A New Efficient Fuzzy Wavelet Neural Network Based Imperialist Competitive Algorithm for Control of Nonlinear Industrial Processes

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Abstract: Among various control methods, artificial intelligence based control techniques, becomes one of the major control strategies and has received much attention as a powerful tool for the control of nonlinear systems. This paper presents a design of Fuzzy Wavelet Neural Network (FWNN) trained Imperialist Competitive Algorithm (FWN-ICA) for control of nonlinear industrial process. The FWNN is applied to approximate unknown dynamic of the system and ICA is employed to train and optimize the FWNN parameters. In the proposed control scheme, neural control system synthesis is performed in the closed-loop control system to provide appropriate control input. For this, the error between desired system output and output of control object is directly utilized to tune the network parameters. The controller is applied to a highly nonlinear industrial process of continues stirred tank reactor (CSTR). Simulation results show that the proposed FWNN-ICA controller has excellent dynamic response and adapt well to changes in reference trajectory and system parameters.

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1. Introduction

Fuzzy technology is an effective tool for dealing with complex, nonlinear processes characterizing with ill-defined and uncertainty factors. Fuzzy rules are based on expert knowledge. The constructing of knowledge base for some complicated processes is difficult. Thus, there are some methods for constructing of fuzzy rules [1, 2]. On the other hand, some characteristics of neural networks such as learning ability, generalization, and nonlinear mapping are used to deal with signal processing, control system, decision making, and so on. However, the main problem of neural networks is that they require a large number of neurons to deal with the complex problems. Moreover, they also result in slow convergence and convergence to a local minimum. In order to overcome these disadvantages, wavelet technology is integrated into neural networks [3].

Recently, based on the combination of feed-forward neural networks and wavelet decompositions, wavelet neural network (WNN) has received a lot of attention and has become a popular tool for function learning [4]. The main characteristic of WNN is that some kinds of wavelet function are used as the nonlinear transformation in the hidden layer of neural network, so time–frequency property of wavelet is incorporated into the learning ability of neural networks.

However, the main problem of WNN with fixed wavelet bases is the selection of wavelet frames because the dilation and translation parameters of wavelet basis are fixed and only the weights are adjustable. The appropriate wavelet transform will result in the accuracy of approximation. Therefore, there are several different methods proposed to solve the problems [5, 6].

The complexity and uncertainty of the system can be also reduced and handled by the concepts of fuzzy logic. The local details of non stationary signals can be analyzed by wavelet transforms. The approximation accuracy of the plant can be improved by the self-learning capabilities of neural networks. Therefore, there are many papers that discuss the synthesis of a fuzzy wavelet neural inference system for signal processing, control problems, identification and pattern recognition [3, 7, 8].

In recent years, Fuzzy Wavelet Neural Networks (FWNN) have become very popular and have been applied in many scientific and engineering research areas such as system identification, function approximation and control of nonlinear systems. This is due to its information processing characteristics such as nonlinearity, high parallelism, fault tolerance as well as capability to generalize and handle imprecise information [4].

The Continuous Stirred Tank Reactor system (CSTR) is a complex nonlinear chemical system that one of its states, reaction consistence, cannot be measured. Anyway, the value of the state is necessary for control, so state estimation is used [9]. In this paper, a FWNN combined with ICA (FWN-ICA) is used for identification and tracking control of a nonlinear continuous stirred tank reactor (CSTR). The FWN is employed to estimate the value of the state and unknown dynamic of system. FWNN consist of a set of fuzzy rules that each rule corresponding to a sub-WNN consists of single scaling wavelets. The difficulties of selecting wavelets are reduced and orthogonal least-square (OLS) algorithm is used to determine the number of fuzzy rules and to purify the wavelets for each rule. Also, ICA is used to train and optimize the FWNN parameters. In the proposed control scheme the error between desired system output and output of control object is directly utilized to tune the network parameters. The capability and efficiency of the proposed method is illustrated by the temperature control of a nonlinear CSTR.

