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퍼지뉴럴네트워크 모델링의 하이브리드 구조에 관한 연구

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The Study on Hybrid Architectures of Fuzzy Neural Networks Modeling

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Abstract - The study is concerned with an approach to the design of a new category of fuzzy neural networks. The proposed Fuzzy Polynomial Neural Networks(FPNN) with hybrid multi-layer inference architecture is based on fuzzy neural networks(FNN) and polynomial neural networks(PNN) for model identification of complex and nonlinear systems. The one and the other are considered as premise and consequence part of FPNN respectively. We introduce two kinds of FPNN architectures, namely the generic and advanced types depending on the connection points (nodes) of the layer of FNN. Owing to the specific features of two combined architectures, it is possible to consider the nonlinear characteristics of process and to get output performance with superb predictive ability. The availability and feasibility of the FPNN is discussed and illustrated with the aid of two representative numerical examples. The results show that the proposed FPNN can produce the model with higher accuracy and predictive ability than any other method presented previously.

1. Introduction

In system modeling and identification procedures, we are usually provided with a vast amount of experimental data. The primordial aim of identification is to develop a model that can properly reflect the very nature of the physical phenomena. Based on these experimental data, most of the modeling techniques derive a mathematical model in the format of some analytical linear or nonlinear functions articulated in the language of differential or difference equations. Although in most of the cases, the rigid mathematical model can describe the system almost completely, it fails to provide much insight into how the system works and what the main and essential dependencies between its variables are.

In order to solve such difficulties, we propose Fuzzy Polynomial Neural Networks(FPNN). The proposed FPNN is generated from the mutually combined structure of both fuzzy neural networks(FNN) and polynomial neural networks (PNN). As the premise part of FPNN, FNN uses both the simplified fuzzy inference and error back-propagation algorithm. FNN has faster learning and better convergence characteristics than other nonlinear models[2]. The parameters of FNN are adjusted using Genetic Algorithms (GAs)[5]. Also, FNN has two connection points for combination with PNN. By considering two types of connection methods, PNN with multi layers structure of multi-input variables and high-order polynomial can be combined and used effectively. As the consequence part of FPNN, PNN based on Group Method of Data Handling (GMDH)[1] is a flexible network architecture whose structure(topology) is developed through learning. In particular, the number of layers of the PNN is not fixed in advance but is generated on the fly. In this sense, PNN is a self-organizing network[3]. Each node of the PNN exhibits a high level of flexibility and realizes a polynomial type of mapping between input and output variables. In order to evaluate the performance of the proposed model, we use time series data for gas furnace process[5-10]. The performance of the proposed FPNN is compared with that of conventional methods from the viewpoint of the identification errors of model. The optimal design procedure of FPNN is presented and results show that the proposed model has higher accuracy than previous other works

2. Fuzzy polynomial neural networks

In this section, we elaborate on the structure and design of FPNN. These networks result as a synergy between two other general constructs such as Fuzzy Neural Networks(FNN)[2] and Polynomial Neural Networks(PNN)[3]. First, we briefly discuss these two classes of models by underlining their most evident features.

2.1 The premise structure of FPNN

The topology of the FPNN is constructed by combining FNN for the premise part of the FPNN with PNN being used as the consequence part of FPNN. As visualized in Fig. 1, FNN can be designed by using space partitioning in terms of individual input variables. We are concerned with a granulation carried out in terms of fuzzy sets defined in each input variable. Also, FNN structure has two possible connection points. The location of this point implies the character of the network. Note that the first connection point allows perceiving each linguistic manifestation of the original variables(viz. these variables are transformed by fuzzy sets and normalized). The location of the other connection point implies that the PNN part of the network does not "see" the individual fuzzy sets in the input space.

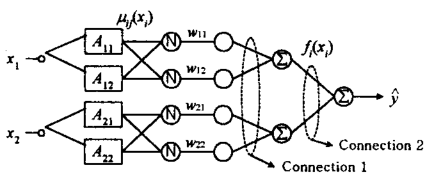


Fig.1 FNN structure with two connection points of interaction with PNN

2.2 The consequence structure of FPNN

We use PNN in the consequence structure of the FPNN. The PNN algorithm based on the GMDH can produce an optimal nonlinear system by selecting significant input variables among dozens of these and forming various types of polynomials. PNN is used in selecting the best ones in partial descriptions(PDs) according to a discrimination criterion. PDs use regression polynomials, Table 1. Successive layers of the FPNN are generated until we reach a structure of the best performance.

