Neural Network-Based Self-Organizing Fuzzy Controller for Transient Stability of Multimachine Power Systems

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Abstract-- An efficient self-organizing neural fuzzy controller (SONFC) is designed to improve the transient stability of multimachine power systems. First, an artificial neural network (ANN)-based model is introduced for fuzzy logic control. The characteristic rules and their membership functions of fuzzy systems are represented as the processing nodes in the ANN model. With the excellent learning capability inherent in the ANN, the traditional heuristic fuzzy control rules and input/output fuzzy membership functions can be optimally tuned from training examples by the backpropagation learning algorithm. Considerable rule-matching times of the inference engine in the traditional fuzzy system can be saved. To illustrate the performance and usefulness of the SONFC, comparative studies with a bang-bang controller are performed on the 34-generator Taipower system with rather encouraging results.

Keywords: Self-organizing neural fuzzy controller, transient stability control, bang-bang controller.

1. INTRODUCTION

Transient stability is one of the most important factors that should be studied in power system planning, operation, and extension. It is mainly concerned with a system's ability to remain in synchronization following a sudden and major disturbance such as a generator trip or line switching due to faults, or abrupt changes in load or generation powers. Modern power systems have placed increased emphasis on the development of effective control schemes to enhance transient stability. In the past, numerous investigations have been conducted to improve the transient stability of power systems, ranging from theoretical studies to advanced control devices [1-6]. Means for transient stability control are usually of the nonlinear discontinuous type, such as generation dropping [1], dynamic braking [2-4], load shedding [5], etc. The conventional control approach most often requires a precise mathematical model of the controlled systems. However, for power systems in practice, since there exist parameter uncertainty problems in the plant modeling and large variations in the environmental conditions, the

conventional controllers often perform satisfactorily over a rather limited range of operation.

Recently, artificial neural networks and fuzzy systems have been successfully applied to various control fields with rather promising results [7-10]. The salient feature of these techniques that distinguish them from the traditional control approaches is that they provide a model-free description of the control systems. A fuzzy logic controller is a special type of knowledge-based controller, and it operates in a linguistic, rule-based manner. Its performance depends strongly on the control rules developed. Generally, designing a fuzzy control system always requires much trial-and-error effort in determining the fuzzy rules and the associated membership functions, thus making the design a time-consuming task. On the other hand, artificial neural networks that mimic the function of the brain in a simplified manner can be considered another candidate for intelligent control systems. The neural systems use a large number of numeric input-output samples to produce the mapping rules through learning. Learning from examples and dynamic adaptation are two major features of neural networks. However, the mapping rules in the neural network are not visible and are difficult to understand.

In this paper, a self-organizing neural fuzzy controller (SONFC) is designed to enhance the transient stability of power systems. By the term self-organizing controller [11-13], it is meant that the controller can create fuzzy control rules to control a plant by learning. First, the neural network-based model for fuzzy logic control [10] is introduced. This model integrates the ideas of the fuzzy logic controller and neural network structure into an intelligent control system. In this ANN structure, the input and output nodes represent the input speed/acceleration states, and output control signal, respectively, and the nodes in the hidden layers function as membership functions and fuzzy rules. Initially, we set up the controller with a set of coarse fuzzy control rules that are based on a simple engineering knowledge concerning the controlled machine. Then, the fuzzy rules and input/output membership functions of the controller can be optimally tuned or adapted by the backpropagation learning algorithm according to the control credit that is evaluated by a performance index table. With the evolving symbiosis of ANN and fuzzy logic theory, the presented controller is shown to be robust, adaptive and capable of learning. In addition, it also has the advantages of efficient hardware usage, easy generalization, and fault tolerance [10,14]. To demonstrate the effectiveness of the proposed controller, comparative studies with a bang-bang controller [3] are conducted on the 34-generator Taipower system.

2. PROBLEM FORMULATION

2.1 Power System Model

The system of equations that govern the power system dynamics of transient stability control are first described. An n-machine power system model including the effects of field flux decay, damper windings, the automatic voltage regulator (AVR), and the exciter concerning a center of inertia (COI) rotating reference frame is given below [15]:

$$\dot{\theta}_i = \tilde{\omega}_i \tag{1}$$

$$M_i \dot{\tilde{\omega}}_i = P_{mi} - P_{ei} - \frac{M_i}{M_T} P_{COI} - U_i \tag{2}$$

$$T'_{doi}\dot{E}'_{qi} = -E'_{qi} + (X_{di} - X'_{di})I_{di} + E_{fdi} \tag{3}$$

$$T'_{qoi}\dot{E}'_{di} = -E'_{di} - (X_{qi} - X'_{qi})I_{qi} \tag{4}$$

$$T_{ai}\dot{V}_{ri} = -V_{ri} + K_{ai}V_{ei} \tag{5}$$

$$T_{ei}\dot{E}_{fdi} = -(S_{ei} + K_{ei})E_{fdi} + V_{rli} \tag{6}$$

$$T_{fi}\dot{V}_{fi} = -V_{fi} + (K_{fi}/T_{ei})[V_{rli} - (S_{ei} + K_{ei})E_{fdi}] \tag{7}$$