The paper is organized as follows. To make a proper background, the basic concepts of FWN and ICA are briefly explained in section II. In section III, the proposed FWN- ICA based controller and its learning algorithm are described. Section IV descried CSTR system. The results of the proposed approach on the simulation example are given in Section V and finally, some conclusions are dawn in Section VI.

2. Fuzzy Wavelet Network and Imperialist Competitive Algorithm

The basic concepts of FWN and ICA are briefly described in this section.

2.1. Fuzzy Wavelet Neural Network

A typical fuzzy wavelet neural network for approximating function y can be described by a set of fuzzy rules such as follow [4]:

R_i : If x_1 is A_1^i and x_2 is A_2^i and … and x_q is A_q^i,

then

$$\hat{y}_i = \sum_{k=1}^{T_i} w_{M_i,t^k} \Psi_{M_i,t^k}^{(k)}(\underline{x}), \quad M_i \in z, t^k \in R^q, w_{M_i}^{t^k} \in R, x \in R^q \quad (1)$$

where R_i is the ith rule, c is the number of fuzzy rules. x_j and $\hat{y}_i$ are jth input variable of $\underline{x}$ and output of the local model for rule R_i, respectively. Also M_i is dilation parameter and T_i is the total number of wavelets for the ith rule. $t^k = [t_1^k, t_2^k, ..., t_q^k]$, where t_j^k denotes the translation value of corresponding wavelet k. Finally, A_i^j is the fuzzy set characterized by the following Gaussian-type membership function.

$$A_j^i(x_j) = e^{-\left(\left(\frac{x_j - p_{j1}^i}{p_{j2}^i}\right)^2\right)^{p_{j3}^i/2}} \quad (2)$$

p_{j1}^i , $p_{j2}^i \in R$ and $p_{j3}^i = 2$ where p_{j1}^i represents the center of membership function, p_{j2}^i and p_{j3}^i determine the width and the shape of membership function, respectively. Wavelets $\psi_{M_i,t^k}^{(k)}(\underline{x})$ are expressed by the tensor product of 1-D wavelet functions:

$$\psi_{M_i,t}^{(k)}(\underline{x}) = 2^{\frac{M_i}{2}} \psi^{(k)}(2^{M_i} \underline{x} - \underline{t}^k) = \prod_{j=1}^{q} 2^{\frac{M_i}{2}} \psi^{(k)}(2^{M_i} x_j - t_j^k)$$
(3)

By applying fuzzy inference mechanism and let $\hat{y}_i$ be the output of each sub-WNN, the output of FWN for function $y(\underline{x})$ is as follow:

$$\hat{y}_{FWN}(\underline{x}) = \sum_{i=1}^{c} \hat{\mu}_i(\underline{x}) \hat{y}_i \quad (4)$$

where $\hat{\mu}_i(\underline{x}) = \mu_i(x) / \sum_{i=1}^{c} \mu_i(x)$, $\hat{\mu}_i(x) = \prod_{j=1}^{q} A_j^i(x_j)$ and for current input $\underline{x}$ and each function, satisfies $0 \le \hat{\mu}_i \le 1$ and $\sum_{i=1}^{c} \hat{\mu}_i = 1$. Also $\hat{\mu}_i(x)$ determines the contribution degree of the output of the wavelet based model with resolution level M_i .

A good initialization of wavelet neural networks leads to fast convergence. Numbers of methods are implemented for initializing wavelets, such as Orthogonal Least Square (OLS) procedure and clustering method [11]. In this paper the OLS algorithm is used to select important wavelets and to determine the number of fuzzy rules and network dimension. More details about construction of FWNN and network parameter initialization can be found in [4]. Also, details of OLS algorithm can be found in [10].The structure of applied FWNN is shown in Fig.1.

Furthermore, it is important to adjust the required network parameters in the design of dynamic systems. In order to avoid trial-and-error, a self-tuning process is used by employing the ICA to determine significant parameters such as dilation, translation, weights, and membership functions. In other words, during the learning process, these network parameters are optimized using ICA. To make a proper background, the concept of ICA is given in the next subsection.

