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Genetic Algorithm-Based Fuzzy Wavelet Neural Network for Control of Dynamic Plants

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***Abstract*— This paper presents a genetic algorithm based approach for designing fuzzy wavelet neural network (FWNN) and its application for control of dynamic plants. The structure of the proposed Fuzzy WNN consists of combination of two network structure. Upper side contains wavelet neural networks and down side contains network structure of the fuzzy inference system. A simple genetic algorithm is applied to train the parameters of the whole network structure. This approach is tested for the control of two dynamic plants commonly used in the literature.**
***Keywords:* Control, wavelet neural network, genetic algorithms, fuzzy inference system, fuzzy wavelet.**

I. Introduction

Fuzzy inference systems (FIS) are one of the most powerful tools for dealing with complex processes, poorly defined and nonlinear. The knowledge base of the fuzzy system can be designed using several approaches that can be classified into two kinds: expert knowledge based FIS and data based FIS. The designing approach of the first kind offers FIS with high semantic level, however for some complicated systems; this Knowledge may not be enough. Designing FIS from data can be decomposed into automatic rule generation and system optimization [1]. In the last decade, methods based on soft computing have been applied for this purpose, the most famous and the widely used being neural networks (NN) and genetic algorithms (GA) [2]-[9]. Numerous different neural and fuzzy structures, called neuro-fuzzy systems, for solving identification and control problems and their parameter optimization algorithms are proposed in literature.

In order to improve the efficiency of such systems, the use of wavelet neural networks (WNN) has gained importance. Thus, the WNN can provide better performance in function learning than conventional feed forward neural networks because some kinds of wavelet functions, incorporating the time-frequency localization properties, are used as the nonlinear transformation function in the hidden layer instead of the usual sigmoid function. This characteristic leads the neuro-fuzzy system to learn faster, require fewer neurons to identify systems of greater complexity and also to get a more accurate convergence.

Recently, several works have used the structure called Fuzzy Wavelet Neural Network (FWNN) for modeling nonlinear systems characterized by uncertainty [11], function approximation [14],[19], system identification and control problems [13][15][16][20][21].

In this work, we investigate the use of a Fuzzy Wavelet Neural Network to solve a control problem. The proposed framework combines several soft computing techniques such as TSK fuzzy system, wavelet neural network and genetic algorithm used as an optimization process to obtain optimal values of parameters of translation, dilation and weights for the WNN and parameters of the Gaussian membership functions of the fuzzy inference system.

This paper is organized as follows. In section 2, the basic concepts of WNN are introduced. The proposed FWNN structure is presented in section 3. In section 4, the optimization of the parameters of the proposed network using GA will be presented. In section 5, the simulation studies for control of two nonlinear dynamic systems are presented. Finally, section 6 gives the conclusion of this paper.

II. Wavelet neural network

A wavelet network consists of a three-layer structure, using wavelets as activation functions [11]. The structure of the adopted wavelet network is given in Fig.1.

The network configuration is as follows:

One output y,
n inputs x={$x_1,x_2,\ldots,x_n$}
And N_w nodes in the hidden layer is given

The output signal of the network is calculated as:

$$y=\sum_{j=1}^{N_w} w_j \Phi_j(z_{jk})+a_0 \tag{1}$$

Where a_0 and w_j are weight coefficients and Φ_j is a wavelet function derived from its mother wavelet ψ, thus:

$$\Phi_j=\prod_{k=1}^{n}\psi(z_{jk}) \tag{2}$$

In this study, the first derivative of a Gaussian function has been used as a mother wavelet which is given by:

$$\psi(x)=-xe^{-\frac{1}{2}x^2} \tag{3}$$

And

$$z_{jk}=\frac{x_k-t_{jk}}{d_{jk}} \tag{4}$$

Where t_{jk} and d_{jk} are translation and dilation parameters. The parameters of the WNN to be optimized are a_0, w_j , t_{jk}

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and d_{jk}.

