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An Adaptive Fuzzy Neural Network Based on Self-Organizing Map (SOM)

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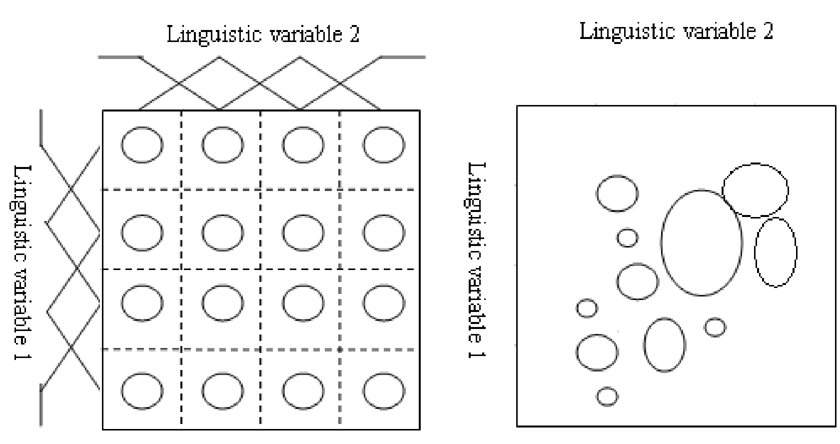
1. Introduction

This chapter shows a new method of fuzzy network which can change the structure by the systems. This method is based on the self-organizing mapping (SOM) (Kohonen T. 1982), but this algorithm resolves the problem of the SOM which can't change the number of the network nodes. Then, this new algorithm can change the number of fuzzy rules; it takes the experienced rules out of the necessary side for the number of the fuzzy rules. We use this new algorithm to control the dissolved oxygenic in the wastewater treatment processes. This proposed algorithm can adjust subjection function on-line, optimize control rules. The results of simulations show that the controller can take the dissolved oxygenic to achieve the presumed request, and prove the superiority of this proposed algorithm in the practical applications.

The research of the structure of the Neural Network is a hotspot currently. A neural network model with strong relations to the area of fuzzy systems is the fuzzy neural network model (T.Poggio and F.Girosi, 1990). Based on the IF-THEN rules, the fuzzy logic rules can be clustered. The functional equivalence of restricted fuzzy neural networks has been shown as Fig1:



(a) (b)

Fig. 1. Relations of the fuzzy linguistic before and after clustering algorithm

Fig (a) is a restricted fuzzy system which distributes the input into a number of fuzzy regions. Fig (b) is the relations of fuzzy linguistic after clustering. Fig (a) and Fig (b) show that the relations of fuzzy linguistic before and after clustering are not the same. In fact, the functions of the fuzzy rules are also not the same in the general control. Especially in the fuzzy neural network (Yu Zhao, Huijun Gao & Shaoshuai Mou, 2008), every node represented a rule in rules layer. But some edge rules are even not be used in the training phase. And every rule must be computing at every training phase, so the time will be lost. In some real-time control systems the conventional fuzzy neural networks can hardly meet the requirement.

In order to solve this problem how to ensure the number of network nodes, Fritzke devised one of the first growing neural networks which is Growing Cell Structure (GCS) (Fritzke, B. 1994). The GCS is based on the SOM (Kohonen T. 1982), the network predefines some rules. A new node is inserted when accumulated error is higher than the predefined parameter, and the network continues to adapt and grow until some stopping criterion is met. This can take the form of a network size. But this structure also has limitation which can only add nodes but can not reduce them.

Merkel and his partners invented Growing Hierarchical Self-Organizing Map (GH-SOM) (Dittenbach. M., Merkel. D & Rauber. A., 2000). The key idea of the GH-SOM is to use a hierarchical structure of multiple layers where each layer consists of a number of independent Self-Organizing Mapping (SOM). The network inserts complete rows or columns when the average error higher than a constant parameter and reduce a node when the average error lower than a constant parameter. The nodes can be added and reduced in this network, so this network structure can solve the former limitations. But the number of the network nodes may be too high about some simple systems. Besides, there are other growing strategies for constructing the RBF neural network (Liying Ma & K. Khorasani, 2005; R. Sentiono, 2001; S. S. Ge, F. Hong, & T. H. Lee, 2003).

Based on the GCS and GH-SOM a new Adaptive Growing Self-Organizing Fuzzy Neural Network (SFNN) will be introduced in the following sections. The number of the conventional fuzzy neural network can be changed by this method. The details of this method can be found in paper (Junfei Qiao, Honggui Han, and Yanmei Jia, 2007).

The organization of this chapter is as follows: we describe the growing self-organizing fuzzy neural network (GSFNN) in the next section. And we divide into three sections in this part to discuss this problem. In Section III, we introduce the controller based on the growing self-organizing fuzzy neural network (GSFNN). In Section IV, we use this proposed algorithm to control the dissolved oxygenic (DO) in the wastewater treatment process and compare the results with the conventional fuzzy neural algorithm. Finally, the merits of the proposed growing self-organizing fuzzy neural algorithm are shown, and the conclusion is given in Section V.