2.2. Imperialist Competitive Algorithm

Imperialist competitive algorithm (ICA) is a new evolutionary optimization algorithm inspired by the socio-political process of imperialistic competition. Compared with the conventional evolutionary optimization algorithms, ICA has proven its superior capabilities, such as faster convergence and better global minimum achievement [12]. Flowchart of the ICA is illustrated in Fig. 2.

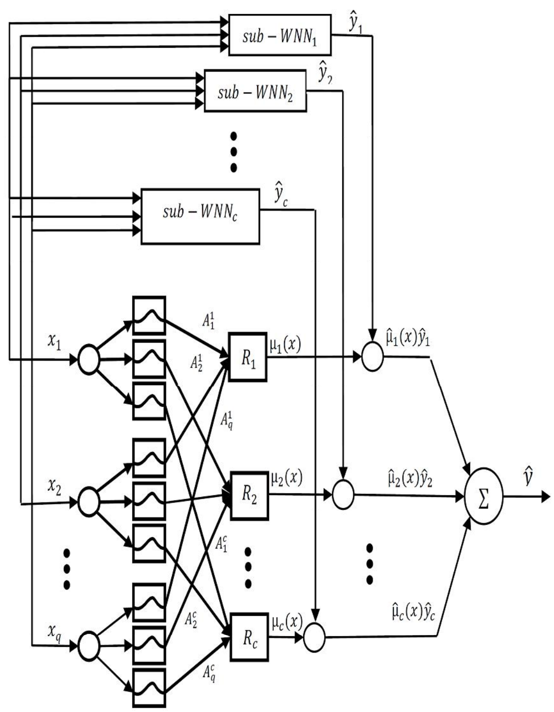

Figure 1. Structure of FWNN [4].

Similar to other evolutionary algorithms, this algorithm begins with an initial population. Each individual of the population is called a country. Some of the best countries (countries with the best fitness value) are selected to be the imperialist states and the rest form the colonies of these imperialists. Based on the imperialists' power, each country is distributed to their states. The power of an empire is proportional to its fitness value.

After creating initial empires, their colonies begin moving toward the relevant imperialist country. This movement is a simple model of assimilation policy that was pursued by some imperialist states [13]. Fig. 3 shows the movement of a colony towards the imperialist.

In this movement, θ and x are random numbers with uniform distribution as shown in (5), (6) and d is the distance between colony and the imperialist.

$$x \sim U(0, \lambda \times d) \tag{5}$$

$$\theta \sim U(-\gamma, \gamma) \tag{6}$$

where λ and γ are arbitrary numbers that modify the area that colonies randomly search around the imperialist.

