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Transient Stability Improvement in Power Systems Using an Adaptive Neuro-Fuzzy Based Intelligent Controller

MEHRAN RASHIDI
Islamic Azad University, Tehran-South Branch
Tehran, IRAN

Abstract: This paper proposes a Neuro-Fuzzy Controller to Thyristor Controlled Series Capacitor (TCSC), which might have a significant impact on power system dynamics. We tune the scaling factors of neuro-fuzzy controller using adaptive critic. The proposed method is used for damping the low frequency oscillations caused by disturbances such as a sudden change of small or large loads or an outage in the generators or transmission lines. To evaluate the usefulness of the proposed method, the computer simulation for single machine infinite system is performed. Simulation results show that this control strategy is very robust, flexible and alternative performance. Also it could be used to get the desired performance levels. The response time is also very fast despite the fact that the control strategy is based on bounded rationality. Obtain results that have been compared with fuzzy PD controller show that our method has the better control performance than fuzzy PD controller.

Key-Words: - Transient Stability Analysis, Fact Device, Neural Network, Fuzzy Logic, Adaptive Critic

1 Introduction

Series capacitive compensation in AC transmission systems can yield several benefits, such as increased power transfer capability and enhanced transient stability. Thyristor controlled series capacitors (TCSC) are beginning to find applications as adjustable series capacitive compensators, as they provide a continuously variable capacitance by controlling the firing angle delay of a thyristor controlled reactor (TCR) connected in parallel with a fixed capacitor. Besides controlling the power flow, TCSCs have a potential to provide other benefits, such as transient stability improvement, damping power swing oscillations, mitigating subsynchronous resonance (SSR) and fault current reduction. Hence, effective firing control strategies are required to exploit all advantages that a TCSC installation might offer. Several different control and intelligent strategies have been developed in recent years to achieve the stated goals fully or partially. Among them, PID controllers, DDC methods, optimal, nonlinear and robust control strategies, adaptive and neural and/or fuzzy approaches are to be mentioned. Though they show a good controller performance in a specific operating point because they are designed using the linearlized system, it is difficult to obtain a good controller performance in a different operating condition. In particular, because the dynamic characteristic of power system with the reactive power compensator has a strong nonlinearity, the controller designed based on linear control can not show an optimal control performance.
The purpose of this paper is to suggest another control strategy, based on adaptive neuro-fuzzy controller, for damping the low frequency oscillations caused by disturbances such as a sudden change of small or large loads or an outage in the generators or transmission lines. Simulation results show that, the proposed method is very robust and the response time can achieve satisfactory performance. To evaluate the usefulness of the proposed method, we perform the computer simulation for a single machine infinite system. We compare the response of this method with fuzzy PD controller. Obtain results show that the performance of the proposed method is better than fuzzy PD controller. In the subsequent sections, we discuss the mathematical model of power system, our proposed controller, and its application in the closed loop control system, simulation and some concluding remarks.

2 Mathematical Model of Generator and TCSC

In this section we give some explanation about mathematical model of generator and TCSC which we have used.

2.1. Mathematical Model of Generator

The differential equations of a single-Machine Infinite System are expressed in (1)-(3), which is for designing TCSC controller to maximize the usage rate of power transmission facilities and power increase of delivery capacity. If a rapid response typed exciter is used, we can model the generator sufficiently using only automatic voltage regulator (AVR) removing the exciter as shown in (4). The turbine/regulator characteristic of the synchronous machine is not considered because of its long time constant, relatively slight variation. A nomenclature is added to appendix.

$$\frac{dE_q^{'}}{dt} = -\frac{1}{T_{do}^{'}}[E_q^{'} + (X_d - X_d^{'})I_d - E_{fd}] \quad (1)$$

$$\frac{d\delta}{dt} = \omega - \omega_{ref} \quad (2)$$

$$\frac{\mathrm{d}\omega}{\mathrm{dt}} = \frac{\omega_{ref}}{2H}[T_m - E_q^{'}I_q - (X_q - X_d^{'})I_d I_q] \quad (3)$$

$$\frac{\mathrm{dE_{fd}}}{\mathrm{dt}} = \frac{K_a}{T_a}(V_{ref} - V_t + V_s) - \frac{1}{T_a}E_{fd} \quad (4)$$