2. Growing Self-Organizing Fuzzy Neural Network (GSFNN)

This section consists of three main parts: The growing self-organizing algorithm; the fuzzy neural network and the growing self-organizing fuzzy neural network. The growing self-organizing algorithm will be described in section2.1; the fuzzy neural algorithm adaptive self-organizing fuzzy neural network will be shown in section 2.2 and the adaptive self-organizing fuzzy neural network will be shown in section 2.3.

2.1 Growing Self-Organizing Algorithm (GA)

The growing self-organizing algorithm in the network model is used to confirm the fuzzy rules of the fuzzy neural network (FNN). In fact, we will confirm the number of the nodes in the FNN, and the nodes can be changed real-time. The details of the algorithm are shown as follows. The whole neural network architecture of GA is shown in Fig. 2.

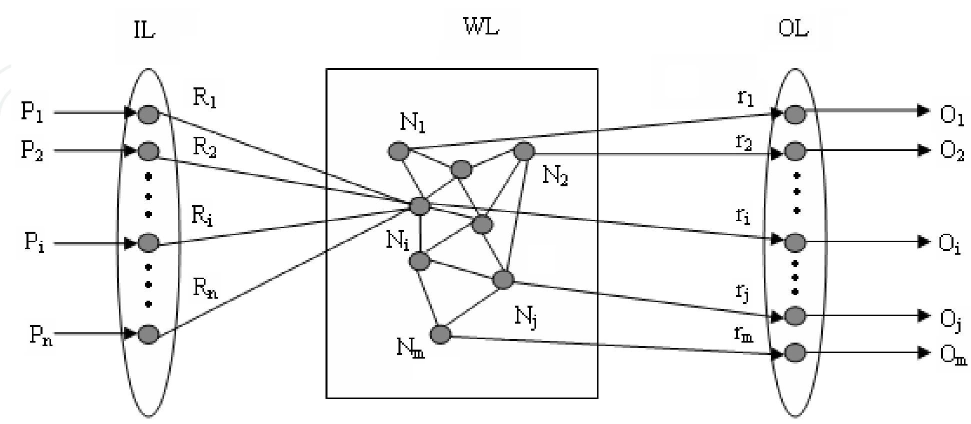


Fig. 2. The schematic of the growing self-organizing algorithm (GA)

where $P=\left((py_1,p^2y_1),(py_2,p^2y_2),\ldots,(py_n,p^2y_n)\right)$ is the external vector, the number of nodes in the working layer (WL) are based on the input layer (IL). The number of the output layer (OL) is the same as the WL.

The main steps of the Growing Self-Organizing Algorithm:

(1) Initialization, taking the number of nodes $N\_num=1$, N_num represents the output nodes number, w represents weight value vector quantities, and w_1 is zero vector; the max time constant T and time $t=0$; parameters σ_o, k_σ, α_0, κ_α.

(2) Changing the data space P into $\overline{P}$.

$$\overline{py}_i = py_i / \sum_{j=1}^{n} py_j , \tag{1}$$

$$\overline{p}^2 y_i = p^2 y_i / \sum_{j=1}^{n} p^2 y_j , \tag{2}$$

$\overline{P}=[(\overline{py}_1,\overline{p}^2 y_1),(\overline{py}_2,\overline{p}^2 y_2),\cdots,(\overline{py}_n,\overline{p}^2 y_n)]$

(3) Using $\overline{P}$ as the input data space and calculating

$$G(\overline{p}) = \left\| \overline{p} - w_i^T \right\|, \; i = 1,2,\cdots,n , \tag{3}$$

where w_i^T is the weight vector of node i.

(4) Judging to add a new node or not according to the following rule:

$$\begin{cases} G(\bar{p}) > \varphi(\bar{p}_i), N\_num+1 \\ G(\bar{p}) \le \varphi(\bar{p}_i), N\_num \end{cases}, \quad i = 1,2,\cdots,n, \tag{4}$$

where $\varphi(\bar{p}_i) = 10^{(-4)} \times r \times e^{(r-3)}$; the value of r can be changed by the real system. If it needs to add a new node, $p = \bar{p}_i$, $N\_num = N\_num+1$. Feed forward coupling weight value $w_{N\_num} = p^T$; and then go to step (5). But if $N\_num = N\_num$, go to step (3).