Table 1. Types of regression polynomial

No. of inputs / Order of the polynomial	2	3	4
1 (Type 1)	Bilinear	Trilinear	Tetralinear
2 (Type 2)	Biquadratic-1	Triquadratic-1	Tetraquadratic-1
2 (Type 3)	Biquadratic-2	Triquadratic-2	Tetraquadratic-2

- Bilinear $= c_0 + c_1x_1 + c_2x_2$
- Biquadratic-1 $=$ Bilinear $+ c_3x_1^2 + c_4x_2^2 + c_5x_1x_2$
- Biquadratic-2 $=$ Bilinear $+ c_3x_1x_2$

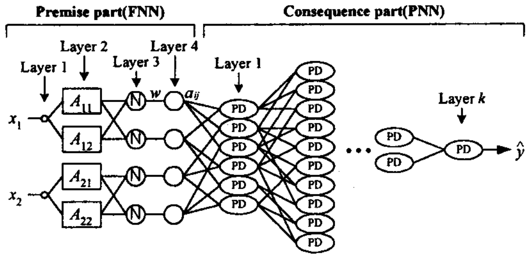
2.3 The architecture of FPNN

According to the alternative of two connection points, combination of FNN and PNN is implemented for generation of FPNN architecture such as (a) or (b) of Fig. 2. Each nodes of input layer of PNN is connected with nodes of output layer or previous output layer of FNN. Especially, PNN with multi-input variables and high-order polynomial can be used effectively by considering two types of connection methods.

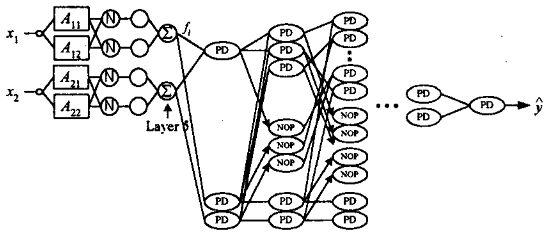
3. Numerical Experiments

In this section, we perform a experiment to illustrate the validity of the proposed architectures. For optimization of a FNN, GAs identifies learning rate, momentum coefficient and parameters of membership function. GAs[4] uses binary type, roulette-wheel in the selection operator, one-point crossover in the crossover operator, and invert in the mutation operator. Also, GAs uses 100 generations, 60 populations, 10 bits of a string, crossover rate 0.6, and mutation probability 0.35. The performance index used in the ensuing numerical experiment is (1).

$$PI = \frac{1}{N}\sum_{p=1}^{N}(y_p - \hat{y}_p)^2 \qquad (1)$$



(a) Generic type of FPNN architecture



(b) Advanced type of FPNN architecture

Fig. 2 The architecture of FPNN

In this experiment, the proposed FPNN is applied to the time series data of gas furnace utilized by Box and Jenkins[5-10]. Consider a gas furnace system in which air and methane are combined to form a mixture of gases containing CO_2(carbon dioxide). We use 2 input, u(t-3) and y(t-1), and 1 output, y(t) for the FPNN. Where, u(t) denotes the flow rate of methane gas and y(t) stands for the carbon dioxide density.

Table 2. Performance index of FPNN

FPNN	Premise part No. of MF	Consequence part structure	layer	PI	E_PI
Generic type	2+2	2 inputs Type 2	1	0.0247	0.339
			2	0.0247	0.337
			3	0.0242	0.310
			4	0.0238	0.295
			5	0.0216	0.270
	2+2	2→4 inputs Type 3→2	1	0.0248	0.328
			2	0.0248	0.329
			3	0.0285	0.280
			4	0.0189	0.260
			5	0.0176	0.250
Advanced type	2+2	2 inputs Type 2	1	0.0247	0.339
			2	0.0247	0.338
			3	0.0242	0.330
			4	0.0226	0.274
			5	0.0231	0.270
	2+2	2→3 inputs Type 3→2	1	0.0248	0.328
			2	0.0237	0.344
			3	0.0209	0.304
			4	0.0222	0.277
			5	0.0199	0.264