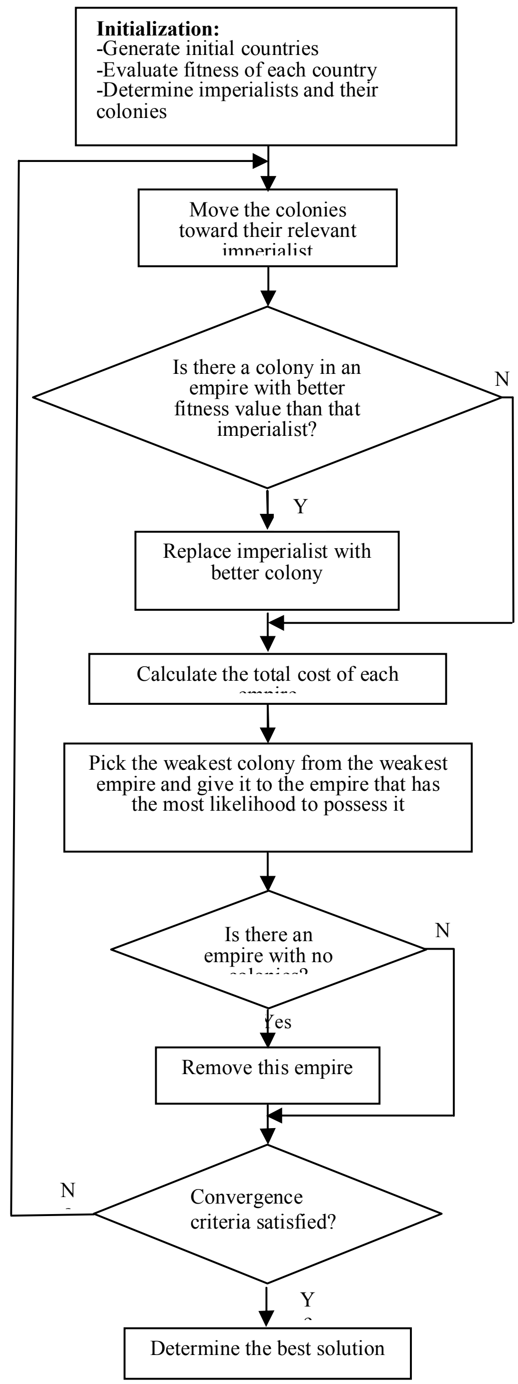

Figure 2. General principle of the ICA

The power of an imperialist country and its colonies represents the total power of an empire. In this algorithm, the total power of an empire is calculated by the power of imperialist state plus a percentage of the mean power of its colonies. In imperialistic competition, every empire tries to take possession of colonies of other empires and control them. As a result, a gradually decrease in the power of weaker empires and therefore increase in the power of more powerful ones will happen.

This competition is done by picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess them (that) colonies. In this competition, each of empires will have a likelihood of taking possession of the mentioned colonies, based on their total power. The more powerful an empire, the more likely it will possess these colonies. In other words, the possession probability of the colonies depends on the power of the empires trying to possess them. Any empire that is not able to succeed in imperialist competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated. The imperialistic competition will gradually result in an increase in the power of great empires and a decrease in the power of weaker ones. The power of weak empires will gradually loose and ultimately they will collapse.

The above procedures cause that all the countries converge to a state in which there exist just one empire in the world and all the other countries are its colonies.

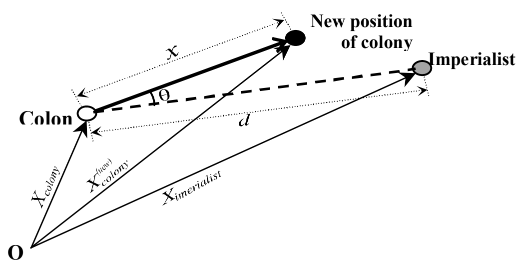

Figure 3. Motion of colonies toward their relevant imperialist

3. Proposed Control Scheme

The FWNN and its learning algorithm are used for identification and control of nonlinear CSTR system. Following, the architecture of proposed control strategy and its optimization method based on ICA are described in subsections A and B, respectively.

3.1. Architecture of Proposed FWNN-ICA controller

The structure of control system is given in Fig. 4. As can be seen, in this diagram FWNN is utilized as a controller and identifier.

The control scheme consists of the FWNN plant model, FWNN controller and the optimization block. Where $r(t)$ is desired output and $y(t)$ is the output of control system. In the proposed control strategy, neural control system synthesis is performed in the closed-loop control system and $e(t)$ is used for tuning network weighs to provide appropriate control input. By minimizing a quadratic measure of the error between desired system output and the output of control object, i.e. $e(t)$, the design problem can be characterized by the ICA formulation. On the other hand, the ICA is used to correct the network parameters for adjusting of FWNN controller and identifier in real time operation.

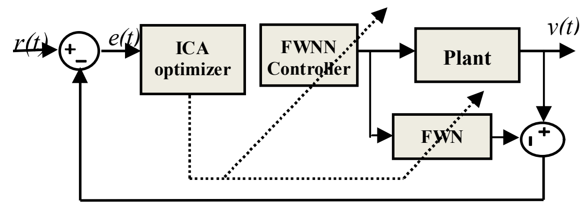

Figure 4. Proposed FWNN-ICA control scheme.