(5) Calculating feed back coupling weight value near node p_t based on :

$$w_{tj} = \exp(-\frac{G(p^T)}{2\sigma(t)^2})(j = 1,2,\cdots,n), \tag{5}$$

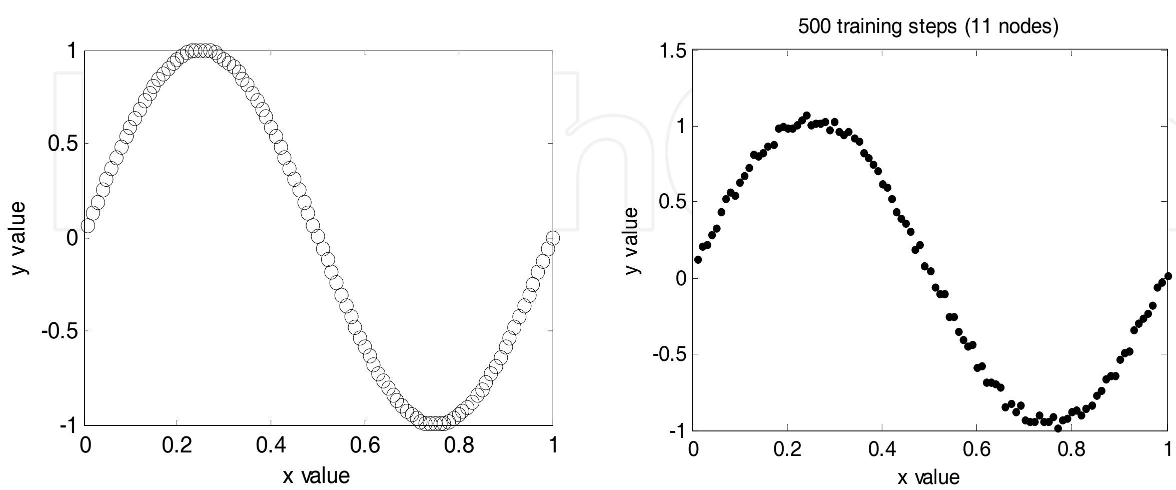
where $\sigma(t) = \sigma_0 \exp(-k_\sigma t)$; and calculating the feed forward weight value such as $w_j(t+1)(j = 1,2,\cdots,n)$ based on the adaptation of SOM.

(6) In order to optimize the neural network, the redundant node need to be reduced. The second training is to reduce the redundant nodes. The judgment is that whether every winner node has enough near nodes. The winner node which is a marginal node without near node will be reduced.

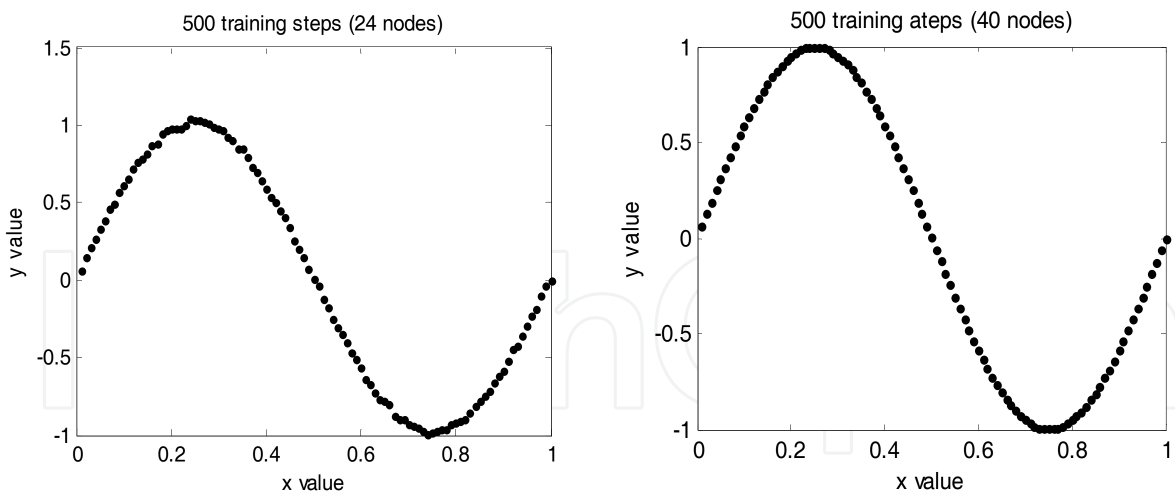
(7) The network stops calculating when every rule is satisfied.

When the number of nodes is confirmed, the network structure is also formed. But this kind of network structure based on the real-time system and can be changed real-time.

And we use this network to track the sine function: $y = \sin(2\pi x)$. The tracking results are shown in Fig. 3. Fig (a) is the restrict figure of the sine function; Fig (b) is the network with 11 nodes and within 500 training steps; Fig (c) is the network with 24 nodes within 500 training steps; Fig (d) is the figure with 40 nodes within 500 training steps. Here the parameters are initiated: $\sigma_o = 0.01$, $k_\sigma = -0.001$, $\alpha_0 = 0$, $k_\alpha = 0.01$.