where
subscript "i" : relating to the i-th generator,
E'_d, E'_q : d- and q-axis stator emfs,
E_{fd} : field applied voltage,
I_d, I_q : d- and q-axis components of armature current,
K_a : regulator gain,
K_e : exciter constant related to self-excited field,
K_f : regulator stabilizing circuit gain,
M : inertia constant,
P_m : mechanical power input,
P_e : real power output,
P_{COI} : COI accelerating power,
S_e : exciter saturation function,
T'_{do}, T'_{qo} : open circuit d- and q-axis time constants,
T_a : regulator amplifier time constant,
T_e : exciter time constant,
T_f : regulator stabilizing circuit time constant,
V_r : regulator output voltage,
V_f : output voltage of regulator stabilizing circuit,
X_d, X_q : d- and q-axis synchronous reactances,
X'_d, X'_q : d- and q-axis transient reactances,
θ_i : rotor angle of generator i with respect to the COI,
$\tilde{\omega}_i$: rotor speed of generator i with respect to the COI,
ω_o : center of system speed.

In (2), the term U_i represents additive real power control for the i-th generator, which is determined by the controller depending on the state of the generator.

2.2 Transient Stability Control

Following a major disturbance in a power system, the system may lose synchronization if proper control action is not taken. The rotor trajectories of the generators may fall apart into different coherent groups during the transient period, and the unstable generators tend to separate from the rest of the system. Therefore, the ultimate goal of transient stability control is to quickly transfer the unstable generator from its initial state to the post-fault equilibrium state under admissible control limits. The rotor speed of each generator must eventually follow the overall system to maintain stability. In other words, for a transient stable system, the target steady state of each generator after a disturbance must be prescribed by:

$$\begin{cases} \tilde{\omega}_i(t_f) = 0 \\ \dot{\tilde{\omega}}_i(t_f) = 0 \end{cases} \quad \text{for } i=1,2,...,n \tag{8}$$

where $\tilde{\omega}_i(t_f)$ and $\dot{\tilde{\omega}}_i(t_f)$ denote the final states of rotor speed and acceleration of generator i, respectively. In a physical system, the control power $U_i(t)$ is usually constrained by:

$$U_{max} \le U_i(t) \le U_{min} \tag{9}$$

In practical applications, control power $U_i(t)$ can be implemented by a braking resistor [2,4] to consume transient surplus power, a fast valve to shed the mechanical power, or it may be implemented by a superconducting magnetic energy storage (SMES) unit [16].

3. THE SELF-ORGANIZING NEURAL FUZZY CONTROLLER

The major difficulty in the design of a fuzzy controller arises from the determination of fuzzy rules and input/output membership functions. Most approaches are based on studying a human-operated system or existing controller, and the membership functions and/or fuzzy rules are then modified when the design fails in the test. Therefore, it always requires a lot of trial-and error effort, thus making the design a time-consuming task. The recent direction of research is to design self-organizing fuzzy logic systems that have capability to create the control strategy by learning [12,13]. Basically, we will follow the ideas of the traditional self-organizing fuzzy logic system with significant modification. The structure of the proposed SONFC is a combination of both the neural network and fuzzy logic techniques. The fuzzy method proves a structural control framework to express the input-output relationship of the neural network, and the neural network can embed the salient features of computation power and learning capability into the fuzzy controller.

3.1 Overall Structure

The schematic structure of the proposed SONFC system is shown in Fig. 1. It consists of: (i) a performance index (PI) table as an instructor for learning the control strategy, (ii) a neural fuzzy controller (NFC) to control the plant, (iii) three scaling factors GS, GA, and GU to adjust the input/output values of the controller into proper ranges, which are set at 1,

0.01, and 1, respectively, and (iv) a limiter to constrain the control action within admissible limits. Typical input variables for transient stability control, for example, are the rotor angle, angular speed, angular acceleration, etc. Since no prior information regarding the rotor angle at postfault equilibrium is known, the shaft speed and acceleration of the generator at each sampled time are employed as the input variables of the proposed controller.

The implementation of the proposed control system mainly comprises two phases: the learning phase and operation phase. In the learning phase, the purpose is to tune the parameters of the NFC to achieve good control performance. The performance of the controller in each learning step is evaluated by a performance index (PI) table, from which a credit is assigned according to the deviation of the control response from the desired response. Then the membership functions and fuzzy rules of the fuzzy controller could be adapted on-line by the credit value using a supervised learning mechanism. When the performance of the NFC is reduced to a preset value, the learning process terminates. In the operation phase, the trained NFC is directly used to control the machine.
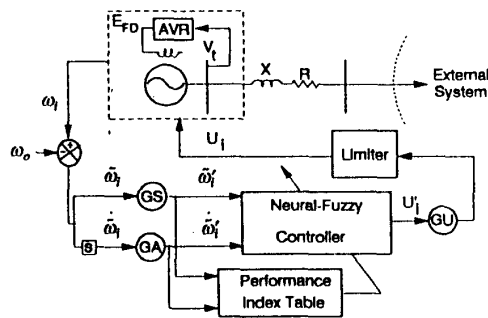

Fig. 1. Schematic structure of the proposed control system.

