Proceedings of the 5th WSEAS Int. Conf. on SIMULATION, MODELING AND OPTIMIZATION, Corfu, Greece, August 17-19, 2005 (pp262-267)

# A Novel Fuzzy Neural Network Approach for Excitation System Modeling

WEIHUA XU, QIAN AI☆, YUGUANG ZHOU, CHUANWEN JIANG
Shanghai Jiaotong University
1954 HuaShan Road, Shanghai, 200030
P R CHINA

*Abstract:* By combining the fuzzy theory and neural network technology, a fuzzy neural network (FNN) is proposed in this paper, whose learning algorithms are developed by steep algorithm. The excitation system model based on FNN is also derived in this paper, which can be used for on-line and off-line analysis and control respectively. The simulation results demonstrate that the FNN models can give precise estimation of practical excitation system.

*Key- words:* Excitation System, System Identification, Fuzzy Neural Network

## 1 Introduction

The excitation system is vital to the generator unit. Excitation system with good performance can not only promise reliable and stable operation of generators but also improve the efficiency of the whole system, such as, improve the capacity of transmission lines and decrease its investment. With the rapid development of modern power electronic technologic and the successful application of auxiliary control in excitation system, such as power system stabilizer (PSS), linear optimized excitation controller and non-linear excitation controller, the research to the excitation gains more and more attention.

However, lacking of proper models and parameters, the electric power system simulation cannot use models including excitation system but classical models with invariable generator transient potential to reflect the regulation effect of the excitation system. To use data gathered from field tests and modern system identification theory, the articles [1,2,3] obtain various excitation system models and their parameters for different practical system. However, a conclusion was drawn after lots of transient stability calculations: the discrepancies between the actual transient process and that described by classic model with invariable transient potential cannot be neglected. Thus, it is essential to build reliable and precise excitation model by field tests.

Excitation systems are various in types, but their structure is almost similar. Excitation system generally includes these units: measurement, magnification, phase shift and firing, exciter and soft feed back [4,5]. In order to get the model of excitation system, firstly, the basic equations should be written according to the physical concept. Then, these equations should be converted to transfer function. Finally, the field test data and the system identification methods are used to develop the model of excitation. Several attempts have been made to obtain excitation system models from field tests. A second order static excitation system has been discussed in [6]. In [7], generalized least square approach is used to model an excitation system. Parameter estimation of a pumped storage power plant using stochastic approaches is discussed in [8]. Identification of exciter constants using weighted least squares is addressed in [9]. The necessity to represent the excitation system in full and close to the practical implementations for accurate and reliable results has been addressed in [10].

Further more, there are different kinds of nonlinearities in an excitation system [13]. Most of the electronic elements, such as bridges are nonlinear elements with limits. Other nonlinearities include main exciter saturation and bridge commutation drop. When an excitation system is modeled, these system nonlinearities should somehow be taken into account. If power systems simulation is only done with linear model, great error must exist. In the past decades, the microcomputer controlled excitation systems, which need accurate model, were widely used in large generators, and aroused a difficult problem for the parameter identification. The feasibility and necessity of a nonlinear structure for excitation system is discussed in [11]. In [12], the importance of modeling the limiters, such as under excitation limiter, is addressed. Although some methods like "black box" approach are proposed, it is still difficult to distinguish the model's orders. Thus it is better to put forward a new method that can deal with the non-linear function such as saturation, amplitude limit etc.

Artificial neural network (ANN) [14, 15] is a nonlinear kinetics system, which consists of a large number of simple transaction units—neurons. ANN can transfer data parallel and distributed, and capable of self-adaptation, self-learning, non-linear mapping, robust under system noises and input noises. It is evident that the ANN is superior to the ordinary modeling methods in non-linear dynamic system modeling. But pure ANN has some defects. With the development of artificial intelligence, the combination of different methods can make use of their advantages and have better performance. This paper combines the fuzzy theory and artificial neural network into the fuzzy neural network (FNN), which improves the learning ability and modeling ability, and then uses the FNN to set up the model of the excitation system.

## 2 Fuzzy neural networks

The ANN has great advantages in dealing with nonlinear problems. But it cannot deal with uncertain problems, such as dealing with the weather condition, which have influence on the load prediction. However, using language rules to express the fuzziness and inexactness, the fuzzy theory can manage these inexact problems conveniently. On one hand, control method based on fuzzy theory, namely fuzzy control, achieves great breakthrough both in research and in practical field, since the fuzzy control is independent with the mathematic model of the target object and adverts the trouble of modeling.