(a) (b)



(c) **(d)**

Fig. 3. The results of the sine function

The results of the Fig (b), (c) and (d) showed the process of the growing self-organizing algorithm. They proved that this growing self-organizing algorithm can change the weight value on-line, and we can find that when there were 40 nodes the algorithm can approach the sine function gradually. And the algorithm was not decided in advance. In the section 2.3 we will associate the growing self-organizing with the fuzzy neural network. The growing self-organizing fuzzy neural network can be used as a controller. The GSFNN controller will be laid in section 3. And we use the controller to control the dissolved oxygenic in the wastewater treatment.

2.2 Fuzzy Neural Network

In this section, we choose a kind of Fuzzy Neural Network (FNN) which consists of four layers. There are input layer, two hidden layers and an output layer. The structure of the neural network is shown in Fig. 4.

Every function of the neural network is such as:

First layer: Input Layer

There are two nodes this layer, which separately represent the error e and its derivative ec.

$$In_i^{(1)} = x_i \, , Out_i^{(1)} = In_i^{(1)} \, , (i = 1,2) \, . \tag{6}$$

Second layer: Fuzzification layer

The input parameter will be fuzzyfied. Each node here represents a language discussion of the input variable. We initiate to divide e into 2 parts and ec into 2 parts separately. So this layer has 4 nodes.

$$In_{ij}^{(2)} = Out_i^{(1)} \, , Out_{ij}^{(2)} = \mu(x_i) = e^{-(x_i - a_{ij})/b_{ij}} \, , \tag{7}$$
$$i = 1, j = 1,2 \, ; i = 2, j = 1,2 \, .$$

In this layer the growing clustering algorithm based on GSOM will be used to change the number of the nodes. Where a are the membership functions of e, and b are the membership functions of ec. The algorithm will be discussed in section 3.

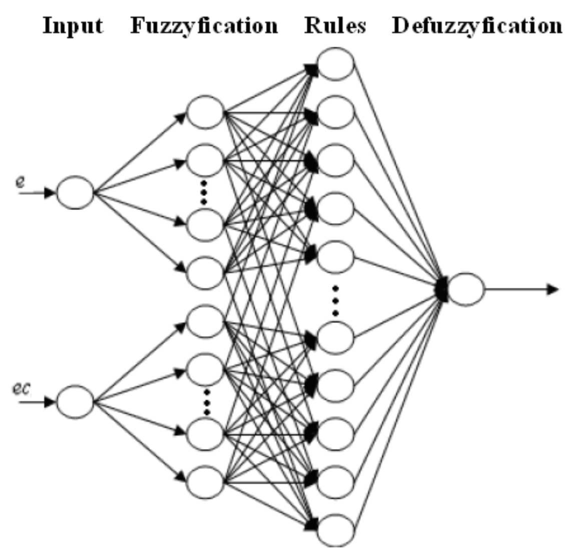


Fig. 4. The structure of the fuzzy neural network

Third layer: rules layer
Every neural cell in this layer represents an existing rule. We combine inputs with each other absolutely then attain expectation nodes. We calculate the fitness value of rule by taking the method of product in this layer.

$$In_{pq}^{(3)} = \mu_{1p}(x_i) \times \mu_{2q}(x_2), Out_{pq}^{(3)} = In_{pq}^{(3)}, \quad p = 1,2,\cdots,n; \; q = 1,2,\cdots,m. \tag{8}$$

The clustering algorithm will be used in this layer to ensure the nodes of the structure. Firstly, we also begin with $n = 2, m = 2$. Then new nodes will be inserted when the systems need.
Forth layer: Defuzzification layer
We clarify the output by gravity method. w_{pq} are the centers of the output languages discussion.

$$In^{(4)} = \sum_{p=1}^{n}\sum_{q=1}^{m}(Out_{pq}^{(3)} \times w_{pq}), \quad Out^{(4)} = \sum_{j=1}^{N}\omega_j^4 In^{(4)}, \quad p = 1,2,\cdots,n; \; q = 1,2,\cdots,m. \tag{9}$$

Initially, $n = 2, m = 2$.

This structure of the fuzzy neural network contains fewer layers than the conventional networks which usually with five or more layers. So this network is simple and can save much time by computing.