3.2 Topology of the neural fuzzy controller

The proposed NFC is a multilayer neural network-based fuzzy controller. Its topology is shown in Fig. 2. The system has a total of five layers. Since two input variables and one output variable are employed in the present work, there are two nodes in layer 1 and one node in layer 5. Nodes in layer 1 are input nodes that directly transmit input signals to the next layer. Layer 5 is the output layer. Nodes in layers 2 and 4 are term nodes that act as membership functions to express the input/output fuzzy linguistic variables. A bell-shaped function, as shown in Fig. 3, is adopted to represent the membership function, in which the mean value m and the variance σ will be adapted through the learning process. The fuzzy sets defined for the input/output variables are positive big (PB), positive medium (PM), positive small (PS), zero (ZE), negative small (NS), negative medium (NM), and negative big (NB), which are numbered in descending order in the term nodes. Hence, 14 nodes and 7 nodes are included in layers 2 and 4, respectively, to indicate the input/output linguistic variables. Each node of layer 3 is a rule node that represents one fuzzy control rule. In total, there are 49 nodes in layer 3 to form a fuzzy rule base for two linguistic input
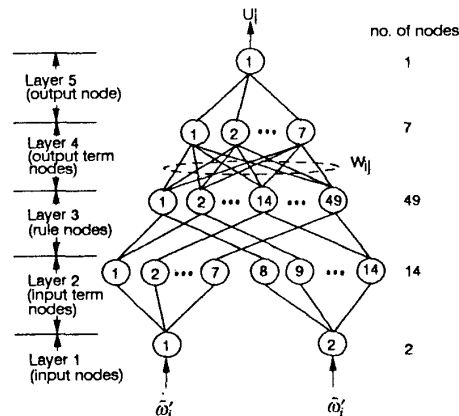

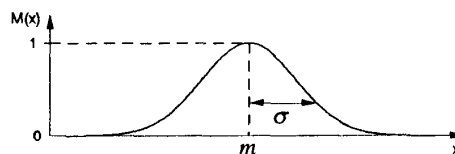Fig. 2. Topology of the neural fuzzy controller.

Fig. 3. Curve of bell shaped function.

variables. Layer 3 links and layer 4 links define the preconditions and the consequences of the rule nodes, respectively. For each rule node, there are two fixed links from the input term nodes. Layer 4 links encircled in dotted line will be adjusted in response to varying control situations. By contrast, the links of layers 2 and 5 remain fixed between the input/output nodes and their corresponding term nodes. In short, the proposed SONFC can adjust the fuzzy control rules and their membership functions by modifying layer 4 links and the parameters that represent the bell-shaped membership functions for each node in layers 2 and 4. In the following, special emphasis is placed on how to adapt these links and parameters through learning. As a convenience in notation, the following symbols are used to describe the functions of the nodes in each of the five layers:

net_i^L: the net input value to the i-th node in layer L,

O_i^L : the output value of the i-th node in layer L,

m_i^L, σ_i^L: the mean and variance of the bell-shaped activation function of the i-th node in layer L,

W_{ij} : the link that connects the output of the j-th node in layer 3 with the input to the i-th node in layer 4.

Layer 1:
The nodes of this layer just directly transmit input signals to the next layer. That is

$$O_1^J = \dot{\omega}_i' \ , \ O_2^J = \ddot{\omega}_i' \tag{10}$$

Layer 2:
The nodes of this layer act as membership functions to express the terms of input linguistic variables. For a bell-

shaped function, they are:

$$net_i^2 = \begin{cases} O_1^1 & \text{for } i = 1,2,...,7 \\ O_2^2 & \text{for } i = 8,9,...,14 \end{cases} \tag{11}$$

$$O_i^2 = e^{-\left(\frac{net_i^2 - m_i^2}{\sigma_i^2}\right)^2} \quad \text{for } i = 1,2,...,14 \tag{12}$$

Note that layer 2 links are all set to unity.

Layer 3:

The links in this layer are used to perform precondition matching of fuzzy rules. Thus, each node has two input values from layer 2. The correlation-minimum inference procedure [10] is utilized here to determine the firing strengths of each rule. The output of nodes in this layer is determined by the fuzzy AND operation. Hence, the functions of the layer are given below:

$$net_i^3 = min(O_j^2, O_k^2), \quad i = 7(7-j)+(k-7)$$
$$\text{for } j = 1,2,...,7 \; ; k = 8,9,...,14 \tag{13}$$

$$O_i^3 = net_i^3 \quad \text{for } i = 1,2,...,49 \tag{14}$$

The link weights in this layer are also set to unity.