On the other hand, the determination of its member functions and control principle depends on people's experience and knowledge, so the fuzzy control lacks the ability of self-learning and adapting. That is to say, in the kernel of fuzzy control, the control principle "if - then" described by language, the condition part (if part) and conclusion part (then part) are all dependent on expert's experience and knowledge. This is the drawback of fuzzy control. But the artificial neural network has learning, association, fault tolerance, parallel processing, and just makes up the weakness of fuzzy control. Thus, the combination of artificial neural network and fuzzy control inevitably becomes the trend. Adaptive fuzzy system, a combination of the artificial neural network and fuzzy control, is presented below.

An adaptive fuzzy system is a fuzzy logic system with learning algorithm. The fuzzy logic system is made up of a set of "if - then" rules, and the learning algorithm is to adjust the parameters of fuzzy logic system according to data. The adaptive fuzzy logic system is known as a fuzzy logic system that can generate fuzzy rules by learning.

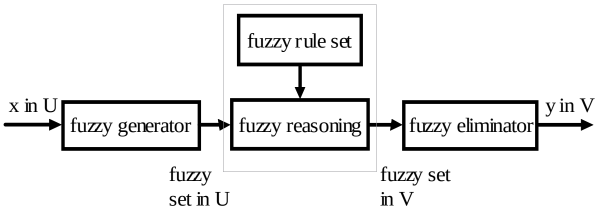



Fig. 1 basic diagram for fuzzy logic system with fuzzy generator and fuzzy eliminator

## 3 Back propagation Learning Algorithm of fuzzy-neural network

Generally, fuzzy system is made up of 4 parts: fuzzy rule set, fuzzy reasoning, fuzzy generator and fuzzy eliminator as shown in Fig. 1. And different parts have different forms.

### 3.1 Fuzzy rule set

A fuzzy system is a set of if-then fuzzy rules:

R: if $x_1$ is $F_1$, and $\cdots$, and $x_n$ is $F_n$, then y is G (1)

Where, $F_i$ and G is fuzzy set of $U_i \subset R$ and $V \subset R$ respectively. And $x = (x_1, \cdots, x_n)^T$ and y both are language variables. Fuzzy logic set is the core of the fuzzy logic system. The function of other three parts of fuzzy logic system is to use these fuzzy rules to solve actual problems.

### 3.2 Fuzzy reasoning

According to fuzzy logic rules, fuzzy reasoning turns the fuzzy if-then rules into some mapping, i.e. maps the fuzzy set in $U = U_1 \times \cdots \times U_n$ to the fuzzy set in V. Multiplication rule is used here.

$$\mu_{F_1^l \times \cdots \times F_n^l}(x) = \mu_{F_1^l}(x_1) \times \cdots \times \mu_{F_n^l}(x_n) \quad (2)$$

Where, $\mu_{F_i^l}(x_i)$ is the member function of $x_i$ in fuzzy set $F_i^l$.

### 3.3 Fuzzy generator

The function of fuzzy generator is to map a certain point $x=(x_1, \cdots, x_n)^T \in U$ to a fuzzy set A' in U. Mapping method at least have two listed below: monotonic fuzzy generator and multi-value fuzzy generator. Monotonic fuzzy generator is used here.

### 3.4 Fuzzy eliminator

Fuzzy eliminator is used to map a fuzzy set in V to a certain point $y \in V$. Central mean fuzzy eliminator is defined below:

$$y = \frac{\sum_{l=1}^{M} \bar{y}^l [\mu_{B^l}(\bar{y}^l)]}{\sum_{l=1}^{M} [\mu_{B^l}(\bar{y}^l)]} \tag{3}$$

Where, $\bar{y}^l$ is the center of the fuzzy set $G^l$.

The form of function $\mu_{F_i^l}(x_i)$ should be chosen first, when choose learning algorithms for a fuzzy system. Generally, Gaussian function listed below can be used:

$$\mu_{F_i^l}(x_i) = a_i^l \exp[-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2] \tag{4}$$

Where, $a_i^l$, $x_i^l$ and $\sigma_i^l$ are parameters which can be adjusted.