Where $\mathrm{V_t} = \sqrt{V_d^2 + V_q^2}$

$$\mathrm{I_d} = \frac{1}{\Delta}[R_e(E_d^{'} - V_\infty \sin\delta) + (X_e + X_q^{'})(E_q^{'} - V_\infty \cos\delta)]$$

$$\mathrm{I_q} = \frac{1}{\Delta}[R_e(E_q^{'} - V_\infty \cos\delta) - (X_e + X_d^{'})(E_d^{'} - V_\infty \sin\delta)]$$

$$\mathrm{V_d} = E_d^{'} + \frac{X_q^{'}}{\Delta}[R_e(E_q^{'} - V_\infty \cos\delta) - (X_e + X_d^{'})(E_d^{'} - V_\infty \sin\delta)]$$

$$\mathrm{V_q} = E_q^{'} - \frac{X_d^{'}}{\Delta}[R_e(E_d^{'} - V_\infty \sin\delta) + (X_e + X_q^{'})(E_q^{'} - V_\infty \cos\delta)]$$

$$\Delta = \mathrm{R_e^2} + (X_e + X_d^{'})(X_e + X_q^{'})$$

2.2. Mathematical Model of TCSC

The conventional series compensator using a breaker is restricted to the usage frequency owing to abrasion and can not compensate dynamically because its compensator speed is slow and include an abnormal oscillation such as subsynchronous resonance (SSR) But TCSC can control promptly and precisely by using a high speed switching thyristor and be operated all time with not restricted to usage frequency and contributes to the improvement of the transient stability.

TCSC function as a fixed capacitor in the steady state, so that it can control the power flow and improve the steady state stability by increasing voltage stability margin. It can increase the dynamic stability of power system by controlling a capacity value in disturbances and protect devices from over voltage and/or over current by bypassing the capacity with adequate protection device in fault and reinstall the capacity promptly in fault restoration.

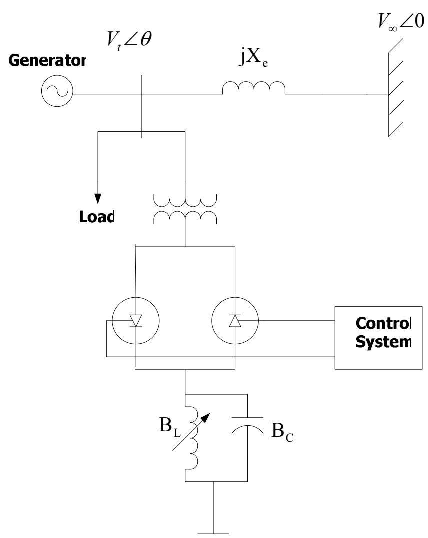


Figure 1. Single-Machine infinite system used in performance evaluation

The line reactance in a conventional PSS analysis model is a fixed, constant value, but the line reactance in the model including TCSC can no longer be considered as a fixed value because of its variation. So, in this paper, we use the modulation control changing the reactance of TCSC continuously by a firing angle control. The fundamental wave of TCSC reactance is (5).

$$X_{TCSC} = -\frac{1}{\omega C} + \frac{A}{\pi\omega C}[2\sigma + \sin 2\sigma] - \frac{4A}{\pi\omega C(k^2-1)}\cos^2\sigma[k\tan k\sigma - \tan\sigma] \quad (5)$$

Where $A = \frac{\omega_0^2}{\omega_0^2 - \omega^2}$, $k = \frac{\omega_0}{\omega}$, $\sigma = \frac{\beta}{2}$,