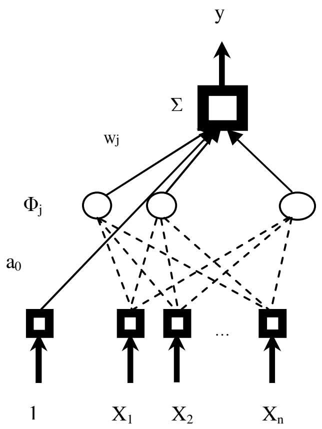

Fig.1. Architecture of the WNN

III. STRUCTURE OF THE FUZZY WAVELET NEURAL NETWORK

The architecture of the proposed FWNN is illustrated in Fig.2. It is a feed-forward multilayer network which integrates traditional Takagi-Sugeno-Kang (TSK) fuzzy model with wavelet neural networks. The wavelet based fuzzy rules have the following form:

R_1: if x_1 is A_{11} and x_2 is A_{21} … and x_n is A_{n1} Then

$$y_1 = \sum_{j=1}^{Nw} w_{j,1}\Phi_j(z_{jk,1}) + a_{0,1}$$

R_2: if x_1 is A_{12} and x_2 is A_{22} … and x_n is A_{n2} Then

$$y_2 = \sum_{j=1}^{Nw} w_{j,2}\Phi_j(z_{jk,2}) + a_{0,2}$$

R_m:if x_1 is A_{1m} and x_2 is A_{2m} … and x_n is A_{nm}Then

$$y_m = \sum_{j=1}^{Nw} w_{j,m}\Phi_j(z_{jk,m}) + a_{0,m}$$

Here $x_1, x_2, \ldots, x_n$ are input variables and $y_1, y_2, \ldots, y_m$ are output of WNN.

The structure of the fuzzy wavelet network consists of combination of two network structures. Upper side contain wavelet neural networks that are denoted by WNN_1, WNN_2,..., WNN_m. Down side contain network structure of fuzzy reasoning mechanism.

The output of each wavelet neural network is calculated by using equations (1-4). The fuzzy reasoning system network consists of three layers: an input layer, a fuzzification layer and an AND layer.

Layer 1 (input layer): The nodes in this layer are input nodes with crisp input x_i, i=1,..., n, they only transmit input values to the next layer. The number of nodes is equal to the number of input signals.

Layer 2 (fuzzification layer): Nodes of this layer compute the membership degree to which the input value belongs to a fuzzy set. In our case a Gaussian membership function is used and is given by:

$$\mu_{A_{ij}}(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \tag{5}$$

Where c_{ij} and σ_{ij} are center and width of the Gaussian membership function.

Layer 3 (AND layer): each node of this layer represents a fuzzy rule. The following AND operation is applied to each rule node:

$$\mu_k(x) = \mu_{A_{1j_1}}(x_1).\mu_{A_{2j_2}}(x_2)\ldots\mu_{A_{nj_n}}(x_n) \tag{6}$$

Where

$$j_i = 1\ldots N_i,\ i = 1\ \ldots n, k = 1\ \ldots \prod_{i=1}^{n} N_i \tag{7}$$

And N_i represents the number of fuzzy sets associated with input i.

The outputs of this layer become inputs to the next layer (consequent layer) of the whole global network. Outputs of the consequent layer are calculated by multiplying the outputs signals of WNN and outputs of the AND layer. Finaly a defuzzification is made to calculate the output of the whole network given by:

$$y = \sum_{k=1}^{m} f_k(x) y_k \tag{8}$$

Where

$$f_k(x) = \frac{\mu_k(x)}{\sum_{l=1}^{m} \mu_l(x)} \tag{9}$$

IV. FWNN OPTIMIZATION

For the network optimization, a real coded genetic algorithm [17] is used to update the best values for both the antecedent part of the rules: the center parameters (c_{ij}) and width parameters (σ_{ij}) of the Gaussian membership function; and the consequent part of the rules: translation (t_{jk}) and dilation (d_{jk}) parameters and the weights $a_{0,l}$ and $w_{j,l}$ of wavelet functions.

In the GA, a population of chromosomes is initialized and then evolves. Each chromosome includes the whole tuning parameters. First, selective reproduction is applied to the current population so that chromosomes make a number of copies proportional to their own fitness; this is done by roulette wheel method. Then new chromosomes are created using the crossover and mutation operations, which are governed by probabilities chosen by trial and error through experiments for good performance. A new population is created after this process is completed. Whatever the stopping criterion, for example, a predefined number of