2.3 Adaptive growing Self-Organizing Fuzzy Neural Network

In this section the adaptive growing self-organizing fuzzy neural network will be shown. In the growing fuzzy neural algorithm, the GA method is used in the second layer and the third layer. And the outputs of the third layer are the fuzzy rules, but in order to make the main algorithm in this chapter be faster, it needs to change the value of the parameters in this layer. And then the rules can catch the requirements of the real systems. The process diagram of the growing fuzzy neural is draw as Fig5:

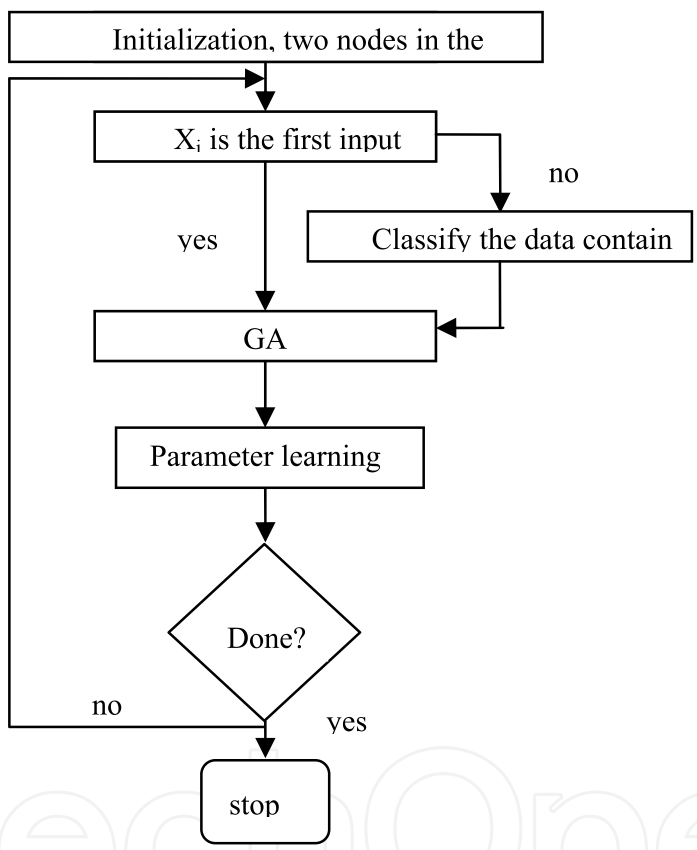


Fig. 5. The process diagram of the growing fuzzy neural algorithm

From the process diagram, the network nodes can be certain by the GA. It can be improved if a “default” rule is used in addition to the “normal” fuzzy rules. But in order to make the algorithm be convergent, there must be do parameter learning. The user can stop the addition of the fuzzy rules when the desired accuracy is reached.

3. The GSFNN Controller (GSFNNC)

Ferrer and his partners used fuzzy algorithm to control the dissolved oxygenic in the wastewater treatment (Ferrer J, Redrigo M A, Seco A, et a1, 1998). Syu and Chen used the BP neural network to control the active sludge age in the wastewater treatment (Syu M J. Chert B C, 1998). In this chapter, we combine the advantages of these algorithm and use the fuzzy neural network to control the dissolved oxygenic in the wastewater treatment. In this network the nodes of the fuzzy nodes can be changed by the growing self-organizing algorithm. The schematic of the control system is shown in Fig. 6:

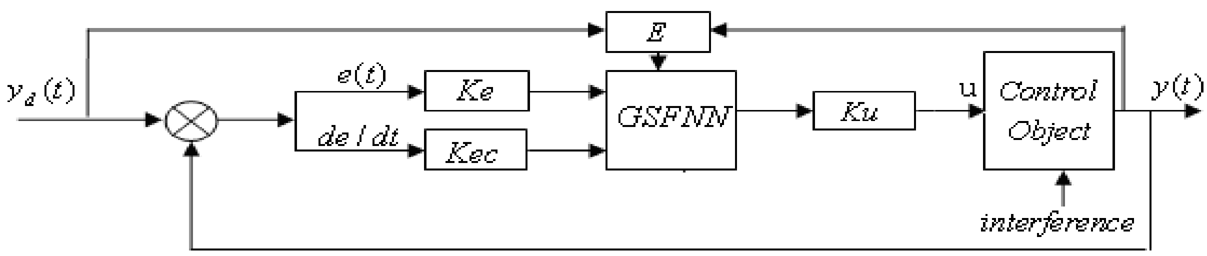


Fig. 6. The schematic diagram of control system

In Fig. 6 Ke and Kec are the quantifications of the controller input, Ku is the quantification of the controller output. GSFNN is the growing self-organizing fuzzy neural network controller. This controller owns the same functions as the traditional fuzzy controller: input, fuzzication, inferences, defuzzication. But this controller can change the nodes of the network, so it can change the structure of the network, realize the control rules real-time.

4. Simulations

Evidently, mathematical models are important not only for optimizing design but also for improving operation and control of these complex biological processes in wastewater treatment plants. Much of the work done on activated sludge bioreactor modeling in recent years has been largely concentrated on improving the understanding of the kinetics of the process (Talat Mahmood, Allan Elliott, 2006). The fundamental scheme of an activated sludge process of the wastewater treatment plant described in this chapter is shown in Fig.7.