$\omega_0^2 = \frac{1}{LC}$ $\pi/2 < \beta < \pi, \beta:$ firing angle

3.1. BEL Algorithm and Its Application in Signal Fusion

Sensor failures are a major cause of concern in many industrial systems such as engine-performance monitoring. In this and similar applications the quantity which must be measured may be physically difficult to access, e.g. temperature. Moreover, the sensors utilized in these situations are susceptible to changes in physical parameters. For instance, the time constant of the sensors may change over time. This fact, may affect the performance of the closed-loop control system whose signals are based on the feedback signals measured from the sensors. Multiple measurements of the same parameter with more than one sensor can be helpful in decreasing the impact of the unfavorable effects, while the correlation between the different sensors can result in a less vulnerable signal. In other words, through a combination of distributed sensing and measurement, deficiencies in any of the parameters of the sensing system can be addressed. Industrial applications of sensory signal fusion algorithms makes the subject important from the standpoint of safety and robust performance. Thus, enhancing the ability of the system to compensate for time delays in the feedback loop is highly motivated. To ameliorate the effects of faults of the sensor fusers, in non-deterministic and novel situation, some stochastic and probabilistic methods have been proposed, while some traditional filtering methods and soft computing intelligent algorithms have also been put forward. This paper demonstrates utilization of an emotional learning algorithm as a signal fuser in the feedback loop which has made the control system capable of being stabilized in the presence of sensor time delays.

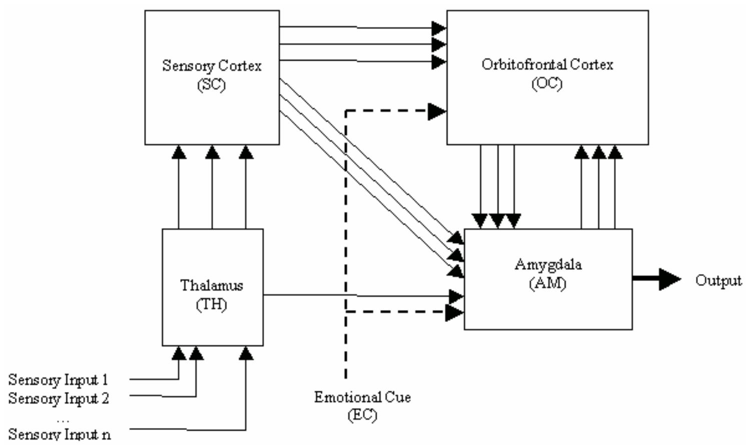


Figure 2. The Schematic Structure of the BEL Model

Algorithms based on models of human emotional processing, is increasingly being utilized by control engineers, robotic designers and decision support systems developers with excellent results. Although, for a long time, emotion was considered as a negative factor hindering the rational decision making process, it has now become clear that far from being a negative trait, emotions are important positive forces crucial for intelligent behavior in natural as well as artificial systems. The emotional model we have studied is a structural node-by-node neural network that mimics those parts of the brain responsible for processing emotions as originally introduced in [10]. The schematic architecture of the model, termed BEL, is demonstrated in Fig. 2. The more cognitive aspects of the model can be found in while the learning strategy as well as detailed adaptation of the model in engineering applications is given in [7] where the algorithm has been utilized as a controller as well as a time-series predictor. For more convenience, we repeated a brief explanation of relations inside the BEL depicted in Figure 2:

$$\Delta G_{AMi} = k_{AMi}.\max\left(0, EC - AM_i\right) \tag{6}$$

$$\Delta G_{OCi} = k_{OCi}.(MO - EC) \tag{7}$$

$$MO = \sum_i AM_i - \sum_i OC_i \tag{9}$$

$$AM_i = G_{AM\,i}.S_i \tag{10}$$

$$OC_i = G_{OCi}.S_i \tag{11}$$

where ΔG_{AMi} s are the gains in the amigdala; k_{AMi} s are the learning steps of the gains in the amygdala; EC is the emotional cue; AM_i s are the amygdale outputs; ΔG_{OCi} are the gains in the orbitofrontal cortex; k_{Oi} are the learning steps of the gains in the orbitofrontal cortex; MO is the output of the whole model (here fused signal) ; OC_i are the orbitofrontal outputs and S_i are the sensory signals (here the signals are supposed to be fused). Generally, the aforementioned model needs to be fed by some sensory inputs and an emotional cue, which reflects the desirability of the current state of the system. Basically, to utilize the model, one must appropriately choose the sensory signals as well as emotional cue signal, and subsequently tune the learning parameters of the relevant blocks. In this connection, it is important to note that the source of the emotional cue signal depends on the application domain. The general idea, however, is to reflect the performance of the system. Regarding these, BEL has been adapted accordingly for the sake of sensory signal fusion task [9]. The overall system as well as the input/output configurations, is given in Fig. 3. As observed in the figure, the emotional cue signal is generated as follow:

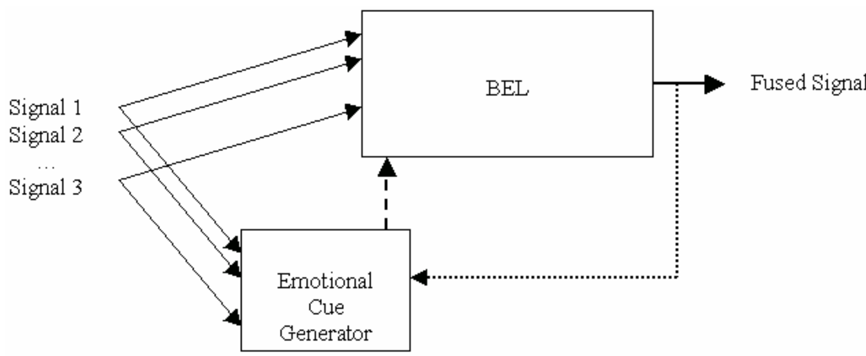


Figure 3. Model of the BEL Signal Fuser

$$EC = K_1.FS - K_2.\sum_i S_i \tag{12}$$

where FS is the returned fused signal; and K_1 and K_2 are also two gains that must be properly selected so as to have a reasonable relative assessment of the input signals for evaluation. So the algorithm tries to adjust its learning parameters in a way improving the emotional signal cue and consequently, moving toward the desired response. It is noteworthy to mention that the most important learning occurs in the orbitofrontal cortex (OC) and amygdala (AM) [8]. Thus, the next step is applying the BEL signal fuser module in the feedback loop of a control system, which is done in the next section.

3.2. Using Signal Fuser in Control Systems

Figure 4 presents the configuration of the closed-loop control system including the BEL signal fuser. As observed in the figure, the BEL block is placed in the feedback loop and provides the controller with the more accurate error signal based on receiving the different measured output signals. The measured output signals may contain different values of time delays depending on the changes in the sensors' physical parameters.

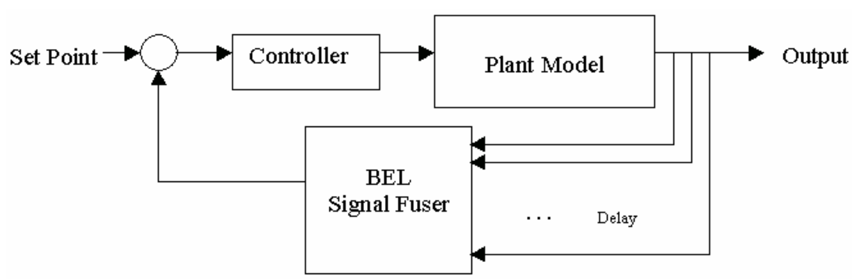


Figure 4. Using BEL Signal Fuser in the Feedback Loop of a Closed-Loop Control System

These time delays may have unfavorable effects on the performance measures of the control system and even may lead to its instability. So the main task of the BEL block is ameliorating such effects and keeping the system stable in the case of unstable conditions.

3.3. Neurofuzzy Controller

Two major approaches of trainable neurofuzzy models can be distinguished. The network based Takagi-Sugeno fuzzy inference system and the locally linear neurofuzzy model. It is easy to see that the locally linear model is equivalent to Takagi-Sugeno fuzzy model under certain conditions, and can be interpreted as an extension of normalized RBF network as well.
The Takagi-Sugeno fuzzy inference system is based on fuzzy rules of the following type:

$$Rule_i: \quad If \ u_1 = A_{i1} \ And \ \ldots \ And \ u_p = A_{ip}$$
$$then \ y = f_i(u_1, u_2, \ldots, u_p)$$

