Design of SVC controller for oscillations damping using Self-learning fuzzy approach

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Abstract— **Application of fuzzy PD controller based on self learning algorithm for SVC device has been investigated in this paper. This approach used sensitivity model for learning Self Learning Fuzzy Logic parameters. This has been improved by adding up an integral term whose gain coefficient is also synthesized by learning that is actuated after completion of the main learning algorithm. The paper considers the conventional PID controller and compares its performance with respect to the proposed SLFLC controller. Several fault and load disturbance simulation results are presented to emphasize the efficiency of the proposed SVC controller in a TNB 25- bus of south Malaysian power system and New England 39 Bus system.**

***Keywords- SVC devices; Power system oscillations; Fuzzy logic controllers (FLC); self learning fuzzy logic controller (SLFLC); Damping oscillation*.**

I. Introduction

Stability based on transient and dynamic stability is given significant consideration for secure operation of power systems due to increased in power transfer in the system. FACTS controllers with appropriate control strategy have the potential to extensively increase the transient stability margin. This allows increased utilization of existing network closer to their thermal loading capacities, which help in avoiding the need to construct new transmission lines. A major thrust of FACTS technology is the development of power electric based systems that provide dynamic control of the power transfer parameters transmission voltage, line impedance and phase angle[1-4].

Power system oscillations normally happened due to the short of damping torque at the generators rotors. The oscillation of the generators rotors cause the oscillation of other power system variables (bus voltage, bus frequency, transmission lines active and reactive powers, etc.). Power system oscillations are usually in the range between 0.1 and 2 *Hz* depending on the number of generators involved in [3, 4,12]. Local oscillations lie in the upper part of that range and consist of the oscillation of a single generator or a group of generators against the rest of the system. In contrast, inter-area oscillations are in the lower part of the frequency range and comprise the oscillations among groups of generators.

To improve the damping of oscillations in power system, a power System Stabilizers (PSSs) applied on selected generators can effectively damp local oscillation modes while for inter-area oscillations a supplementary controller can be applied to SVC devices. Most of these controllers are designed base on conventional approach that is designed based on a Linearized model which cannot provide satisfactory performance over a wide range **of** operation points and under large disturbances [5].

Recently, applications of the **fuzzy** logic theory to the FACTS devices has attracted a lot of attention for designing an effective control law to enhance the system stability [4-8].The fuzzy controller has a number of distinct advantages over the conventional one. It is not so sensitive to the variation of system structure, parameters and operation points and can be easily implemented in a large-scale nonlinear system. The most attractive feature is its capability of incorporating human knowledge to the controller with ease[9,12].

The authors in Ref. [10,] have presented coordination of SVC and Power system stabilizer(PSS) using fuzzy model scheme which has been tested on a five-machine infinite-bus study system. Dash et al. [11] have suggested a hybrid fuzzy controller for FACTS devices which have been tested on two area four machines, eleven bus system (Kundur) with TCSC, UPFC and SVC installed in the study system. In Ref. [13], the authors have proposed a Fuzzy PI design method, to design the fuzzy controller for UPFC. The usefulness of their proposed controller has been tested on a four machines, eleven bus systems also. Salman Hammed[14]have presented a self-tuning fuzzy PI controller for TCSC. The performance of the proposed TCSC controller has been **tested on** the 11 bus, four machines system and 39 bus system. From the above discussion it is observed that the different fuzzy control strategies proposed in the literature have been tested on

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relatively small test systems or using simple method of turning.

So many authors have presented a work on Self-organizing fuzzy logic controller which includes [16-18]. Though was initially proposed by Procyk and Mamdani [15]. Other types of fuzzy logic based learning controllers has also been proposed by [19- 24,]. The term, self-organizing fuzzy logic controller, is to be abbreviated as SOFLC in the sequel.

The PD type SLFLC whose learning algorithm utilizes a sensitivity model and a 2nd-order reference model has been effectively used for control of static and astatic nonlinear systems [25]. This paper aims to extend the work on application of SLFLC control technique for SVC control design further.

To verify the efficiency of the new SLFLC SVC controller, the performance of the TNB-25 bus power system is compared with both conventional control and a SLFLC algorithm based fuzzy control.