Layer 4:

Each node of this layer performs the fuzzy OR operation to integrate the fired rules leading to the same output linguistic variable. Based on extensive simulations and an engineering knowledge concerning the dynamic nature of the generator, 15 heuristic fuzzy rules are designed, as shown in Fig. 4. For example, fuzzy rule 7 indicates that if both the speed and acceleration of the machine are "positive big ", then a "positive big" deceleration control effort must be exerted by increasing U_i in (2). Also, fuzzy rule 25 means that if the generator is close to the equilibrium state, then no control action is taken by issuing a "ZE" signal. Hence, the initial link weights can be set according to the initial fuzzy rules. Taking rule 4 for example, only the weight that connects rule node 4 to the output term node "PB" is set at unity. Except for the weights predetermined from the initial rules, the rest of layer 4 links are all set to zero initially. As will be demonstrated in Sec. 4.2, starting with the good initial fuzzy control rules will provide much faster convergence in the learning phase. The functions of this layer are expressed as follows:

	Speed						
	NB	NM	NS	ZE	PS	PM	PB
PB	1	2	3	4 PB	5	6	7 PB
PM				PM			
PS				PS			
ZE	NB	NM	NS	25 ZE	PS	PM	PB
NS				NS			
NM				NM			
NB	NB			NB			49

Fig. 4. Initial fuzzy rule matrix of the proposed SONFC.

$$net_i^4 = \sum_{j=1}^{49} W_{ij} O_j^3 \tag{15}$$

$$O_i^4 = min(1, net_i^4) \quad \text{for } i = 1,2,...,7 \tag{16}$$

The link weight W_{ij} in this layer expresses the probability of the j-th rule with the i-th output linguistic variable.

Layer 5:

The node in this layer computes the control signal of the NFC. The output node together with layer 5 links act as a defuzzifier. The defuzzification aims at producing a nonfuzzy control action that best represents the possibility distribution of an inferred fuzzy control action. The center of area defuzzification scheme [17], in which the fuzzy centroid constitutes the controller output signal, can be simulated by

$$net_j^5 = \sum_{j=1}^{7} m_j^4 \sigma_j^4 O_j^4 \tag{17}$$

$$O_j^5 = \frac{net_j^5}{\sum_{j=1}^{7} \sigma_j^4 O_j^4} \tag{18}$$

where m_j^4 and σ_j^4 can be as viewed the center and width of the membership function. Hence the link weight in this layer is $m_j^4 \sigma_j^4$.

3.3 Self-Organizing Learning Algorithm

The self-organizing controller should be able to evaluate its performance in order to adapt the controller strategy by modification of the fuzzy rules and their membership functions. For this purpose, a performance index (PI) table (meta rules) and its related lookup table, as shown in Fig. 5, are used to assess the status of the controlled plant, and take proper control actions accordingly to improve performance. The linguistic rules of the table can be read as:

IF $\dot{\omega}_i$ = PB and $\ddot{\omega}_i$ = NB, THEN PI = ZE;
ELSE......

Note that the meta rules bear no relationship to the controlled plant; they are based on the control objective. The zero elements in the rule table are in the desired response regions, and the other regions indicate where the corrective control action needs to be taken. The output values of the PI table can be taken from its lookup table by traditional fuzzy logic theory or implemented by a trained neural network. The appropriate control action of the NFC could be modified by the credit value in each learning step, which measures the deviation of the actual response from the desired response. For the k-th learning step, the required change $\Delta U(k)$ of the NFC can be defined as

$$\Delta U(k) = \zeta \times PI\left[\dot{\omega}(k), \ddot{\omega}(k)\right] \tag{19}$$

where $PI[.]$ represents lookup values in the PI table, and ζ

Speed

Acceleration	NB	NM	NS	ZE	PS	PM	PB
PB	ZE	PS	PS	PM	PM	PB	PB
PM	NS	ZE	PS	PS	PM	PB	PB
PS	NS	NS	ZE	PS	PS	PM	PM
ZE	NM	NS	NS	ZE	PS	PS	PM
NS	NM	NM	NS	NS	ZE	PS	PS
NM	NB	NB	NM	NS	NS	ZE	PS
NB	NB	NB	NM	NM	NS	NS	ZE

(a)

Speed

Acceleration	-0.6	-0.3	-0.3	0.	0.3	0.3	0.6
3.	0.	0.3	0.3	0.6	0.6	1.	1.
2.	-0.3	0.	0.3	0.3	0.6	1.	1.
1.	-0.3	-0.3	0.	0.3	0.3	0.6	0.6
0.	-0.6	-0.3	-0.3	0.	0.3	0.3	0.6
-1.	-0.6	-0.6	-0.3	-0.3	0.	0.3	0.3
-2.	-1.	-1.	-0.6	-0.3	-0.3	0.	0.3
-3.	-1.	-1.	-0.6	-0.6	-0.3	-0.3	0.