Where $i = 1 \ldots M$ and M is the number of fuzzy rules. $u_1, \ldots, u_p$ are the inputs of network, each A_{ij} denotes the fuzzy set for input u_j in rule i and $f_i(.)$ is a crisp function which is defined as a linear combination of inputs in most applications

$$y = \omega_{i0} + \omega_{i1}u_1 + \omega_{i2}u_2 + \ldots + \omega_{ip}u_p$$

Thus the output of this model can be calculated by

$$y = \frac{\sum_{i=1}^{M} f_i(\underline{u})\mu_i(\underline{u})}{\sum_{i=1}^{M} \mu_i(\underline{u})}, \quad \mu_i(\underline{u}) = \prod_{j=1}^{p} \mu_{ij}(u_j)$$

A simple form of $f_i(u)$ can be as

$$f_i(u) = a_i u_1 + b_i u_2 + c_i$$

The out put of controller is in the following form:

$$y = \frac{\sum_{i=1}^{n} \mu_i (a_i u_1 + b_i u_2 + c_i)}{\sum_{i=1}^{n} \mu_i}$$

e → Δe ↓	NL	NS	ZE	PS	PL
PL	ZE	PS	PM	PL	PL
PS	NS	ZE	PS	PM	PL
ZE	NM	NS	ZE	PS	PM
NS	NL	NM	NS	ZE	PS
NL	NL	NL	NM	NS	ZE

PL: Positive Large
PM: Positive Medium
PS: Positive Small
ZE: Zero
NS: Negative Small
NM: Negative Medium
NL: Negative Large

Where n is number of controller fuzzy rules, μ_i is the firing strength of ith rules, u_1 is the first and u_2 is the second one for two input type controller (for example error and its derivative). In this paper we choose $u_1 = e$ and $u_2 = \dot{e}$. The neurofuzzy controller applied in this paper, is a standard Sugeno fuzzy controller composed of four layers. In the first layer, all inputs are mapped into the range of [-1, +1]. In the second layer, the fuzzification process is performed using gaussian membership functions with five labels for each input. In layer 3, decision-making is done using Max-Product law and defuzzification is carried out in the fourth layer in order to calculate the proper control input using previous equation, a_i, b_i, c_i are parameters to be determined via learning mechanism.

$$a_{iNew} = a_{iOld} + \eta \, r \, e \frac{u_i}{\sum_{i=1}^{n} u_i}$$

$$b_{iNew} = b_{iOld} + \eta \, r \, \dot{e} \frac{u_i}{\sum_{i=1}^{n} u_i}$$

$$c_{iNew} = c_{iOld} + \eta \, r \frac{u_i}{\sum_{i=1}^{n} u_i}$$

4. Simulation Results

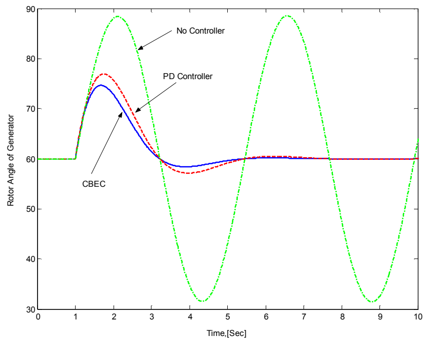
To evaluate the usefulness of the proposed method, we have performed the computer simulation for a single-machine infinite system and then compared it with Fuzzy PD controller in terms of the control performance. The analysis conditions, which are used for comparing control performance of Fuzzy PD controller with CBEC, are summarized in table 1. Table 1 is classified according to the power system operating conditions used in designing CBEC and evaluating the robustness of the CBEC. As shown in table 1, case-1 is used in designing the CBEC and we used case-2 to case-4 in evaluating the robustness of the PSS.