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II. Sensitivity- Based Self Learning Fuzzy Logic Controller(SLFLC)

The concept of the SLFLC block allows control of unknown inherently stable static and astatic linear or nonlinear systems providing that a desired closed-loop system behavior can be represented with a linear second-order reference model. The fuzzy controller has two inputs *e(k)* and $\Delta y_f\ (k)$, and one output $u_{FC}(k)$. The basic structure of the SLFLC block contains a PD-type fuzzy controller, a feedforward control element and a P controller.

In fuzzy model reference learning control (FMRLC) scheme, shown in Figure1, model tracking error e_M is fed into a learning mechanism which establishes an organized iterative way of changing the core of the fuzzy controller [26].Power systems can be generically described by a nonlinear differential-algebraic-equations (DAE) model of the form,

$$\begin{aligned} \dot{x} &= f(x, y, \lambda) + g_1 u \\ 0 &= g(x, y) \end{aligned} \tag{1}$$

Where: **x** =state vector, *f* = unknown nonlinear function, $g_1 > 0$ - unknown process gain, *u*=- control input, *g* = unknown nonlinear algebraic function, *y* - output, **λ** - parameter vector

The relation between $\Delta\mathbf{x}$ and $\Delta\boldsymbol{\lambda}$ for small parameter variations around nominal parameter values vector $\boldsymbol{\lambda}_0$ is as follows:

$$\Delta x \approx S(\lambda_0)\Delta\lambda = \left[S_{ij} = \left.\frac{\partial x_i}{\partial \lambda_j}\right|_{\lambda 0} \right]\Delta\lambda \tag{2}$$

Where **S** is the sensitivity function matrix and S_{ij} is an element of matrix **S**.

In time domain let us suppose that the solution of system (1) for nominal parameters has a form:

$$y_0 = y(u, t, \lambda_0) \tag{3}$$

For changed parameter values, system (1) has a solution:

$$y = y(u, t, \lambda) \tag{4}$$

Using any numerical method, the solution of equation (1) can be express as:

$$\begin{aligned} & y \approx y_0 + \left.\partial y/\partial\lambda\right|_{\lambda_0} \Delta\lambda \Rightarrow \Delta y = y - y0 \approx \left.\partial y/\partial\lambda\right|_{\lambda_0} \\ & \Delta\lambda = \eta_\lambda \Delta\lambda \end{aligned} \tag{5}$$

Where η_λ is the system output sensitivity function vector of the following form:

$$\eta_\lambda = \left[\frac{\partial y}{\partial \lambda_1}, \frac{\partial y}{\partial \lambda_2} .... \frac{\partial y}{\partial \lambda_v} \right]_{\lambda_0} \tag{6}$$

This method described here calculates a new parameter vector in the moments when sensitivity functions in (6) reach their maximum and then sets a new vector up before a new change of the reference input u_r takes place.

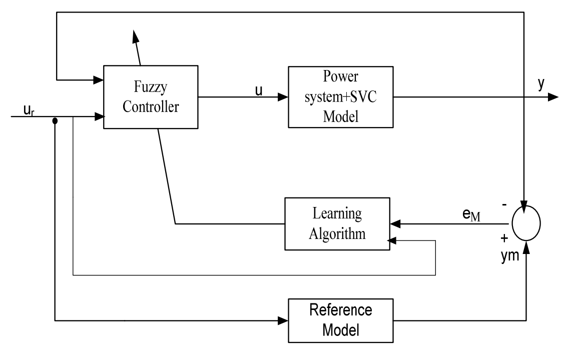

Figure 1 model reference Self Learning Fuzzy Controller

Assuming that reference input signal $u_r(k)$ has a constant value or that it is changing slowly (i.e., $ur(k) = ur(k-1)$),The fuzzy PID controller of Variant A equation (3.21) of [26] becomes.

$$u(k) = k_1 e(k) + k_2 \Delta e(k) + k_3 u_r(k) \tag{7}$$

Controller (7) can be split into two parts
Where

$$u_{FC}(k) = k_1 e(k) + k_2 \Delta e(k) \tag{8}$$

$$u_{FF}(k) = k_3 u_r(k) \tag{9}$$

Coefficient k_3 represents feedforward gain coefficient and Equation (9) represents the feedforward part of a controller that works in parallel with the "fuzzy" part of controller equation (8).