In all, the fuzzy logic system discussed in this article consists of central mean fuzzy eliminator, multiplication reasoning rule, Monotonic fuzzy generator and Gaussian member function, and has the form shown below:

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left[ \prod_{i=1}^{n} a_i^l \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2) \right]}{\sum_{l=1}^{M} \left[ \prod_{i=1}^{n} a_i^l \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2) \right]} \tag{5}$$

So, the fuzzy logic system described above can be expressed by feedforward network of three layers, as shown in Fig 2, then the back propagation Learning Algorithm can be used to adjust the parameter, such as $\bar{y}^l$, $\bar{x}_i^l$, $\sigma_i^l$, in the network.

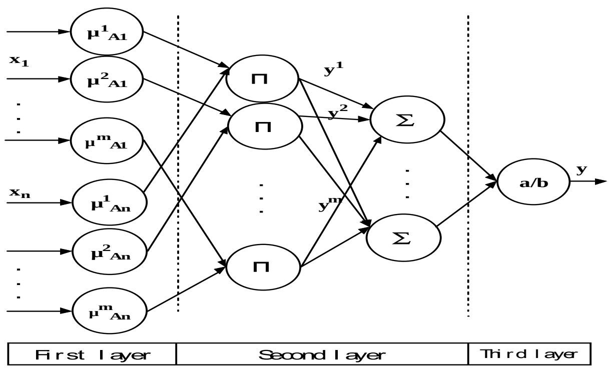



Fig. 2 the network expression of fuzzy system

Where, $f$=a/b , $a = \sum_{l=1}^{m} \bar{y}^l z^l$ , $b = \sum_{l=1}^{m} z^l$ , and

$$z^l = \prod_{i=1}^{n} \exp[-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2]$$

The adjusting of parameter is shown below:

Assume there are a set of input and output data $(x^p, y^p)$, p=1,…,Q ($x^p \in U \subseteq R^n$, $y^p \in R$). Back propagation learning algorithm is used to adjust the parameters of the network, and minimize the mean square error $E_T$.

$$E = \frac{1}{2}\left[f(x^p) - y^p\right]^2 \tag{6}$$

$$\min E_T = \frac{1}{Q}\sum_{p=1}^{Q} E = \frac{1}{Q}\sum_{p=1}^{Q}\frac{1}{2}\left[f(x^p) - y^p\right]^2 \tag{7}$$

If there are m fuzzy rules and n fuzzy sub-set, $\bar{y}^l$ can be adjust by the equation below:

$$\bar{y}^l(k+1) = \bar{y}^l(k) - \eta \frac{\partial E}{\partial \bar{y}^l}(k) \tag{8}$$

Where, $l$=1,2,…,m; η is learning factor.

As shown in Fig. 2, the network output $f$ (and E) only depend on $\bar{y}^l$ via $a$. The equation below can be:

$$\frac{\partial E}{\partial \bar{y}^l} = (f - y^p)\frac{\partial f}{\partial a}\frac{\partial a}{\partial \bar{y}^l} = (f - y^p)\frac{1}{b}z^l \tag{9}$$

Thus, the learning algorithm about $\bar{y}^l$ will be:

$$\bar{y}^l(k+1) = \bar{y}^l(k) - \eta \frac{f - y^p}{b} z^l \tag{10}$$

Where, $l$=1,2,…, m; k=0,1,2,… .

As well, $\bar{x}_i^l$ can be adjusted by the equation below:

$$\bar{x}_i^l(k+1) = \bar{x}_i^l(k) - \eta \frac{\partial E}{\partial \bar{x}_i^l}(k) \tag{11}$$

And $f$ (and E) is depending on $\bar{x}_i^l$ only in $z^l$, so according to chain rule, equation below can be:

$$\frac{\partial E}{\partial \bar{x}_i^l} = (f - y^p)\frac{\partial f}{\partial z^l}\frac{\partial z^l}{\partial \bar{x}_i^l} = (f - y^p)\frac{\bar{y}^l - f}{b} z^l \frac{2(x_i^p - \bar{x}_i^l)}{\sigma_i^{l2}} \tag{12}$$

When substitute the equation into the equation (11), the learning algorithm of $\bar{x}_i^l$ can be reached.