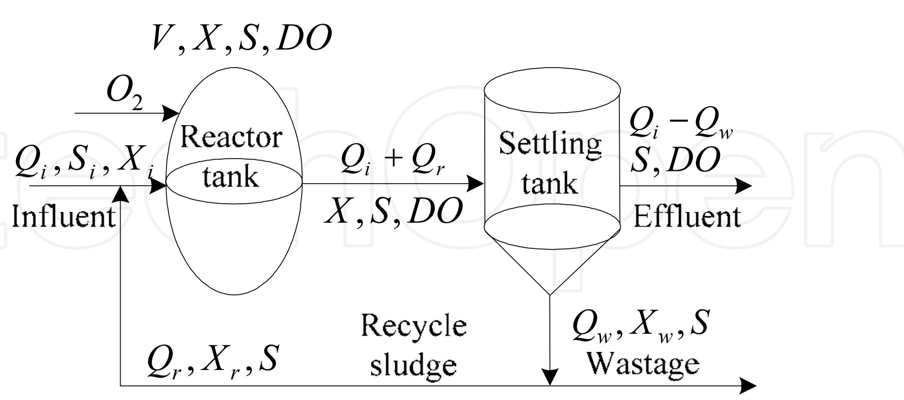


Fig. 7. The fundamental scheme of activated sludge process

The activated sludge process mainly includes the aerator system and the activated sludge recycling system. The process is a continuous system in which aerobic biological growths are mixed and aerated with wastewater in the reactor tank and separated in the settling tank. The aerobic biological growths get rid of organic matter included in wastewater.

In order to obtain the respective mathematical model, the following facts are assumed (Edgar N. Sanchez, Jose M. Gonzalez, Esperanza Ramirez, 2000):
1) The microorganisms' growth rate is bigger than their death rate and obeys the Monod law;
2) No biochemical reactions take place inside the settling tank;
3) Biomass in the sedimentation tank is negligible;
4) The inflow stream contains no biomass;
5) Complete settling is achieved, hence the sludge wastage is restricted to waste stream.
By means of mass balance for biomass concentration, substrate concentration and oxygen concentration, we obtain the following model:
A typical model of active sludge wastewater treatment is such as the following (FENG Yu-zhao, LONG Teng-rui, GUO Jing-song, et al., 2003):

$$\begin{cases} \dfrac{dx}{dt} = \bar{\mu}\dfrac{sx}{k_s + s} - k_d x + \dfrac{Q}{V}x_i - \dfrac{Q_w}{V}Cx \\ \dfrac{ds}{dt} = \dfrac{\bar{\mu}}{Y_{SH}}\dfrac{sx}{k_s + s} + \dfrac{Q}{V}(s_i - s) \\ \dfrac{do}{dt} = \dfrac{(1 - ff_s Y_{SH})}{fY_{SH}}\dfrac{sx}{k_s + s} - f_s k_d x + \mu \end{cases}, \tag{10}$$

where x is the biomass concentration in the aeration tank, x_i is the inflow biomass concentration, s is the reactor substrate concentration, s_i is the substrate concentration contained in inflow, ***o*** is the oxygen concentration in reactor tank, $\bar{\mu}$ is the maximal specific growth rate, k_s is the half-velocity constant, substrate concentration at one-half the maximal growth rate, k_o is the oxygen half-saturation coefficient for heterotrophic biomass, k_d is the endogenous decay coefficient, Q is the inflow, V is the reactor volume, Q_w is the wastage flow, C is the factor of concentration in the sedimentation tank (2), Y is the yield coefficient, Y_{obs} is the observed yield coefficient, f is a factor, which correlates substrate with oxygen demand, f_x is the consumption factor, and u is the oxygen transfer rate with BOD_5 standing for biochemical demand of oxygen during 5 days, VSS for volatile suspended solids, and COD for chemical demand of oxygen.Because of the character of the wastewater treatment, the paper (FENG Yu-zhao, LONG Teng-rui, GUO Jing-song, et al., 2003) gave the dynamic parameter of the process. The limitations of the parameters are given as follow.

$\bar{\mu} - k_d - CQ_w / V \in [2.9495, 5.9495]$;

$\bar{\mu} - Y_{NH} \in [9.0634, 18.1296]$;

$Q / V \in [6.05, 10.05]$;

$Q_{Si} / V \in [0.012, 0.142]$;

$$\frac{\bar{\mu}(1-ff_s Y_{NH})-ff_s Y_{NH} K_d}{fY_{NH}} \in [4.936,9.943]$$

In this chapter, we choose a group numbers within these limitations, and one of the models will be obtained.

$$\begin{bmatrix} \dot{x}(t) \\ \dot{s}(t) \\ \dot{o}(t) \end{bmatrix} = \begin{bmatrix} 3.95 & 0 & 1 \\ 15.05 & -8.05 & 0 \\ 7.05 & 0 & -1 \end{bmatrix} \begin{bmatrix} x(t) \\ s(t) \\ o(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} u(t) \\ q(t) \end{bmatrix} \tag{11}$$

$$y(t) = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(t) \\ s(t) \\ o(t) \end{bmatrix} \tag{12}$$