(b)

Fig. 5. Performance index table, (a) linguistic definition, (b) look up table.

is a learning constant, which is set at 0.005 in this study. The desired control action $U^d(k)$ of the NFC can be obtained by

$$U^d(k) = U(k) + \Delta U(k) \qquad (20)$$

Then the optimal membership functions and fuzzy rules can be found by gradient-descent search techniques. Define the error function or energy function of the control system as

$$E = \frac{1}{2}(U^d(k) - U(k))^2 \qquad (21)$$

It is observed from (19) to (21) that minimization of the error function E corresponds to guiding the controlled plant into the desired response regions, where the error function reaches a local minimum. In the following, the generalized delta learning rule [14] is applied to solve the training task of the NFC to achieve the energy minimization. In standard notation, the generalized delta learning rule can be expressed as

$$\chi_i(k+1) = \chi_i(k) + \eta(-\frac{\partial E}{\partial \chi_i}) + \lambda \Delta \chi_i(k) \qquad (22)$$

where x_i is the parameter to be updated, and η and λ are the learning rate and the gain of the momentum term, which are set to 0.2 and 0.8, respectively. The error signal term δ_i^L called delta produced by the i-th neuron in layer L is defined as

$$\delta_i^L(k) = -\frac{\partial E}{\partial net_i^L} \qquad (23)$$

Using (22) and (23), the learning rules of each layer are derived below:

Layer 5:

The error signal of the output node is

$$\delta_1^5 = (U^d(k) - U(k)) \qquad (24)$$

The mean and variance of each output membership function are adapted by

$$m_i^4(k+1) = m_i^4(k) + \eta \delta_1^5 \frac{\sigma_i^4 O_i^4}{\sum\limits_{j=1}^{7} \sigma_j^4 O_j^4} + \lambda \Delta m_i^4(k) \qquad (25)$$

$$\sigma_i^4(k+1) = \sigma_i^4(k) + \eta \delta_1^5$$
$$\frac{m_i^4 O_i^4(\sum\limits_{j=1}^{4} \sigma_j^4 O_j^4) - O_i^4(\sum\limits_{j=1}^{7} m_j^4 \sigma_j^4 O_j^4)}{(\sum\limits_{j=1}^{7} \sigma_j^4 O_j^4)^2} + \lambda \Delta \sigma_i^4(k) \qquad (26)$$

for $i=1,2,...,7$

Layer 4:

The error signal of each node is

$$\delta_i^4 = \delta_1^5 \frac{m_i^4 \sigma_i^4(\sum\limits_{j=1}^{7} \sigma_j^4 O_j^4) - \sigma_i^4(\sum\limits_{j=1}^{7} m_j^4 \sigma_j^4 O_j^4)}{(\sum\limits_{j=1}^{7} \sigma_j^4 O_j^4)^2} \qquad (27)$$

for $i=1,2,...,7$

The weights between the i-th output linguistic variable and j-th rule is updated by

$$W_{ij}(k+1) = W_{ij}(k) + \eta \delta_i^4 O_j^3 + \lambda \Delta W_{ij}(k) \qquad (28)$$

for $i=1,2,...,7; \; j=1,2,...,49$

Layer 3:

No parameter needs to be adjusted in this layer, and only the error signal needs to be computed and propagated backward. That is,

$$\delta_i^3 = \sum\limits_{j=1}^{7} W_{ij} \delta_j^4 \qquad (29)$$

Layer 2:

The mean and variance of the input membership functions can be updated by

$$m_i^2(k+1) = m_i^2(k) - \eta \frac{\partial E}{\partial O_i^2} O_i^2 \frac{2(O_j^1 - m_i^2)}{(\sigma_i^2)^2} + \alpha \Delta m_i^2(k) \qquad (30)$$

$$\sigma_i^2(k+1) = \sigma_i^2(k) - \eta \frac{\partial E}{\partial O_i^2} O_i^2 \frac{2(O_j^1 - m_i^2)^2}{(\sigma_i^2)^3} + \alpha \Delta \sigma_i^2(k) \qquad (31)$$

for $i=1,2,...,14$

It should be noted that the function of layer 1 is only to distribute the input signal, and hence it is not involved in the learning process. The links connecting layers 4 and 3 can be deleted when the weight is negligibly small or equals zero after learning because it means that this rule node has little or no relationship to the output linguistic variable.

4. SIMULATION RESULTS

4.1 Test Condition

The proposed method was tested on the Taipower system, a practical medium-sized system in Taiwan. This system has a longitudinal structure covering a distance of 400 KM from north to south. It consists of 191 buses, 34 generators, and 234 transmission lines. The one-line diagram is shown in Fig. 6. The disturbance is a three-phase short circuit fault with various clearing times. Unless otherwise stated, the controller is installed for only one particular generator with the others uncontrolled in the test cases. The lower limit U_{imin} and upper limit U_{imax} of control power are set between $-0.5P_{im}$ and $0.5P_{im}$, respectively. The delay time involved in the practical implementation is assumed 5 cycles in all simulations to complete the control procedure, including fault detection, telecommunication time, and computation time required for transient stability control [18]. To evaluate the performance of various controllers employed, a quadratic performance index J is defined below:

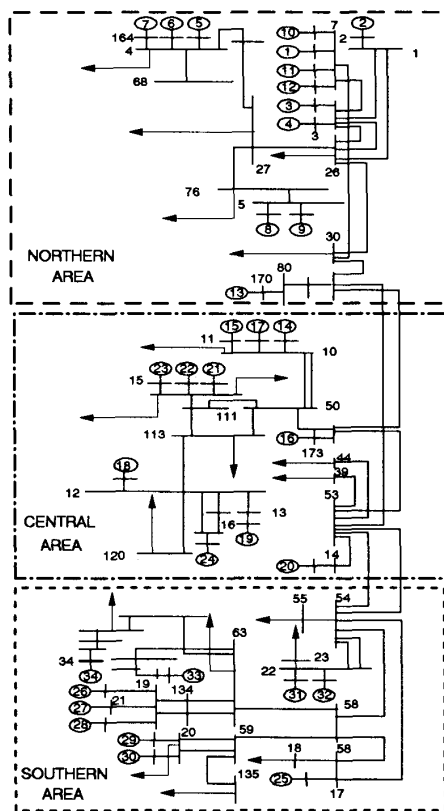$$J = \int_0^{t_f} \tilde{\omega}^2 dt \qquad (32)$$

Fig. 6. One-line diagram of Taiwan power system.

In (32), t_f (= 1.5 s in the study) denotes the final time of the study period. The sampling time of system measurements is set at 0.01 s, thus there has a total of 150 training patterns in each learning process. The rotor speed $\tilde{\omega}_i$, rotor acceleration $\dot{\tilde{\omega}}_i$, and the credit value ΔU issued by the performance index table at each sampling time constitute a training pattern. Digital simulations with a bang-bang controller previously reported in [3] are also conducted for comparison.

4.2 Illustrative Examples

To demonstrate the learning capability and the applicability of the proposed controller, several experimental simulations coded in "FORTRAN" language were run on a VAX-6440 computer.

Example 1 (Learning capability)

To show the learning capability of the proposed SONFC, consider a particular three-phase fault at bus #170 with the fault cleared at 0.15 s. In this case, generator G13 is the most severely disturbed unit. Fig. 7(a) shows the curve of the performance index with respect to the number of epochs. It indicates that only 50 epochs are required to meet the performance criterion. The fast learning time is due to the fact that the priori knowledge of the controller is incorporated into the training. Fig. 7(b) shows the dynamic responses of controlled generator G13 between the first and last run of learning process. Results obtained apparently show that the control performance can be significantly improved through the learning process. Fig. 8 and Fig. 9 show the membership functions of the input and output linguistic variables, before and after the supervised learning process. Obviously, some of the membership functions have been largely modified in appearance. Fig. 10 shows the final fuzzy rules of the SONFC after the supervised learning process. It is obvious that the proposed SONFC has automatically created thirteen new fuzzy rules.
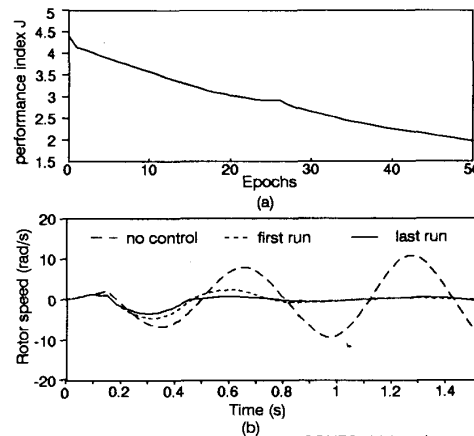

Fig. 7. Learning results of the proposed SONFC: (a) learning pattern, (b) dynamic responses of generator G13.
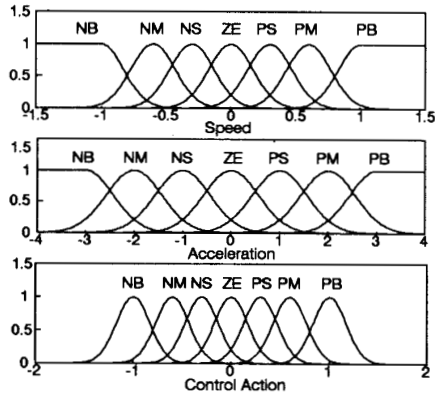
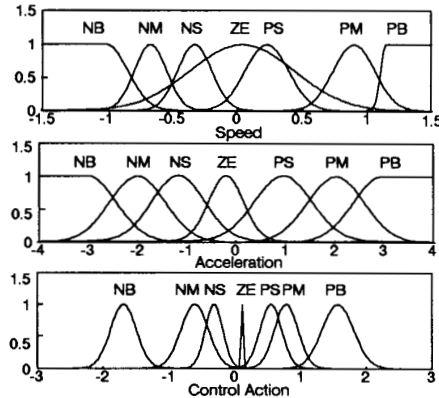Fig. 8. Initial membership functions of the proposed SONFC.

Fig. 9. learned membership functions of the proposed SONFC.