As well, learning algorithm of $\sigma_i^l$ can be got below:

$$\sigma_i^l(k+1) = \sigma_i^l(k) - \eta \frac{\partial E}{\partial \sigma_i^l}(k) = \sigma_i^l(k) - \eta \frac{f - y^p}{b}(\bar{y}^l - f) z^l \frac{2(x_i^p - \bar{x}_i^l(k))^2}{\sigma_i^{l3}(k)} \tag{13}$$

Where, i=1,2,…,n; l=1,2,…,m; k=0,1,2,… .

### 3.5 The initialization of fuzzy neural network

Parameters of the fuzzy neural network above have physical meaning: The parameters $\bar{x}_i^l$ and $\sigma_i^l$ are corresponding to the center and the width of $x_i$ in fuzzy set $l$. This is also the main factor of fuzzy neural network superior to pure neural network. As we all know, the neural network is generally initialized by generating data randomly. However, in fuzzy neural network, network parameters can be initialized by input and output data, according to the parameter's physical meaning.

To a fuzzy neural network with m fuzzy rules, first, m data couples ( $x^j, y_d^j$), (j=1,2,…,m) are used to initialized the parameters, i.e.

$$\begin{aligned} \overline{x}_i^j &= x_i^j \\ \sigma_i^j &= \frac{1}{2m}[\max(x_i^j) - \min(x_i^j)] \\ \overline{y}^j &= y_i^j \end{aligned} \tag{14}$$

Where, i=1,…,n; j=1,…,m.

Then, the learning steps of fuzzy neural network are summarized below:

1. Initialize the fuzzy neural network: set m fuzzy rules, error limit $\varepsilon$ and learning time N etc;
2. Read in samples $\{X(t), Y(t)\}$ $t = 1,2,\cdots,T$, and initialize the network parameter according equation (9);
3. Adjust network parameter according formula (10), (11) and (13);
4. Calculate output error and total error

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{n} e_k^2(t) \\ E_T &= \frac{1}{T}\sum_{t=1}^{T} E \end{aligned} \tag{15}$$

5. If both $E$ and $E_T$ are less than the error limit $\varepsilon$, or the learn time reaches the given limit, save and exit. Otherwise, continues from step 3.

## 4 FNN in excitation system modeling

In this article, first, an excitation system model of real system is used to generate necessary data for modeling. Then, the FNN is used to modeling. The input and output of excitation system: the changing of terminal voltage of the generator ⊿V(t) and Exciting potential $E_{fd}$(t) and the delays are used to describe the dynamic characteristics of the excitation system. The transfer function of the excitation systems adopted is shows in Fig. 3. Correspondingly, the parameters are: $K_s$ =1. 886, $K_A$ =26. 31, $K_E$ =2. 649, $K_F$ =0. 688, $E_{max}$ =4. 0, $E_{min}$ =0. 0, $T_s$ =0. 053, $T_1$ =3. 124, $T_2$ =0. 386, $T_3$ =4. 385, $T_4$ =0. 072, $T_E$ =0. 466, $T_F$ =0. 398.

According to the space reconstruction theory of Takens, multi-layer feedback FNN is used to simulate power system dynamic characteristics. The equation of the model can be described below:

$$y(t) = f(y(t-1), y(t-2), \cdots, y(t-n), U(t), U(t-1), \cdots, U(t-m)) \tag{16}$$

Where n is the input order, m is the output order. Conceptual diagram is shown as Fig. 4, the dotted line part is FNN.

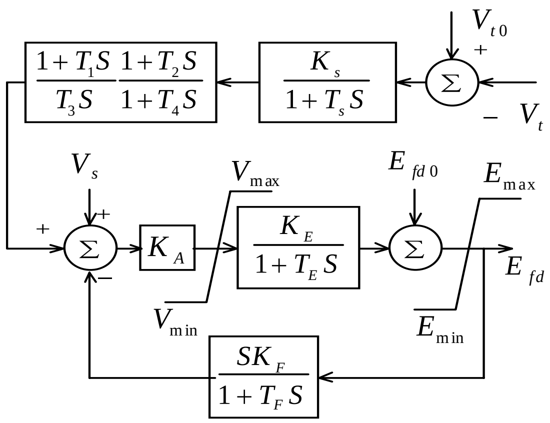



Fig.3 Block diagram for excitation system

The adopted excitation system is a Five-Order SISO system. The model can be expressed as:

$$E_{fd}(t) = f(\Delta V(t), \Delta V(t-1), \cdots; \Delta V(t-5), E_{fd}(t-1), E_{fd}(t-2), \cdots; E_{fd}(t-5)) \tag{17}$$

The corresponding FNN has 11 inputs and 1 output.

