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A New Adaptive Controller of Facts-Based FMRLC Aimed at Improving Power System Stability

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Abstract: Various control techniques using Advanced Super-conducting Magnetic Energy Storage (ASMES) aimed at improving power system stability have been proposed. As fuzzy controller has proved its value in some applications, the number of investigations employing fuzzy controller with ASMES has been greatly increased over recent period. Nevertheless,it is sometimes difficult to specify the rule base for some plants, or the need can arise for tuning the rule-base parameters if the plant changes. In order to solve such problems, the Fuzzy Model Reference Learning Controller (FMRLC) is proposed. This paper investigates multi-inputs/multi-outputs FMRLC for time-variant nonlinear system. This provides the motivation for adaptive fuzzy control, whereby the focus is placed on the automatic on-line synthesis and tuning of fuzzy controller parameters (i.e., the use of on-line data for continuous learning of the fuzzy controller which ensures that the performance objectives are met). The simulation results show that the proposed robust controller is able to work with nonlinear power system (i.e., single machine connected at infinite bus), under various fault conditions and significant disturbances.

Keywords: Transient Power System Stability, FACTS, ASMES, Current Source Inverter (CSI), MIMO Fuzzy Controllers, Reference Model, Learning Control.

1 Introduction

The power stability of electrical systems basically implies its capability of reaching and sustaining an operating point in a controllable way following a disturbance and that the steady-state post-disturbance system voltages are acceptable. Furthermore, the term voltage instability denotes the absence of voltage stability and voltage collapse*,* the transition phase during which a power system progresses towards an unacceptable operating point due to voltage problems. The dynamics of voltage phenomena can be divided into two main groups: short- and long-term dynamics. Short-term phenomena acts on a time scale of seconds or shorter including, e.g. the effect of generator excitation controls and FACTS devices.

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Relatively recent development and the use of FACTS controllers in power transmission systems has led to many applications of these controllers to improve the power system stability [1, 2]. Several distinct models have been proposed to represent FACTS (i.e., SVC, TCR, TCSC, STATCOM…) in static and dynamic analysis [3]. The STATCOM is a structure based on a PWM Voltage Source Inverter (VSI). It is a bi-directional converter able to absorb sinusoidal network currents and exchange only reactive power with the network to improve voltage stability [4]. Many studies have been carried out and reported in the literature on the use of the Super-conducting Magnetic Energy Storage (SMES) in a variety of voltage and angle stability applications, proposing diverse control schemes and location techniques for voltage and angle oscillation control [5, 6].

These studies showed that the use of the SMES makes it possible to improve the transitory stability of the systems compared to other structures of family FACTS. In many papers, this SMES is based on a conventional structure (Grætz Bridge) using thyristor firing angle control and requires the P-Q modulation for operating in the four quadrants, therefore this structure presents certain disadvantages such as:

- The control of the delay angle is affected by the voltage drop.
- The injection of the harmonic currents in the network, which requires passive filters.
- The use of twelve thyristors to ensure operation in the four quadrants.

In [8, 9], a novel structure was proposed. It is a new concept of bi-directional PWM Current Source Inverter (CSI) associated with super-conducting magnetic storage (SMES) unit. The idea lying behind this concept is called Advanced-SMES (ASMES) is in regarding the ASMES as a current source, with acceptable harmonic currents. The ASMES is controlled in amplitude and phase separately by the active and reactive powers regulators to improve voltage and angular speed stability. Details of the implementation of the ASMES model proposed that can be used for steady state and transient stability analyses of power systems are discussed in this paper.

The power system models for transient stability studies are nonlinear and complex. Their parameters change with time, either slowly, due to environmental effects, or rapidly due to faults. Thus it is necessary to update the control law with system changes. The design of adaptive controllers aimed at improving the power system stability has been a topic of research for a long time now. However, there are many practical experiences and heuristic decision rules that can be applied to particular parts to avoid system instability. These results have been caused by the use of non-mathematical algorithms, such as the fuzzy control method which seems attractive for the transient stability control. In this case, the fuzzy control is used for both the angular speed and terminal voltage control loops for computing an active and reactive power to be absorbed or released by ASMES unit. However, the fuzzy control methodology which has been reported to display numerous problems, since the structure of fuzzy rule, membership function and parameters in fuzzy controller are determined by trial and error depending on computer simulations and human factor. In this paper, we introduce a learning controller developed by synthesizing several basic ideas from fuzzy set and control theory, self-organizing control, and conventional adaptive control. A learning control system is designed so that its "learning controller" has the ability to improve the performance of the closed-loop system by generating command inputs to the plant and utilizing feedback information from the plant. In this case, we utilize a learning mechanism, which observes the terminal voltage and adjusts the membership functions of the rules in a direct fuzzy controller so that the overall system behaves like a "reference model". The effectiveness of this Fuzzy Model Reference Learning Controller (FMRLC) is illustrated by showing that it can achieve high performance learning control for a nonlinear power system time-varying parameters control problem.