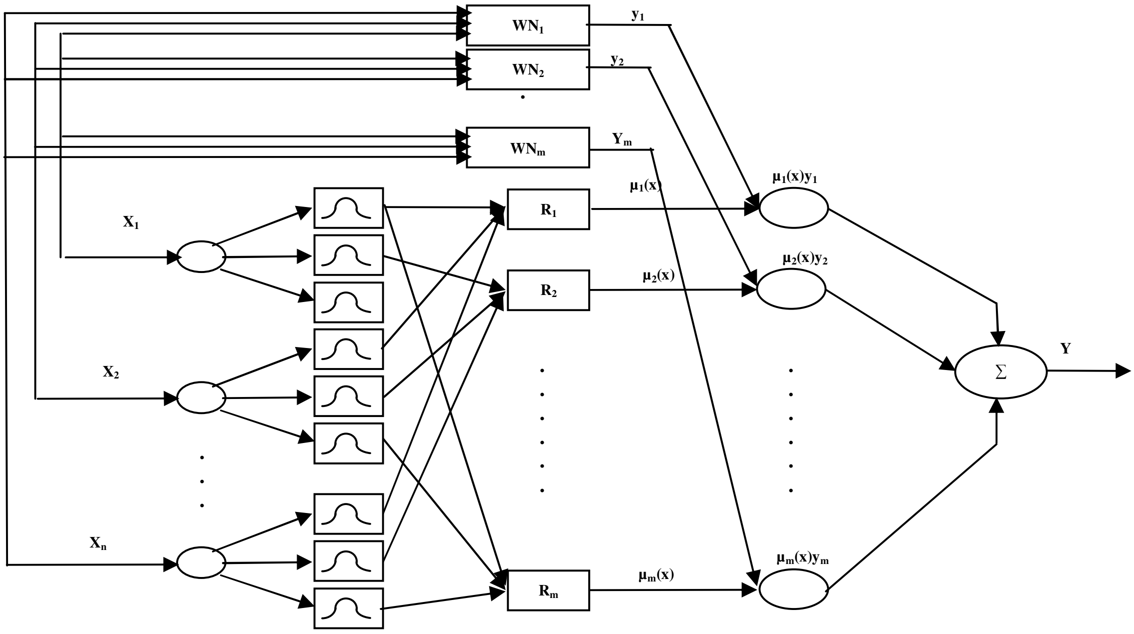

Fig.2. Structure of the Fuzzy wavelet Neural Network

generations have been reached; the chromosome with highest value of the fitness in the last generation is taken as the solution to the problem.

In general the fitness function to be maximized by the GA is defined as:

$$fitness = \frac{1}{1+J} \tag{10}$$

Such that, J is the performance index to be minimized and by setting the chromosome to be:

$(t_{jk,l})$ $(d_{jk,l})$ $(a_{0,l})$ $(w_{j,l})$ (c_{ij}) $(\sigma_{ij})\}$

V. SIMULATION RESULTS

In this section, we investigate the use of the proposed genetic algorithm-based fuzzy Wavelet Neural Network for control purposes. We adopt the structure of control illustrated in Fig.3.

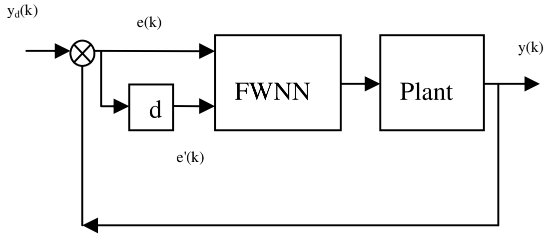

Fig.3. Structure of control

Here, the output signal of the plant is denoted by y(k), $y_d(k)$ represents the set-point signal, e(k) and e'(k) denotes respectively error and change in error.

A. *Example 1:*

The nonlinear dynamic system to be controlled by the proposed GA-based FWNN is described as [13]:

$$y(k) = \frac{y(k-1)\,y(k-2)(\,y(k-1)+2.5)}{(1+y^2(k-1)+y^2(k-2))} + u(k) \tag{11}$$

Our FWNN controller has two inputs error e(k) and change in error e'(k) and one output u(k). Each of these inputs has three Gaussian membership functions, thus forming nine rules, which results to 12 parameters to be adjusted in the antecedent part of the rules. Also, nine WNN are used to perform the consequent part of the rules resulting to 54 parameters to be updated. The number of data points used for training is 2000. The genetic algorithm is carried with following parameters:

Generation = 200;
Population size = 100;
Crossover probability = 0.7;
Mutation probability = 0.01

The fitness function to be maximized by the GA is given by:

$$f = \frac{100}{1+J} \tag{12}$$

Where J is a performance criterion, the root mean square error (RMSE) is used with k=2000:

$$j=\sqrt{\frac{\sum_{i=3}^{k}(y_d(i)-y(i))^2}{k}} \tag{13}$$

As a result of training, the best value of RMSE obtained was 0.2122 which is less than that obtained in [13].

Fig.4 and Fig.5 show the time response characteristics of the control system for learning process and test process respectively, it can be seen that the GA-FWNN controller has a good control performance.