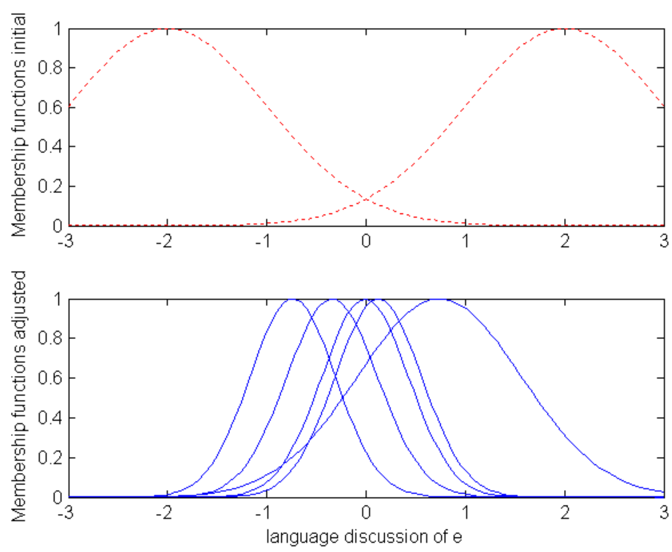
The dissolved oxygenic concentration of the wastewater treatment always contains about from 1.6 mg/L to 2.4 mg/L; in the simulations we use the dissolved oxygenic concentration near this requirement. In the traditional fuzzy neural network, the region value and the number of the nodes were ensured by the experience or experimentations. But these methods may be not applicable in the real-time systems. Besides, the control results of the simulations by the traditional fuzzy neural network with 7×7 fuzzy rules (or neural nodes) are nearly the same as the fuzzy neural network with 9×9 fuzzy rules. But the time of the experiments was not the same. The later was nearly twice as the former. It is unsuitable in the control systems. But the number of the fuzzy neural nodes can be ensured by the adaptive growing self-organizing algorithm. So the adaptive growing self-organizing fuzzy neural network controller can be used to control the systems without the experience.

Based on the neural network controller in the section 3, and the parameter of the dissolved oxygenic of the wastewater treatment system in the former of this section, we do some researches.

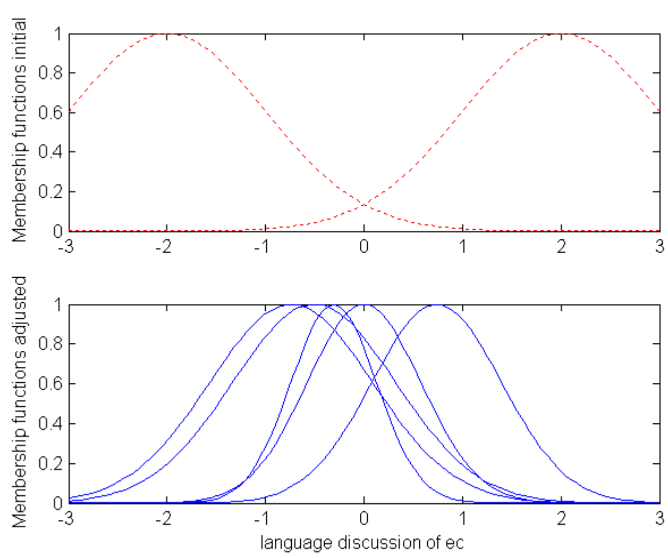
In the conventional fuzzy neural network, the region value and the number of the nodes were ensured by the experience or experimentations. And in this chapter we choose 49(7×7) fuzzy rules for the conventional fuzzy neural network. The growing self-organizing fuzzy neural network was initially given 4(2×2) fuzzy rules. After learning the number of the fuzzy rules can add to adapt the requirement of the system. The membership functions of linguistic variable e and ec are shown as Fig 8.

The results of the simulations are shown in Fig.9. In the process of wastewater treatment, the system requires dissolved oxygenic concentration to be 1.6 mg/L, and then 2.0 mg/L. Fig(a) shows the result of conventional fuzzy neural control by 49(7×7) fuzzy rules; Fig(b) shows the result of growing self-organizing fuzzy neural control by 25(5×5) fuzzy rules. We can find that the growing self-organizing fuzzy neural algorithm is faster than the conventional fuzzy neural algorithm by the same required error. Sometimes, the fuzzy rules need to be concerted by experience, the parameters of the fuzzy neural network need to be trained off-line. But we know from the former, the growing self-organizing fuzzy neural algorithm