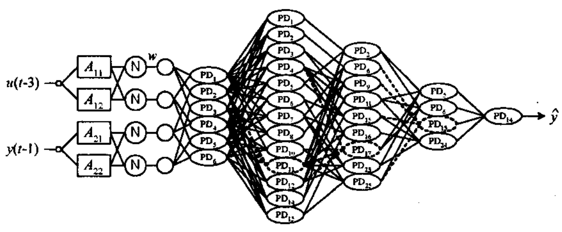
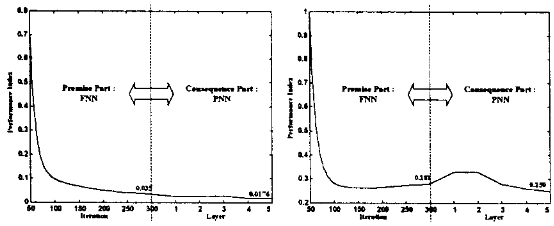


Fig. 3 Optimal generic type of FPNN



(a) PI (b) E_PI

Fig. 4 Learning procedure of FPNN

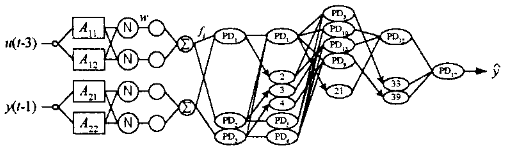


Fig. 5 Advanced type of FPNN

Table 2 shows the training and testing performance results for the FPNN. FNN used premise part of FPNN has 2 membership functions for the each inputs. PNN used consequence part of FPNN consists of 2→4 inputs and Type 3→2, i.e., each nodes of 1st layer in consequence part are polynomials with 2 inputs and Type 3 and nodes of 2nd or more are numeric formats with 4 inputs Type 2 such as Table 1. In Table 2, PI is a performance index for learning data set and E_PI is a performance index for testing data set. FNN identified by GAs for gas furnace has performance index PI=0.035, E_PI=0.281. The results show in Table 2 that FPNN has better accuracy than FNN. Fig. 3 shows optimal generic type of FPNN architecture that is composed of FNN and PNN with 2→4 inputs and Type 3→2 in Table 2. Where PD is partial description and number is the selected node number. The bold dotted nodes that may not be used to generate optimal FPNN mean the ones, which have the best performance index in each layer. The dotted nodes aren't used to generate overall networks. Fig. 4 shows the learning procedure of FPNN. Fig. 4(a) is the performance index for learning data and (b) is the performance index for testing data. Fig. 5 show the performance index and modified architecture of FPNN, respectively. Table 3 compares the performance of the FPNN with that of some other models. The experimental results represent that the proposed model outperforms the other models from the viewpoint of both approximation and as generalization abilities.

Table 3. Comparison of identification errors with previous models

Model		PI	E_PI
Lin and Cunningham's model[9]		0.071	0.261
Kim's model[10]		0.034	0.244
Oh's Fuzzy model[7]		0.020	0.264
Oh's Adaptive FNN[8]		0.021	0.332
Oh and Pedrycz's Fuzzy model[6]		0.020	0.271
FPNN	Generic type	0.0176	0.250
	Advanced type	0.0199	0.264

4. Conclusions

In this study, the composite architectures of FPNN are presented to obtain a optimal model for nonlinear and complex systems. The main features of FPNN include the following. 1) Depending on the characteristics of nonlinear system, several kinds of the proposed FPNN can be selected. 2) The number of input variables and the polynomial order in PNN structure can be chosen flexibly for the FPNN modeling with higher accuracy. 3) The PNN, which is the consequence part of proposed FPNN, is not predetermined unlike in the case of the popular multilayered perceptron structure and is like a kind of self-organizing networks, which can be generated by itself. The diversity and flexibility of proposed FPNN architecture leads to better approximation and generalization capability for identification of nonlinear systems.

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