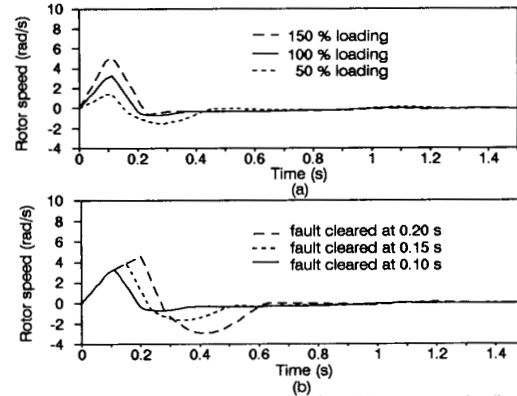Fig. 10. Leared fuzzy rule matrix of the proposed SONFC.

Fig. 11. Dynamic responses of generator G13 with (a) different loading conditions, (b) different fault clearning times.

test including different fault locations and disturbances in the Taipower system has been performed. The controlled generators involved in the simulation studies are of different dynamic characteristics. The partial results of the test are shown in Table I. Note that the proposed SONFC can consistently provide better dynamic performance than the bang-bang controller. For example, consider a three-phase fault occurring at bus #2 with the fault cleared at 0.1s. The sample responses of generator G2 with various controllers are shown in Fig. 12, where curve "NC" is with no control,

TABLE I
COMPARISON OF PERFORMANCE INDEX WITH VARIOUS CONTROLLERS

Fault bus	Clearing time (s)	Controlled generator	Performance index J	
			bang-bang controller	proposed controller
#2	0.1	G2	1.92	1.63
#3	0.1	G4	1.50	0.63
#4	0.1	G7	1.12	0.91
#170	0.1	G13	6.75	1.45
#11	0.1	G15	23.57	11.13
#15	0.1	G23	0.93	0.32
#173	0.1	G16	30.92	11.88
#21	0.2	G27	6.55	5.09
#22	0.2	G31	5.42	5.00
#34	0.2	G34	4.57	2.93

Fig. 12. Dynamic responses of generator G2 with various controllers.

Example 2 (Robustness test)

To test the robustness of the trained SONFC concerning a wide range of operating conditions, consider a three-phase fault at bus #170. The dynamic responses of generator G13 are shown in Fig. 11, where Fig. 11(a) depicts the dynamic responses with the loading varied from 50% to 150% and the fault cleared at 0.1 s, and Fig. 11(b) with the fault cleared at 0.1, 0.15, and 0.2 s and 100% loading. Noticeably, although the SONFC was trained from past control trends, it is still capable of yielding satisfactory transient responses for a large alternation concerning loading and operation conditions. The rotor trajectories can be quickly recovered to the steady state in less than 0.6 s.

Example 3 (Performance Comparison)

To compare the control performance of the proposed SONFC and the bang-bang controller [3], a comprehensive

curve "BBC" is with the bang-bang controller, and curve "SONFC" is with the proposed self-organizing neural fuzzy controller. With no control action, the system is unstable as indicated in curve "NC". In comparison with the bang-bang controller, the proposed SONFC can yield a better dynamic response with less overshoot and shorter settling time.

Example 4 (Cooperation characteristic)

The purpose of this example is to illustrate the

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cooperation characteristic of the proposed controller. Consider a particular fault occurring at bus #20 with line switching (#20-#59) at 0.1 s. Fig. 13 (a) and (b) show the dynamic responses of rotor trajectories of G29 and G30 with the proposed controller installed on the latter and both units, respectively. The response curves reveal that the two controllers cooperate with each other very well in their efforts to damp out system oscillations under large disturbance conditions. In addition, even when only generator G30 is equipped with a SONFC, generator G29 can also benefit from the control action of G29.
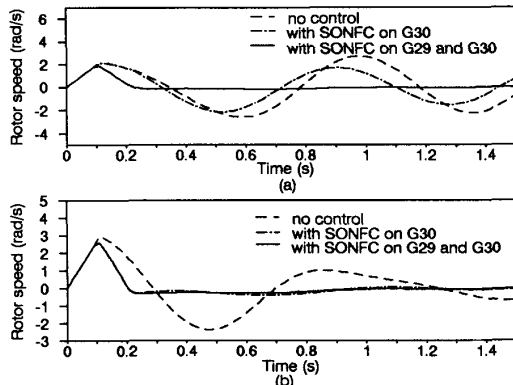

Fig. 13. Dynamic responses with SONFC on both generators: (a) rotor speed of G29, (b) rotor speed of G30.

CONCLUSIONS

This paper has designed an efficient self-organizing neural fuzzy controller (SONFC) to improve the transient stability of power systems. The basic control scheme is developed by the fuzzy logic theory, and implemented with a multilayer neural network. The fuzzy control rules and their membership functions can be optimally tuned from training examples by the backpropagation learning algorithm. As a result of the evolving symbiosis of these new techniques, the SONFC can prove to be more adaptive and robust in responding to a wide range of operating conditions. In addition, the rule-matching time in traditional fuzzy logic systems can also be saved. From the experimental results on the study system, several interesting and important observations can be deduced as follows:

(i) Starting with a set of coarse fuzzy control rules, the proposed SONFC can automatically adjust the fuzzy control rules and their membership functions using its learning capability to achieve fairly good damping characteristics.