Following the same idea which has been used for the determination of the fuzzy rule table that emulates P-I-D and P-I algorithms [17, 26]. We may choose the values of controller inputs $e_i(k)$ and $\Delta e_j(k)$ such that $\mu_i^e\left((e_i\right))=1$ and $\mu_j^{\Delta e}\left(\Delta e_j\right)=\mathbf{1}$ (which means that $e_i(k)$ and $\Delta e_j(k)$ correspond with the centers c_i^e and $c_i^{\Delta e}$ of the ith and the jth input fuzzy sets, respectively). In that case crisp fuzzy controller output is determined by only one fuzzy rule, that is,

$$u_{FC}=k_1c_i^e+k_2c_j^{\Delta e}=\mathrm{A_q} \tag{10}$$

Equation (10) directly defines values of all output singletons Aq, $1 \le q \le l_2$ by inserting values of all input fuzzy set centers c_i^e and $c_i^{\Delta e}$ j for $i, j = 1, 2, \ldots, l$.

III. SELF-LEARNING FUZZY ALGORITHM

A. Fuzzification process

PD-type fuzzy controller structure is adopted in this paper though for self-learning fuzzy controller system, the structure may vary depending on the type of process.

The fuzzy controller used in the SLFLC scheme is a singleton fuzzy controller. How much will the j-th fuzzy control rule contribute to the defuzzified controller output depends on a degree of contribution described with the fuzzy basis function **[15].**

$$\varphi_i\left[e(k),\ \Delta y(k)\right]=\frac{\mu_i\left[e(k),\ \Delta y(k)\right]}{\sum_{j=1}^{r}\mu_j\left[e(k),\ \Delta y(k)\right]} \tag{11}$$

dy(k j)=y(k)-y(k-1) - change of system output,
p - number of fuzzy subsets of e(k),
q - number of fuzzy subsets of dye),
r = pq - number of rules,
μ_i= membership function of *fuzzy* relation

The SLFLC *(*Figure 1) contains a nonintegral (PD) *fuzzy* controller to be organized and a proportional (P) controller.

$$u(k)=\sum_{i=1}^{n}A_i\varphi_i\left[e(k),\ \Delta y(k),\ \lambda\ \right]+k_p \tag{12}$$

where: A_i- centroid of the fuzzy controller output subset activated by the i-th fuzzy rule
ϕ_i - fuzzy basis function of the i-th fuzzy rule,
k_p- proportional gain coefficient,
$\boldsymbol{\lambda}$**-** fuzzy controller parameter vector.

The change of error $\Delta e(k)$, usually applied in fuzzy controllers, is replaced by the change of system output $\Delta y(k)$ The reason why $\Delta y(k)$ is preferred to $\Delta e(k)$is in its more convenient response to stepwise changes of the reference input[12].

Input fuzzy sets take only a differentiable Gaussian form and an α-cut operation is applied to all input fuzzy sets (α = 0.05).Seven Gaussian linearly distributed membership functions have been determined for both SLFLC inputs $e(k)$ and Δy (k):The input membership functions will have a differentiable form[1]. The membership set for the fuzzy output variable is comprised of the singletons set.

B. Fuzzy inference engine

A sensitivity model of a fuzzy controlled system can be built only if fuzzification and defuzzification operations have a form that allows a fuzzy input-output mapping function to assume an analytical and differentiable form. In this sense, the inference engine will utilize a product operator:

$$\begin{aligned}&\mu_j\left[e(k),\Delta y(k)\right]=\mu_k^e\left[e(k)\right].\mu_l^{\Delta y_f}\left[\Delta y(k)\right]\\&j=1,2,\ldots..r,\ k=1,2,\ldots..,p,\ l=1,2,\ldots..,q\end{aligned} \tag{13}$$

and input membership functions will also have a differentiable form

$$\begin{aligned}&\mu_k^e(x)=e^{-(x-c_k^e)^2/(2(w_k^e)^2)},\\&\mu_l^{\Delta y}(x)=e^{-(x-c_l^{\Delta y})^2/(2(w_l^{\Delta y})^2)}\end{aligned} \tag{14}$$

Where c_i^j is the center of a membership function μ_i^j *,and* w_i^j is the width of a membership function μ_i^j**.** Accordingly, controller parameter vector $\boldsymbol{\lambda}c$ contains the following parameters: output singletons A_i, centers of input sets, c_k^e and $c_l^{\Delta y f}$ and widths of input sets, w_k^e and $w_l^{\Delta y f}$

C. Defuzzification process

The crisp output of the fuzzy controller used in the SLFLC scheme is computed according to the center of gravity principle. How much the i-th fuzzy control rule will contribute to a crisp controller output depends on the degree of contribution described with the fuzzy basis function:

$$\varphi_i\left[e(k),\ \Delta y(k)\right]=\frac{\mu_i\left[e(k),\ \Delta y(k)\right]}{\sum_{j=1}^{r}\mu_j\left[e(k),\ \Delta y(k)\right]} \tag{15}$$

This form is also differentiable.