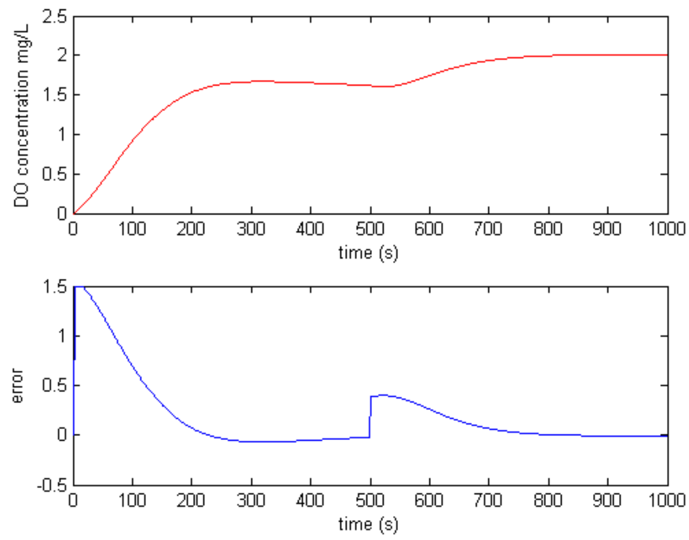
concerts the fuzzy rules by the real system, and trains the parameters on-line. Because we introduce the dynamic descent gradient method, the learning speed is faster than the conventional fuzzy neural algorithm. Besides, the storage space of the growing self-organizing fuzzy neural algorithm is about 101424 bytes. But the conventional fuzzy neural algorithm is about 298432 bytes. This is very useful in industry. So the new algorithm proposed in this chapter is more superiority than the conventional fuzzy neural algorithm.
Fig. 9 provides the growing self-organizing fuzzy neural network is faster and smoother than the traditional fuzzy neural network, and the Fig. 9 (b) provides the new method is robustness when applied to wastewater treatment system that has strong disturbances, and has strong self-adaptability when changing the requirement of dissolved oxygen (DO) concentration.



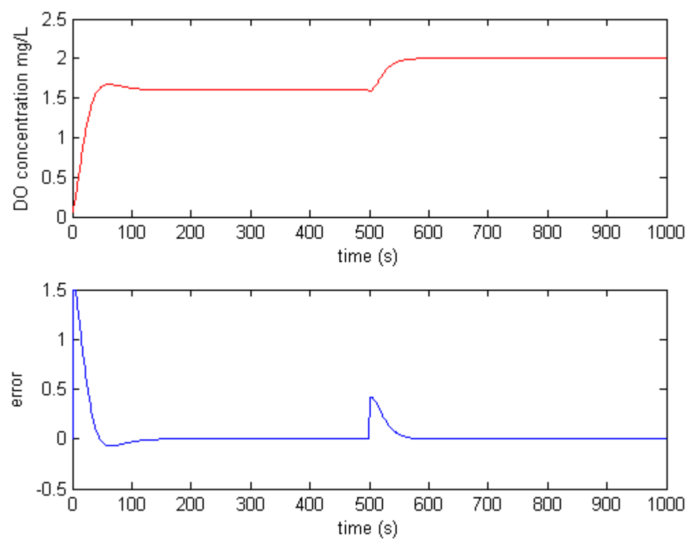
(a) Membership functions of *e* initial and after adjusted



(b) Membership functions of *ec* initial and after adjusted
Fig.8. Membership functions of inputs



(a) The result of conventional fuzzy neural control



(b) The result of growing self-organizing fuzzy neural control
Fig. 9. The results of the simulations

5. Conclusions

To summarize, the Adaptive Growing Self-Organizing Fuzzy Neural Network controller in this chapter solves the limitations of the traditional fuzzy neural network. The number of the neural network can be changed by the real systems. This chapter provides a new approach to the research of wastewater treatment process, and GSFNNC presents a good respond to a variety of conditions and offers the advantages of certain degree of robustness over the changes that the process can undergo. The simulation results have demonstrated that GSFNNC has abilities as follows:

1. The growing self-organizing algorithm can ensure the nodes' number by real systems;
2. This network controller can keep dissolved oxygen concentration at a proper level, avoiding sludge swelling;

3. This network controller can adjust membership function on-line, optimize control rules, and has strong robustness. It can work well under the condition of continuous influent and makes the effluent meet the discharge standard.

6. Referring

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Self-Organizing Maps

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The Self-Organizing Map (SOM) is a neural network algorithm, which uses a competitive learning technique to train itself in an unsupervised manner. SOMs are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space and they have been used to create an ordered representation of multi-dimensional data which simplifies complexity and reveals meaningful relationships. Prof. T. Kohonen in the early 1980s first established the relevant theory and explored possible applications of SOMs. Since then, a number of theoretical and practical applications of SOMs have been reported including clustering, prediction, data representation, classification, visualization, etc. This book was prompted by the desire to bring together some of the more recent theoretical and practical developments on SOMs and to provide the background for future developments in promising directions. The book comprises of 25 Chapters which can be categorized into three broad areas: methodology, visualization and practical applications.