Table.1 : Simulation cases used in evaluation of controller performance
A: Three phase fault
B: Mechanical torque was changed as 0.1pu

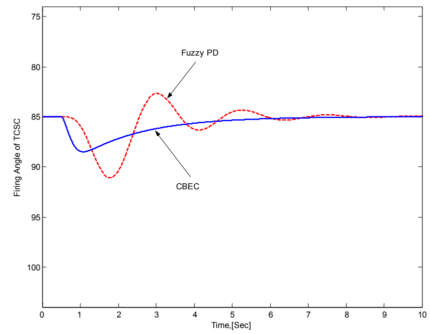
Simulation Cases	Operating condition	Disturbance	Fault time [msec]
Case-1	Heavy load $P_e = 1.5[\,pu\,]$	A	45
Case-2	$Q_e = 0.02[\,pu\,]$	B	_
Case-3	Nominal load $P_e = 1.0[\,pu\,]$	A	45
Case-4	$Q_e = 0.02[\,pu\,]$	B	_

4.1. Heavy load condition

Fig .4 shows the generator angle and firing angle when the three-phase fault occurs under the Case-1 of table 1. As shown fig.4 the CBEC shows the better control performance than Fuzzy PD controller in terms of setting time and damping effect. To evaluate the robustness of the proposed method, fig.5 shows the generator response characteristic in case that Fuzzy PD controller and the proposed CBEC are applied under the Case-2 of table1 As shown in Fig.5, CBEC shows the better control performance than Fuzzy PD controller in terms of setting time and damping effect.



a: Rotor angle of generator



b: Firing angle of TCSC

Figure 4: Generator responses when three-phase fault was occurred (Heavy Load)

4.2. Nominal load condition

To evaluate the robustness of the CBEC, Fig 6-7 show the generator response characteristic in Case that Fuzzy PD controller and the proposed CBEC are applied under the Case-3 and 4 of table1. As shown in Fig 6-7, the CBEC shows the better control performance than Fuzzy PD controller in terms of setting time and damping effect.

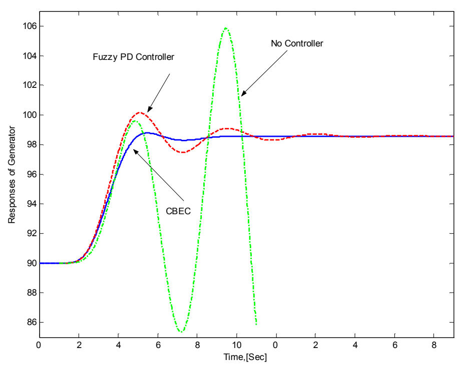


Figure 5: Generator responses when mechanical torque is changed by 0.2[pu] (heavy load)

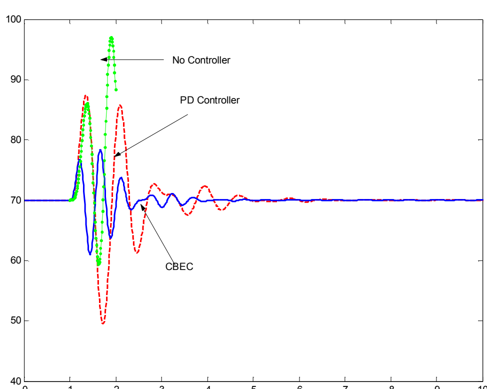


Figure 6: generator responses when three-phase fault was occurred (Nominal load)

5. Conclusion

The purpose of this paper, as seen, was to suggest another control approach, based on a modified version of Context Based Emotional Controller (CBEC), for TCSC for low frequency oscillation of power system. Simulation results showed that, the proposed method is very robust and the response time can achieve satisfactory performance. To evaluate the usefulness of CBEC, we performed the computer simulation for a single machine infinite system. We compared the response of the CBEC with fuzzy PD controller. Simulation results showed that the performance of the CBEC is better than fuzzy PD controller. Then, To evaluate the robustness of the CBEC, we simulated dynamic characteristic of generator for a changeable mechanical torque and three-phase fault in nominal and light load. The CBEC showed the better damping effect than fuzzy PD controller

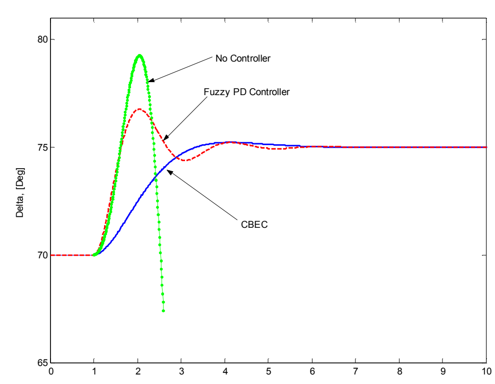


Figure 7: Generator responses when mechanical torque is changed by 0.2[pu] (Nominal load)

Reference

[1]- Lei. X., D. Jiang, and D. Retzmann, "Stability Improvement in Power Systems with Non-Linear TCSC Control Strategies", ETEP, vol 10, No. 6, November/December 1998, pp. 339–345.