In order to training and check the performance of the FNN, first, three-phase short-circuit fault of a real transmission line is simulated. A fault occurs at 0.06s, three phases trip at 0.1s, failed to re-close in 1s, and trip again. The terminal voltage change curve of the generator is shown as Fig. 5(a). The output of the corresponding real excitation system shows as solid line in Fig. 5(b). The output of the corresponding FNN modeled excitation system is illustrated as dotted line in Fig. 5 (b).

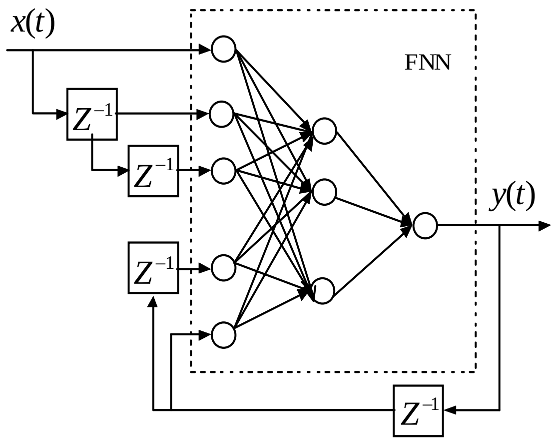
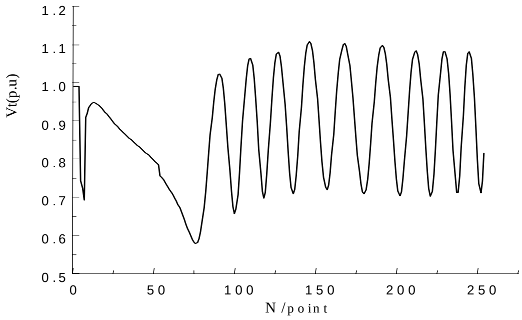



Fig. 4 Schematic diagram of FNN with time delays

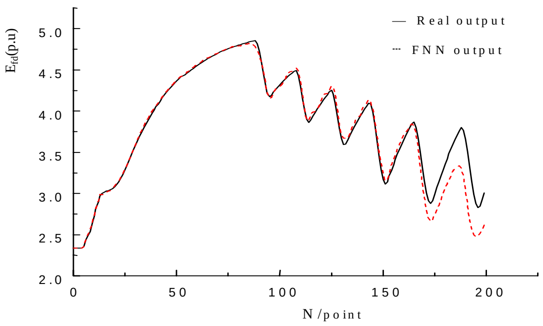
In order to examine the validity of the FNN model of excitation system, we change the fault types:

a) Single-phase to ground fault takes place at 0.06s，cuts off at 0.1s, single-phase re-closes at 0.7s successfully;
b) Two-phase short-circuit fault takes place at 0.06s, three phase trip at 0.12s, and re-close at 0.7s successfully.

Solid curves are demonstrated in Fig. 6 as outputs of the practical excitation system. The dotted lines are the outputs of FNN. It is evident that FNN model can simulate real excitation system very well.