Sensitivity functions can be very useful to express how much influence some variable or parameter has on the focused variable. In this sense, sensitivity functions represent information about interactions between causes and consequences which may be very useful for planning interventions in the system

Having this concept in mind, a total differential of the system output with respect to small variations of fuzzy controller parameters is determined by

$$\Delta y(k,\lambda) = \sum_{i}^{n} \eta_{\lambda_{ci}}(k)\Big|_{\lambda_{ci}} \Delta\lambda_{ci} \qquad (16)$$

where $\eta_{\lambda_{ci}}(k), k$, i=1,…n, are system output sensitivity functions related to fuzzy controller parameters:

$$\eta_{\lambda_{ci}}(k) = \frac{\partial y(k,\lambda)}{\partial \lambda_{ci}} = \frac{\partial y(k,\lambda)}{\partial u(k)}\frac{\partial u(k)}{\partial \lambda_{ci}} = Gp\frac{\partial u(k)}{\partial \lambda_{ci}} \qquad (17)$$

where Gp is the process transfer function.

It may be seen that sensitivity functions related to controller parameters λ_{ci} depend on generally unknown dynamic characteristics of the control process Gp. To overcome these some approximation, denoted as Gpa, must be used which assumed a reference model dynamics that is $G_{pa} = G_M$.

The system parameter variations will be compensated only by modifying the fuzzy output singletons A_i, i.e. $\lambda_c = [A_1, A_2, ...A_r]$ which gives:

$$\eta_{\lambda_{ci}}(k) = \frac{\partial y(k,\lambda)}{\partial A_i} = \frac{\partial y(k,\lambda)}{\partial u(k)}\frac{\partial u(k)}{\partial A_i} = G_M\frac{\partial u(k)}{\partial A_i} \qquad (18)$$

$$\frac{\partial u(k)}{\partial A_i} = \frac{\partial}{\partial A_i}\left\{\Gamma\left[e(k),\ \Delta y(k),\lambda\right]\right\} = \varphi_i\left[e(k),\ \Delta y(k),\lambda\right] \qquad (19)$$

The given change of system output $\Delta y(k)$ in (18) coincides in the model reference control concept with model tracking error $e_M(k)$. Therefore, the sensitivity functions attain a form:

$$\frac{\partial u(k)}{\partial A_i} = \eta_{Ai}(k) = a_{M1}.\eta_{Ai}(k-1) + a_{M2}.\eta_{Ai}(k-2) +$$
$$b_{M1}\varphi_{Ai}(k-1) + a_{M2}.\varphi_{Ai}(k-2) \qquad (20)$$

where a_{M1}, a_{M2}, b_{M1} and b_{M2} are parameters of the second order reference model

$$e_M(k) = \sum_{i=1}^{r}\eta_{A_i}(k)\Delta A_i \qquad (21)$$

Since tracking error $e_M(k)$ is known in every control interval, equation (21) converts into a learning algorithm of the form

$$\Delta A_j^{\kappa}(k) = \frac{e_M^{\kappa}(k) - \sum\limits_{i=1, i\neq j}^{r}\eta_{A_i}^{\kappa}(k).\Delta A_i^{\kappa}}{\eta_{A_i}^{\kappa}(k)} \qquad (22)$$

Where κ denotes the current learning iteration (i.e. the current run of the system). The meaning of this is that singletons Aj are changed only once during each run of the system. A new run of the system starts with a new change of $u_r(k)$ (for learning purpose input signal should comprise set of stepwise changes around a set point). It must be noted, that approximate equality in (6) is intentionally replaced by normal equality in (21) and (22) [1].