(ii) The proposed SONFC can effectively control the transients over a wide range of operating conditions and yield better dynamic performance than the bang-bang controller.

(iii) The proposed SONFC is a model-free controller, and it can be applied to generators of various dynamic natures.

(iv) It can cooperate with other controllers of the same type, i.e., SONFC, to damp out system oscillations under disturbance conditions.

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BIOGRAPHIES

Hong-Chan Chang was born in Taipei, Taiwan on March 5, 1959. He received his B. S., M. S., and Ph. D. degrees in electrical engineering from National Cheng Kung University in 1981, 1983, and 1987, respectively. In August of 1987, he joined National Taiwan Institute of Technology as a faculty member where he is presently an associate professor in the electrical engineering department. His major areas of research include power system stability and neural network applications to power systems.
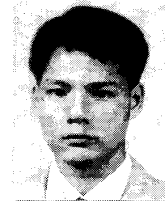
Mang-Hui Wang was born in Taiwan on June 22, 1963. He received his M. S. degree in electrical engineering from National Taiwan Institute of Technology, Taipei, in 1990. He is a candidate for the Ph. D. degree in the Electrical Engineering Department at National Taiwan Institute of Technology, Taipei. His current research interests are power systems control, neural networks, and fuzzy systems.

Discussion

A. Hariri and **O. P. Malik** (The University of Calgary, Calgary, Alberta, Canada):

The authors have presented an interesting approach to the design of a fuzzy controller using neural network topology to represent the various aspects of fuzzy logic based device. The discussors would appreciate authors' comments on the following points:

(i) It appears that the proposed controller involves two processing phases. In phase one, the learning phase, the parameters of the controller are adjusted for the desired output. In operation phase, after the learning phase is completed, the controller is used to control the system. In this phase, the controller parameters are kept constant and do not change with changes in the system operating conditions. Will the authors elaborate on how the controller, once trained, exhibits "dynamic adaptation" as stated in the Introduction.

(ii) The centres of the bell-shaped membership functions for the inputs and the output are determined by the learning processing, and therefore, it seems that the scaling factors, GS, GA and GU, are not necessary for this kind of neuro-fuzzy controller.

The scaling factors can be used for normalizing the universe of discourse, which in turn requires that all membership functions in Fig 8 be between -1 and +1.

(iii) Will the authors elaborate on how the proposed performance index table in Fig. 5 has been set up and the criteria on which the learning constant value of 0.005 was arrived at?

(iv) As this paper is devoted to the transient stability of multimachine power systems, have the authors investigated the performance of the proposed controller in the presence of multi-modal oscillations exhibited in multi-machine power systems?

H. C. Chang and M. H. Wang: The authors would like to thank the discussers for their interests in the paper and their insightful questions about the application of the neural network-based fuzzy controller to power system transient stability.

The conventional fuzzy control rules are rigid in the sense that once the fuzzy rules are developed at the design stage, they will not be modified in the course of controller operation until further refinement is necessary. Therefore, with the fixed set of fuzzy control rules, the fuzzy controller may perform rather poorly when large load disturbances or sudden parameter variations of the plant that are not foreseen at the design stage occur. By the term "dynamic adaptation" as stated in the Introduction, we emphasize that the neural network-based fuzzy controller is able to tune the control rules and membership functions dynamically in the learning phase. Therefore, after the proposed controller has been trained, it is used to control the system. If the performance of the controller is not satisfactory when drastic changes in the system operating conditions occur, a new training session must be initiated.

Indeed, the centers of the bell-shaped membership functions for the inputs and the output can be determined through the learning process. Since the physical input variables differ widely in values, our intention for the introduction of the scaling factors is to adjust the inputs and output of the controller into proper ranges so that the convergence of the learning process can be significantly improved.

The meta rules shown in Fig. 5 are based on our previous experience with the design of a transient stability controller. It is strongly motivated by the close analogy between Eqs. (1)-(2) and a spring-mass system. Compared with the mechanical analogy, θ corresponds to a displacement, the terms in the right-hand side of Eq. (2) except for U_i a nonlinear spring force, and U_i an applied retarding force. The ultimate control goal of transient stability is equivalent to quickly recovering the mass to the equilibrium point by applying an appropriate control force. Towards this goal, the linguistic rules are established by a simple engineering appreciation of the system behavior. This fact is evidenced by the resultant simple structure of the performance index table. To achieve good results, extensive simulations must be followed to justify the usefulness of the developed meta rules. As to the learning constant value of 0.005, it is chosen experimentally for the problem being solved. There is no single optimum value for different training cases.

The multi-modal oscillations are observed, in practice, with weakly interconnected power systems. They are characterized by local and inter-area modes. Since the input variables adopted are with respect to the center of inertia reference frame, the composite mode of electromechanical rotor oscillations can be damped out efficiently. Our experiences for various simulation scenarios revealed that the proposed controller can provide good damping characteristics in the presence of multi-modal oscillations.