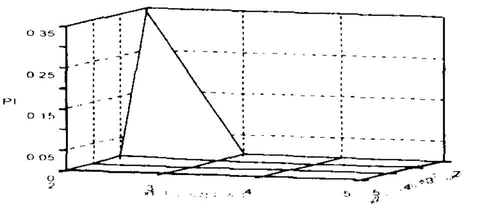
(c)



(a)



(b)



(c)

Figure 3. PI changes of NOx emission process model in new fuzzy model's structure, in the case of (a) simplified (b) linear and (c) regression polynomials.

The identified output of new fuzzy model is compared with real measured data in Figure 4. The identification error of the model is also compared with other fuzzy modeling methods in Table Ⅳ.

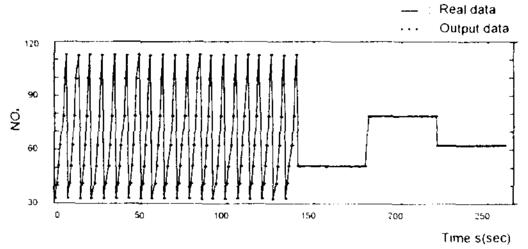


Figure 4. Comparison of output of new fuzzy model with real data for gas turbine

Table Ⅳ. Comparison of identification error with conventional modeling methods

Model	PI
Fuzzy	0.1253
FNN	0.0520
PNN	0.2009
New Model	0.0002

4. Conclusions

In this paper, a fuzzy model based on the Polynomial Neural Network structure is proposed to estimate the emission pattern for air pollutant in power plants with small data sets.

Both time series data for the gas furnace and data for the NOx emission process of gas turbine power plants are used for the purpose of evaluating the performance of the fuzzy PNN.

Some results are drawn from computer simulation as follows:

a) This new model gives a more sophisticated model and a more accurate prediction than the PNN or other fuzzy modeling methods, from a very limited data set and/or a system with intense non-linearity.

b) This new model with regression polynomial inference can obtain more accurate results in performance than fuzzy PNN model with simplified inference.

c) This new model can easily give author information that determines the number of layers on the basis of some prescribed small quantity.

d) This new model can contribute to develop the standard model of emission pattern for air pollutant in power plants.

Finally, this new model can be utilize to develop the high value-added products like the simulator and model-based controller.

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