(a) Terminal Voltage of Generator




(b) The curves of model and real system output

Fig.5 Curves of real system and model output under three phase to ground fault

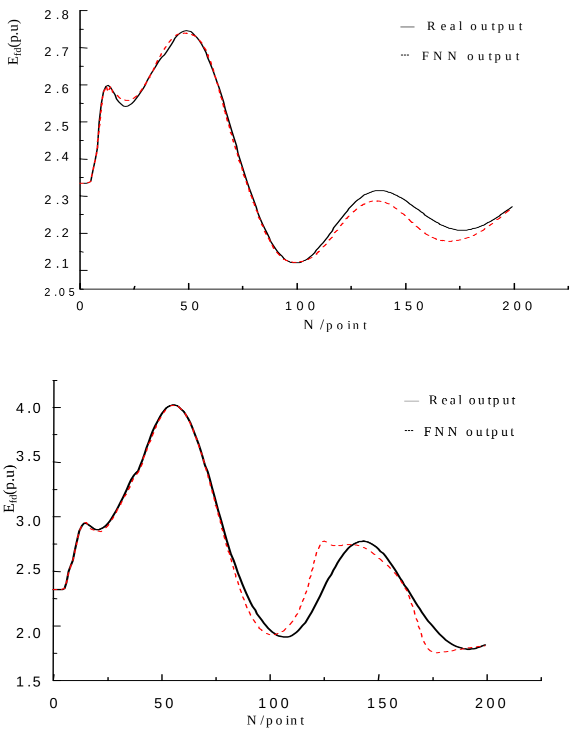



Fig. 6 Curves of real system and model output under different faults

## 5 Conclusions

The method using FNN to build excitation model is introduced in this paper. Combining the fuzzy theory and the neural network and uses of their advantages makes a kind of FNN. First, the learning algorithm of FNN is developed step by step. Then, FNN is utilized to build real generator's excitation system model. The simulation results illustrate that the FNN model can simulate the factual excitation system accurately.

*References*

[1] ShanDe. Shen, *Power Systems Identification. BeiJing*, Prsss of Tsinghua University，1993.

[2] ShanDe. SHEN, JianMin. Jiang, ShouZhen. Zhu, An on-line identification approach for excitation system parameter model of large generator, *Automation of Electric Power Systems*, Vol.15, No.1, 1991, pp.33-37.

[3] ShouZhen. Zhu, ShanDe. Shen, HouLian. Chen, et al. The direct parameter identification approach for continuous time model of power system, *Proc of IEEE TENCON'93, Beijing, China*, 1993, pp.179-182.

[4] ChingTien. Lion, YiShyong. Chou, Piecewise Linear Polynomial Function and Application to Analysis and Parameter Identification, *International Journal of System Science*, 1987

[5] Qian. AI, ShanDe. Shen, ShouZhen. Zhu, Transient stability study using artificial neural networks models of generation unit. *Journal of Tsinghua University Science and Technology*, Vol. 39, No.5, 1999, pp.43-46.

[6] A. Zazo, J. L. Zamora, L. Rouco, F. L. Pagola, Identification of excitation systems from time response tests, *Proc. Contr. 1994, Inst. Elect. Eng. Conf. Publication 389*, 1994, pp. 839-843.

[7] T. Y. Guo, C. S. Liu, C. T. Huang, Identification of excitation system model parameters via finalization field tests, *Proc. Inst. Elect. Eng. 2nd Int. Conf. Advances Power Syst. Contr., Oper. Manage.*, 1993, pp. 833-838.

[8] C. M. Liaw, T. S. Liu, A. H. Liu, Y. T. Chen, C. J. Lin, Parameter estimation of excitation systems from sampled data, *IEEE Trans. Automat. Contr.*, Vol.37, 1992, pp.663-666.

[9] C. S. Liu, Y. Y. Hsu, L. H. Jeng, C. J. Lin, C. T. Huang, A. H. Liu, T. H. Li, Identification of exciter constants using a coherence function based weighted least squares approach, *IEEE Trans. Energy Conversion*, Vol.8, 1993, pp. 460-467.

[10] S. Rangnekar, R. B. Ghodgoakar, K. K. Patel, A study of the performance of detailed and

simplified models of IEEE Standard DC1A excitation control system, *Proc. 8th Eur. Conf. Power Electron. Applicat.*, 1999, pp.1-5.

[11] R. Bhaskar, M. L. Crow, K. Erickson, K. Shah, R. Bhaskar, Excitation system nonlinear parameter estimation for power system stability studies: Feasibility study, *Proc. 30th North Amer. Power Symp.*, 1998, pp. 453458.

[12] C. R. Mummert, Excitation system limiter models for use in system stability studies, *Proc. IEEE Power Eng. Soc. Winter Meeting,* Vol.1, 1999, pp.187-192.

[13] M. Rasouli, M. Karrari, Nonlinear Identification of a Brushless Excitation System Via Field Tests, *IEEE Transactions on energy conversion*, Vol.19, No.4, 2004.

[14] Qian. Ai, ShanDe. Shen, Shouzhen. Zhu, et al. Application of neural networks for power generator and excitation system modeling. *The 4th APSCOM Conference, Hong Kong*, 1997, pp.151-155.

[15] Qian. Ai, Chen. Chen, Aggarwal. A novel approach to generator stator full winding protection against faults using fuzzy neural networks. *Proceedings of CSEE*, 2003, Vol.23, No.10, pp.130-135.