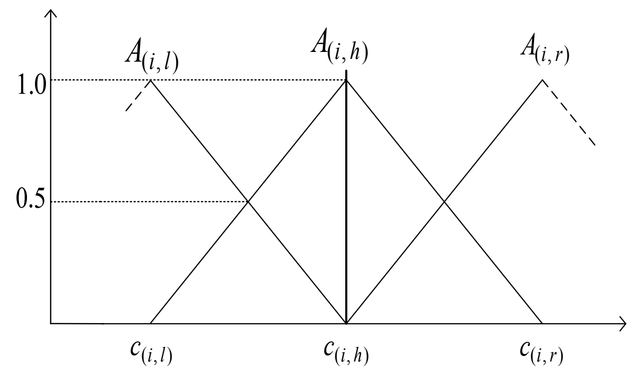

Figure 2 fuzzy singletons

IV. SVC and Power System Model

A. SVC Devices

The Static VAr Compensator (SVC) is a shunt connected device whose main functionality is to regulate the voltage at a chosen bus by suitable control of its equivalent reactance. A basic topology consists of a series capacitor bank, C, in parallel with a thyristor-controlled reactor, L, as shown in Figure 1. In practice the SVC can be seen as an adjustable reactance [1] that can perform both inductive and capacitive compensation.

1) Power Flow Modulation model

The reactive power injection of a SVC connected to bus k is given by:

$$Q = -B_{SVC}V^2 \qquad (23)$$

Where $B_{SVC}=B_C-B_L$ and B_C and B_L are the susceptance of the fixed capacitor and thyristor controlled reactor respectively. It is also important to note that a SVC does not exchange real power with the systems [2].

2) *Dynamic model*

The small signal dynamic model is shown in figure 3; the model that is used here assumes a time constant regulator.

In this model, a total reactance b_{SVC} is assumed and the following differential equation holds [3, 14].

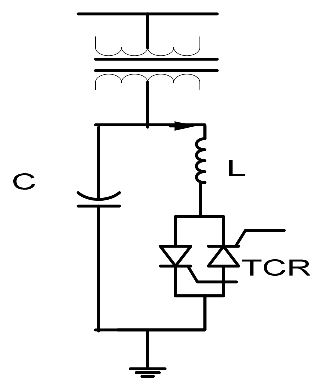

Figure 3 SVC topology

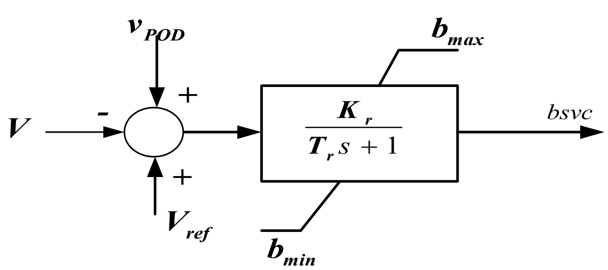

Figure 4 SVC Regulator

$$\dot{b}_{SVC} = (K_r(V_{ref} + v_{POD} - V) - b_{SVC})/T_r \qquad (24)$$

The regulator has an anti-windup limiter, thus the reactance b_{SVC} is locked if one of its limits is reached and the first derivative is set to zero [3, 14]..

The supplementary input Δ_{POD} is used to connect the POD controller for damping oscillation while V_{ref} to maintain acceptable voltage at the SVC bus.TCR of 150MVAr is connected in parallel with fixed capacitor of 200MVAr correspond to a limit of 2.0pu to -1.5 pu at 1.0 pu voltage

$$\zeta = \sqrt{\frac{\ln^2(\sigma_m(\%)/100)}{\pi^2 + \ln^2(\sigma_m(\%)/100)}} \quad \omega_n = \frac{\pi}{t_m\sqrt{1-\zeta^2}} \qquad (25)$$

$$G_M(s) = \frac{Y_M(s)}{U_r(s)} = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \qquad (26)$$

V. Results and Discussion

Five Gaussian linearly distributed membership functions have been determined for both SLFLC inputs (universes of discourse *e(k)* and *Δy(k)*): LN, MN, Z, MP, LP. The membership set for the fuzzy output variable is comprised of the singletons set. The fuzzy rule-table has 25 control rules. Fuzzy input scaling coefficients were estimated at k_e =1.2 and $k_{\Delta y}$ = 60. The initial feedforward gain k_3 value was set to zero. A minimal value of the sensitivity function β_{min} = 0.02 is selected, the limit for an allowed change of singletons is considered to be χ = 1, while gain coefficient K_S has been set to 3.0. The proportional gain Kp is assigned to be 1.2. Desired performance indices of the reference model were as follows: σ_m =5%, t_m = 0.02 sec (sampling interval T_d is 0.005 sec). The input membership function is shown in figure 4 and the rule base table is depicted in Table 1 after learning. The reference model parameters is identifying from the step response approach assuming the following specifications: percent overshoot (σ_m) = 5%, Peak time(t_m) = 0.02 sec. Then from equations (17) and (18) we can determine damping coefficient ξ and natural frequency ω_n which figure as parameters in the reference model transfer function.