3.2. FWNN Training

In the learning step, the FWNN parameters are calculated by minimizing a fitness function that using the difference between the desired and real output as follow:

$$E_k = \sum_{l=1}^{H} \left| \hat{y}_{RNN_k}(x(l)) - y(l) \right|^2 \qquad (7)$$

and, the *Kth country* is represented as

$$F_N = [p_{j1}^{iN} p_{j2}^{iN} \underline{t}^{kN} w_{M_i}^{N}] \qquad (8)$$

which are all free design parameters that to be updated by ICA in our FWNN model. *H* is number of network training data. According to Fig. 1, the output is measured in each iteration and will be given to the ICA optimizer after being compared to the reference. Then the solution vector is obtained by ICA by minimizing the fitness function which gives the FWNN parameters. By using the obtained parameters, the network output is calculated and applied to system followed by calculating the new output. The procedure continues until a termination criterion is met. The termination criterion could be the number of iterations, or when a solution of minimal fitness is found.

Equation (8) shows that the free parameters to be trained in FWNN are $[p_{j1}^{iN} p_{j2}^{iN} \underline{t}^{kN} w_{M_i}^{N}]$.Our task is to design the FWNN structure such that the error between output and reference is minimized. Therefore ICA is applied for tuning parameters of FWNN by optimizing the (7) objective or cost function. Where E_N is the fitness of *N*th chromosome. In the ICA, each population is a solution to the problem which determines the parameters of FWNN, i.e. $[p_{j1}^{iN} p_{j2}^{iN} \underline{t}^{kN} w_{M_i}^{N}]$.

4. The Continuous Stirred Tank Reactor system

Continuous stirred tank reactor (CSTR) is a highly nonlinear process. A schematic of the CSTR system is shown in Fig.5. The process model consists of two nonlinear ordinary differential equations [14]:

$$
\begin{aligned}
\frac{dC_A}{dt} &= \frac{Q}{V}(C_{Af} - C_A) - k_0 \exp\left(\frac{-E_a}{RT}\right)C_A \\
\frac{dT}{dt} &= \frac{Q}{V}(T_f - T) - \frac{H_r}{\rho c_p V} k_0 \exp\left(\frac{-E_a}{RT}\right)C_A + \frac{UA}{\rho c_p}(T_j - T) \qquad (9) \\
\frac{dT_j}{dt} &= \frac{UA}{\rho c_p V_j}(T - T_j) + \frac{u}{V_j}(T_{jf} - T_j)
\end{aligned}
$$

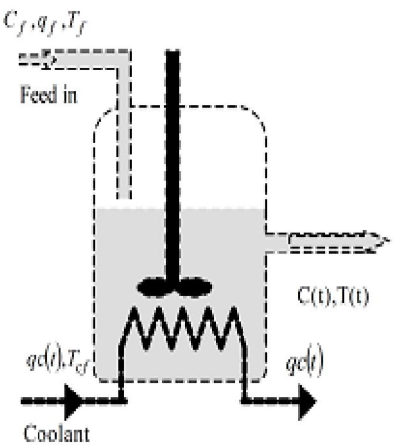

Figure 5. CSTR plant model

where the x = [x1; x2; x3] state-variables of the model are the CA (mol/m3) concentration of the A component in the reactor, the T (oC) reactor temperature, and the Tj (oC) temperature of the jacket of the reactor, while the input of the process is the u [m3/min] flow rate of the cooling material. The controlled output y of the process is the reactor temperature, y = x2. The parameters and its nominal values of the model are given in Table 1. Details of the system data and its properties are given in [15].

5. Simulation Study

In the first stage, we should generate input-output data for obtaining the FWNN model of the process (Fig. 4). The training data was generated by closed-loop experiment and the proposed approach in section III is used to train the model. Fig. 6 shows the obtained training data set.