[2]- Woo-Geun Kim, Gi-Hyun Hwang, Hyeon Tae Kang, Seok-Oh Lee, June Ho Park, "Design of Fuzzy Logic Controller for Firing Angle of TCSC Using Real-Type Tabu Search", IEEE Conference, pp.575-579, 2001

[3]- Y. Wang, Y. L. Tan, and G. Guo, "Robust Nonlinear Coordinated Excitation and TCSC Control for Power Systems," IEE Proc. Generation, Transmission and Distribution (UK), Vol. 149, No. 3, pp 367 - 372, 2002.

[4]- K.A. Ellithy and S.M. Al-Alawi, "Tuning a Static Var Compensator Controller Over a Wide Range of Load Models Using an Artificial Neural Network", Electric Power Systems Research, 38, pp. 97-104, 1996.

[5]- G. El-Saady, M. El-Sadek and M. Abo-Elsaoud, "Fuzzy Adaptive Model Referente Approach-Based Power System Static VAR Stabilizer", Electric Power System Research 45, pp. 1-11, 1998.

[6]- Min-Soeng Kim; Sun-Gi Hong; Ju-Jang Lee, **"**Self-organizing fuzzy inference system by Q-learning", FUZZ-IEEE '99. 1999 IEEE International, Volume: 1, pp.372-377, 22-25 Aug. 1999

[7]- Q. Sun "Sensor Fusion for Vehicle Health Monitoring and Degradation Detection" Proceedings of the Fifth International Conference on Information Fusion, Vol. 2, July 8-11, 2002, PP: 1422-1427

[8]- J. Gu, M. Meng, A. Cook, P. X. Liu "Sensor Fusion in Mobile Robot: Some Perspectives" Proceedings of the 4th World Congress on Intelligent Control and Automation, Vol. 2, June 10-14, 2002, PP: 1194-1199

[9]- S. P. Luttrell "Adaptive Sensor Fusion Using Stochastic Vector Quantisers" DERA/IEE Wokshop on Intelligent Sensor Processing, February 14, 2001, PP: 2/1-2/6

[10]- J. Gu, M. Meng, A. Cook, P. X. Liu "Sensor Fusion in Mobile Robot: Some Perspectives" Proceedings of the 4th World Congress on Intelligent Control and Automation, Vol. 2, June 10-14, 2002, PP: 1194-1199

[11]- M. M. Zheng, S. M. Krishnan "Decision Support by Fusion in Endoscopic Diagnosis" The Seventh Australian and New Zealand Intelligent Information Systems Conference, 18-21, (Nov. 2001), 107-110

[12]- S. O. T. Ogaji, R. Singh, S. D. Probert "Multiple-Sensor Fault-Diagnoses for a 2-Shaft Stationary Gas-Turbine" Applied Energy (71), 2002, PP: 321-339

Nomenclature

δ : Rotor angle of generator

ω : Rotor speed of generator

ω_{ref} : Reference rotor speed of generator

H: Inertia constant of generator

T_m : Mechanical input of generator

X_d : d-axis synchronous reactance of generator

X_d' : d-axis transient reactance of generator

X_q : q-axis synchronous reactance of generator

E_q' : q-axis voltage of generator

T_a : Exciter time constant

E_{fd} : Generator field voltage

T_{do}' : d-axis transient time constant of generator

I_d : d-axis current of generator

I_q : q-axis current of generator

V_t : Terminal voltage

V_{ref} : Reference voltage

V_s : PSS signal

V_∞ : Voltage of infinite bus

k_a : AVR gain

R_e : Equivalent resistance of transmission line