A. *Simulation Results of SLFLC Controller*

In this Section SVC device installed in TNB 25 Bus System of south Malaysian peninsular and New England 39 Bus system are taken into consideration in evaluating the performance of SLFLC controller.

1) *TNB 25 Bus System*

To evaluate the performance of SVC SLFLC controllers, the simulations are carried out under the following cases:

i) A three phase fault applied at bus 7 for 80ms followed by an outage of line 7-10

ii) A three phase fault applied at bus 8 for 80ms followed by an outage of line 8-12.

The dynamic responses of the system following the described disturbances are shown in Figures 6 to 9 for SVC SLFLC. In Figures 7 and 8 the speed separation between machines G14 and G17 are chosen to display the performance of SVC SLFLC and it can be seen that in both cases the system with SLFLC has low overshoot and settled with short period of time. Figures 9 and 10 shows the real power of remaining line 7-10 response and voltage response of bus 14 where SVC is connected with SLFL Controller respectively. It can be seen that the response settled within 2.4 seconds and 6.2 seconds for Case1 and Case 2 respectively with SVC SLFLC controller. However, with conventional PID controller, the response settled within 2.6 seconds and 6.5 seconds

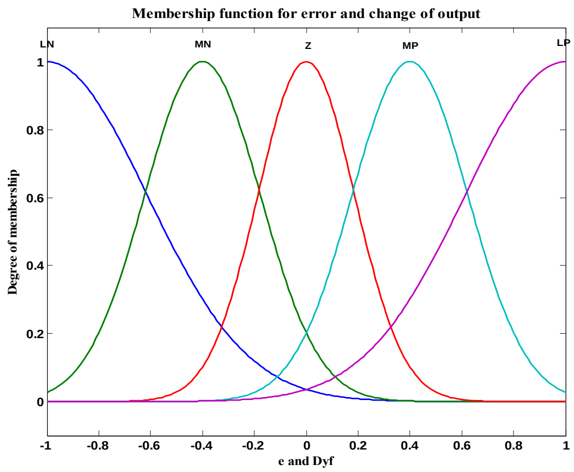

Figure 5 Input Membership functions

TABLE 1 The Fuzzy Rule-Table Obtained after Learning

Δy_f / Δe	LN	MN	Z	LP	MP
LN	0.002	-0.011	-0.518	0	0
MN	0.001	0.025	0.055	0	0
Z	0.064	-0.125	0.011	0.055	0
MP	-0.939	-0.228	0.055	0	0
LP	-0.35	-0.12	-1	0	0

2) *New England 39-bus system*

This system [4] consists of 10 generators, with generator 31 taken as reference generator. The single-line diagram of the New England system is given in Figure.10. Modal analysis shows that, in the base case, the critical mode is an interarea mode having eigenvalues, -0.07934 +j6.223 and damping ratio 0.0127, which is relatively low. Analysis of phase angle of right eigenvectors shows that in this interarea mode, generator G31 oscillates against a cluster of generators G35, G36 and G37.

For testing the effectiveness of SLFLC SVC controllers placed in the system, a three-phase fault was applied at bus 16 for 100 ms, and the rotor angle difference between generators G30 and G39, was plotted and is shown in Figure 11. It can be seen from Figure 11 that when the SLFLC SVC controllers is used, the transient response improves and the oscillations of the comparative angles between generators G30 and G39 decreases considerably compared with conventional controller.