The combined servo and regulatory control problem was defined between two unstable operating points: 70 0C - 80 0C. The coolant feed temperature changed from 10 0C to 20 0C at t = 10 h what was the unmeasured disturbance. In the ICA, each country represents a candidate solution for the problem. In the initialization step, a set of countries are generated randomly where *n* is set to be 200. The numbers of *imperialist states* is set to be 20 and thus, 180 *colonies* will be existed. Based on the author's previous experience λ and γ are set to 2 and 0.5 (radian), respectively. The number of iterations is considered to be 200, which is the stopping criteria used in other methods available in the literature. Fig. 7 shows the model's output and the real output. From Fig. 7 can see that performances of the controllers are good, and the FWNN controller based on ICA achieved good dynamic performance.

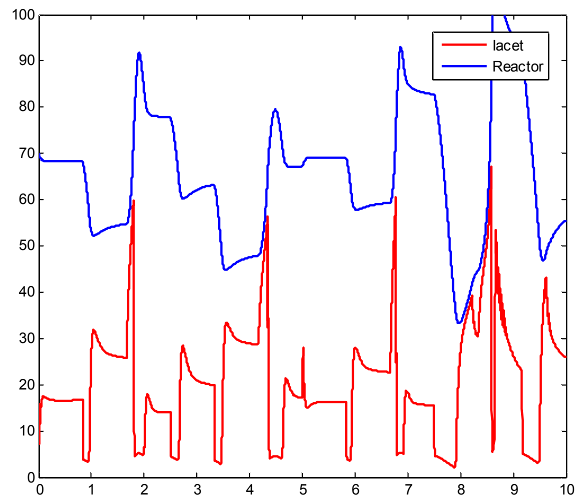

Figure 6. Traning date

Table 1. Nominal values of the model parameters

Notation	Description	Value and unit
Q	Feed flowrate	0.2 m^3/min
V	Reactor volume	2 m^3
K_0	Reaction rate coefficient	3.5 . 10^6 1/min
E_a	Activation energy	49.884 kJ/mol
R	Ideal gas constant	8.314 . 10^{-3} kJ/mol °C
H_r	Heat of reaction	500 kJ/mol
C_{Af}	Concentration of A in feed	1000 mol/m^3
T_f	Feed temperature	30 °C
ρ	Density of solution	1000 kg/m^3
c_p	Heat capacity of solution	4.2 kJ/kg °C
UA	Heat transfer coefficient	252 kJ/min °C
V_j	Jacket volume	0.4 m^3
T_{jf}	Inlet temperature of coolant	10 °C

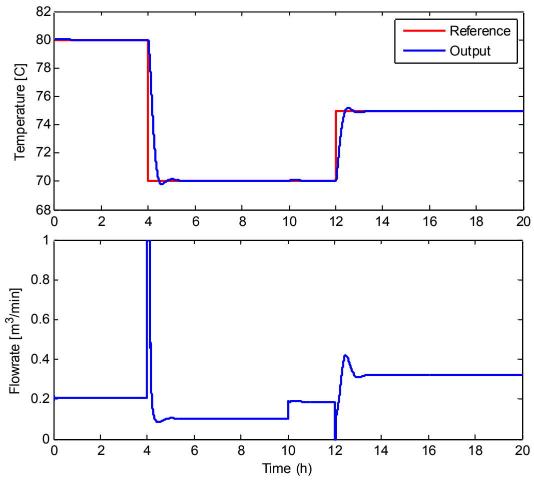

Figure 7. Model's output and real output

6. Conclusion

This paper presented the development and evaluation of an FWNN based ICA controller. The controller was designed to control the temperature of a CSTR. The nonlinear plant identification was done on-line using the ICA for quick learning. With this method any changes in the parameters of the system could be detected and remedial functions can be done. Simulation results show good dynamic performance of the proposed FWNN-ICA controller.

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