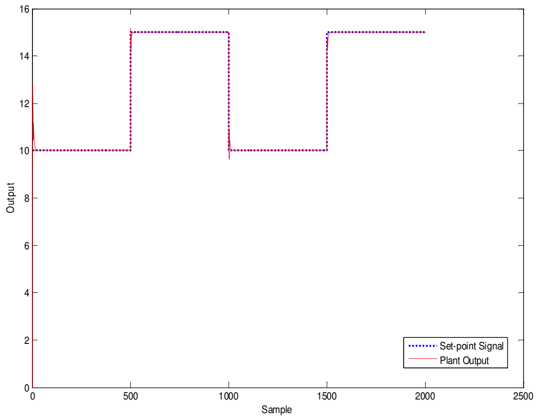

Fig.4. Time response characteristic of control systems with GA-FWNN (Learning process)

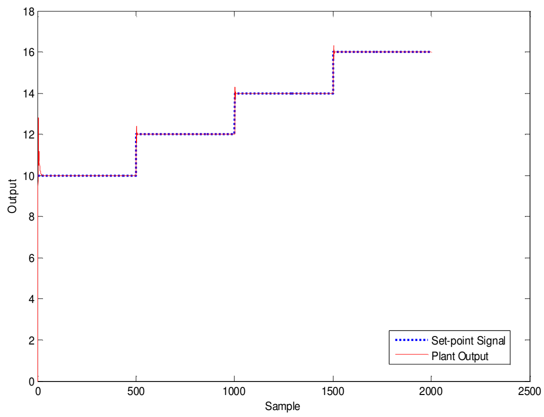

Fig.5. Time response characteristic of control systems with GA-FWNN (Test process)

B. Example 2:

The second dynamic plant to be controlled by the proposed GA-based FWNN is described as [13]:

$$y(k)=0.72y(k-1)+0.025y(k-2)u(k-1) \\ +0.01u^2(k-2)+0.2u(k-3) \tag{14}$$

Here, the current output of the plant depends on two previous outputs and three previous inputs. However, the structure of the GA-FWNN controller has two inputs e(k) and e′(k); and one output u(k). As before, three Gaussian membership functions are considered for each input, thus forming nine rules. Also, nine WNN are used. The number of data points used for training is 2000. For optimization, a GA with the same parameters as indicated the previous example is used to maximize a fitness function given by:

$$f=\frac{100}{1+J} \tag{15}$$

Where J is the root mean square error (RMSE) with k=2000:

$$j=\sqrt{\frac{\sum_{i=4}^{k}(y_d(i)-y(i))^2}{k}} \tag{16}$$

As a result of training, the best value of RMSE obtained was 0.2567.

Fig.6 and Fig.7 show the performance of the GA-FWNN control system for learning process and test process respectively.

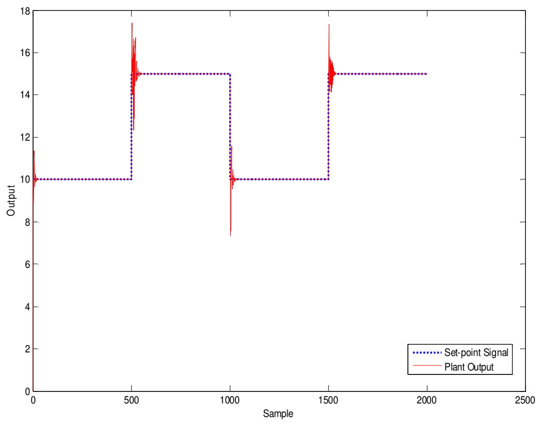

Fig.6. Time response characteristic of control systems with GA-FWNN (Learning process)

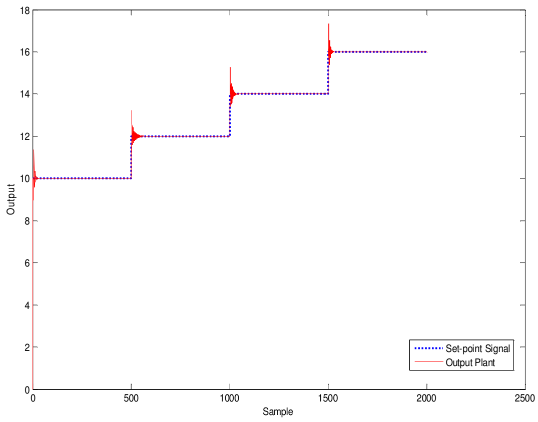

Fig.7. Time response characteristic of control systems with GA-FWNN (Test process)

VI. CONCLUSION

In this work, a FWNN based on a GA optimization that combines the advantages of fuzzy logic, Neural Networks, wavelet functions and Genetic Algorithm is proposed for control of dynamic plants. Simulation results demonstrate that the obtained controller can converge faster and more adaptive to new data with smaller RMSE values

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