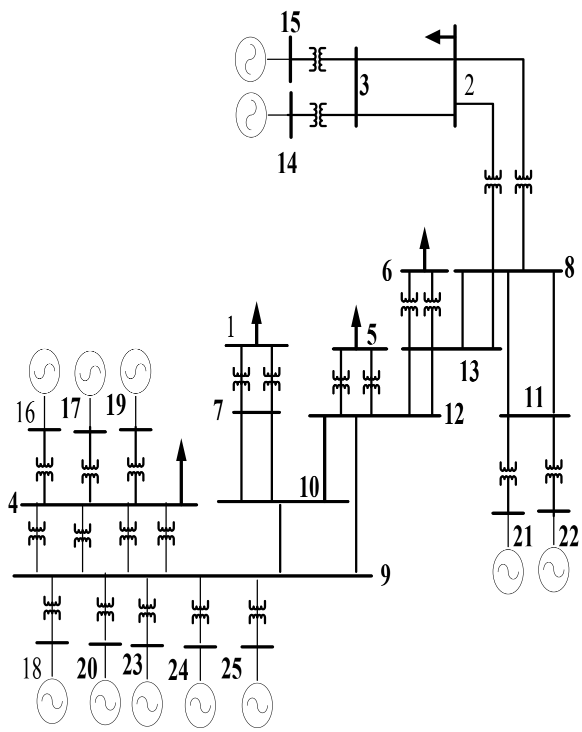

Figure 6: **25** Bus equivalents of South Malaysian Network

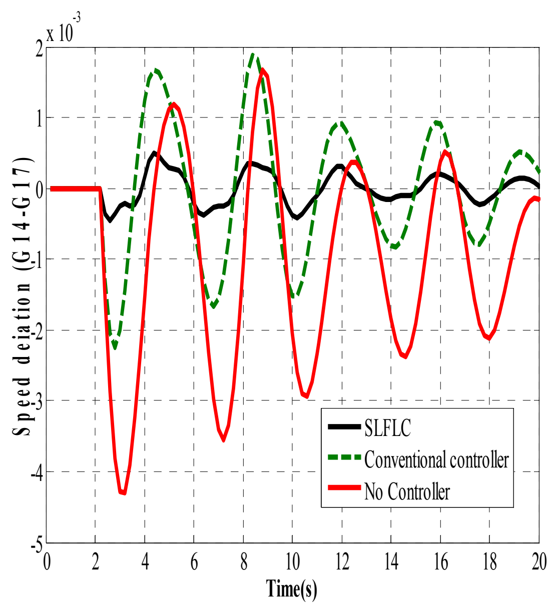

Figure 7 Speed deviation of (G14-G17) for line 7-10 outage

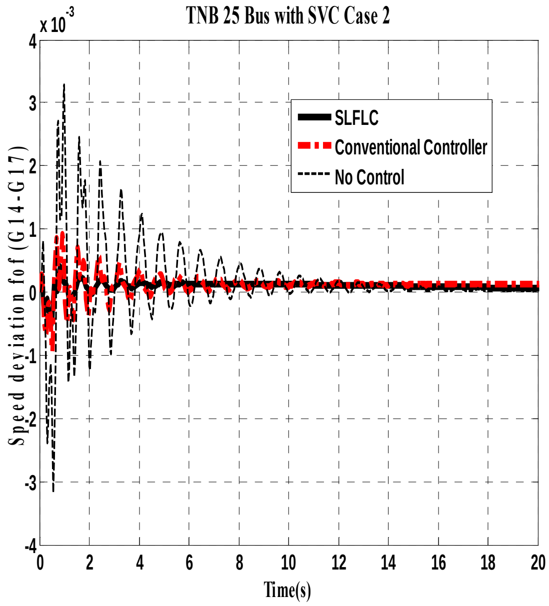

Figure 8 Speed deviation of (G14-G17) for line 8-12 outage

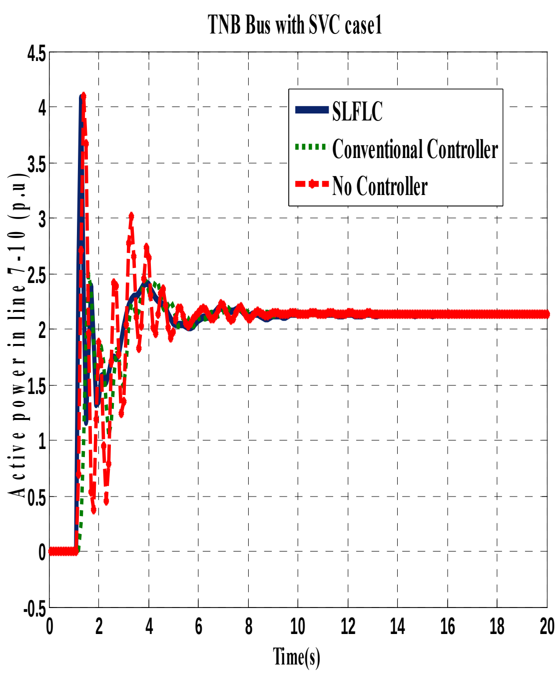

Figure 9 active powers in controlled line for line 7-10 outage

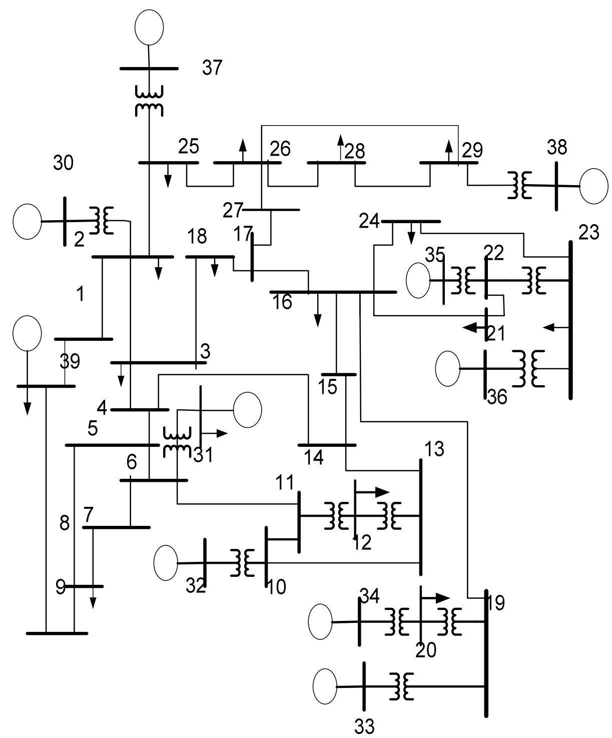

Figure 10: One-line diagram for the New England system

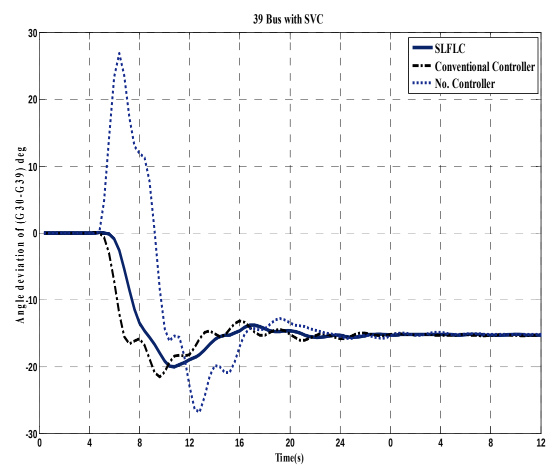

Figure 11 **Angle** deviation of (G30-G39)

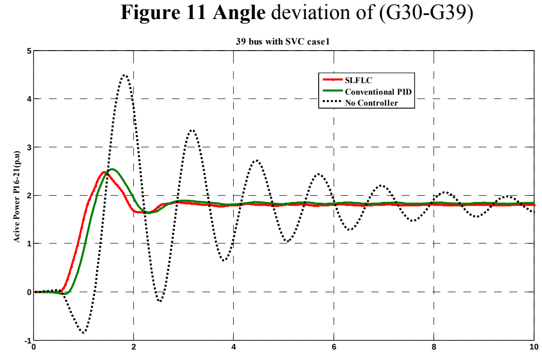

Figure 12 active powers in controlled line

NOMENCLATURE

A	State matrix
B	Input matrix
C	Output Matrix
D	Disturbance matrix
B_C	susceptance of the fixed capacitor
B_L	susceptance of the thyristor controlled reactor
*K*s	Gain coefficient
u	Control vector
η_λ	is the system output sensitivity function
x	State vector
y	Output matrix
δ	Machine rotor angle
ω	Rotor speed
e_d'	Direct axis transient voltage
e_q'	Quadrature axis transient voltage
e_d''	Direct axis subtransient voltage
e_q''	Quadrature axis subtransient voltage
v_m	Regulator output voltage
v_r	Exciter regulator voltage
ζ	Damping ratio
ς_C	Damping threshold
p-	Numberof fuzzy subsets of e(k),
q -	Number of fuzzy subsets of dye),
μ	Membership function of fuzzy relation

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BIOGRAPHIES

Dr. Nuraddeen Magaji received his B Eng , M Eng. degrees from Bayero University, Kano-Nigeria in 1999 and 2005 respectively, and Ph.D at the Universiti Teknologi Malaysia in 2010. His current research interests are FACTS modeling and control, AI application in power system stability, power system deregulation and application of control system in power system.

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