2 Power System and ASMES Equations

The modeling and the control of this converter aimed at enhancing the transient stability of power system were studied. Fig. 1 represents the general diagram of the ASMES unit. It is about a current source inverter (CSI) comprising six GTO.

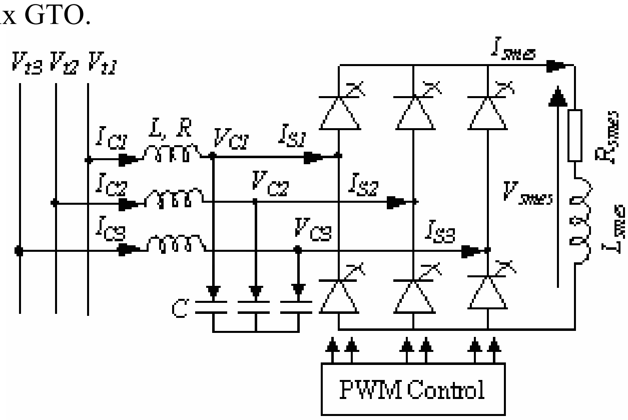


Fig. 1 – *General diagram of the* ASMES *unit.*

The ASMES unit is modelled according to *dq* axis by the derived equations in the AC side as follows:

$$L\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix} I_{Cd} \\ I_{Cq} \end{bmatrix} = \begin{bmatrix} -R & L\omega \\ -L\omega & -R \end{bmatrix}\begin{bmatrix} I_{Cd} \\ I_{Cq} \end{bmatrix} + \begin{bmatrix} V_{td} - V_{Cd} \\ V_{tq} - V_{Cq} \end{bmatrix}, \tag{1}$$

and those of the inverter output voltage by:

$$C\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix} V_{Cd} \\ V_{Cq} \end{bmatrix} = \begin{bmatrix} 0 & C\omega \\ -C\omega & 0 \end{bmatrix}\begin{bmatrix} V_{Cd} \\ V_{Cq} \end{bmatrix} + \begin{bmatrix} I_{Cd} - I_{Sd} \\ I_{Cq} - I_{Sq} \end{bmatrix}. \tag{2}$$

The inverter output currents I_{Sd} and I_{Sq} in dq axis are given by:

$$\begin{bmatrix} I_{Sd} \\ I_{Sq} \end{bmatrix} = \begin{bmatrix} S_d \\ S_q \end{bmatrix} I_{Smes}, \tag{3}$$

where S_d, S_q are switch orders in dq axis and C is the current in super-conducting coil.

The active and reactive powers of the ASMES unit are respectively expressed by:

$$\begin{aligned} P_C &= V_{td} I_{Cd} + V_{tq} I_{Cq} \\ Q_C &= V_{tq} I_{Cd} - V_{td} I_{Cq}. \end{aligned} \tag{4}$$

In the DC side, the supra-conducting coil can be characterized by:

$$V_{smes} = S_d V_{Cd} + S_q V_{Cq} \tag{5}$$

$$L_{Smes}\frac{\mathrm{d}I_{smes}}{\mathrm{d}t} = V_{Smes} - R_{Smes} I_{Smes} \tag{6}$$

and $I_{Smes}(0) = I_{ref}$, where I_{ref} indicates the initial current, L_{Smes} the inductance of the super-conducting coil normally charged on an energy level E_{ref} without any active power. The losses of connection are gathered in a resistance R_{Smes} which in practice can be neglected.

When the ASMES imposes a transaction of active power P_{Smes}, the level on date of the current I_{Smes} in the coil dictates a value of the continue voltage V_{Smes}. From measuring I_{Smes} current, one can estimate the level of storage of the ASMES which is given by:

$$E_{Smes} = \frac{1}{2} L_{Smes} I_{Smes}^2. \tag{7}$$

Let us consider that a power system consists of the synchronous generator connected through two parallel transmission tie-lines to a very large network that can be approximated by an infinite bus whose on-line diagram is as shown in Fig. 2. This synchronous generator is represented by one axis model [7]. The ASMES unit is located near the generator bus terminal in order to improve the dynamic performance of power system.

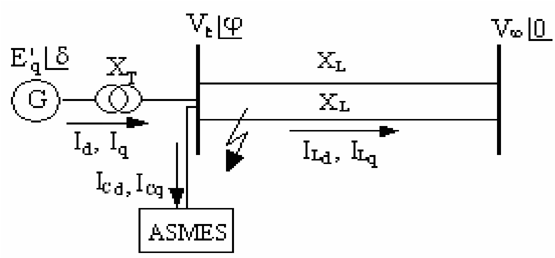


Fig. 2 – *Online diagram of power system with* ASMES *unit.*

The synchronous machine is represented by one axis model [7]:

$$\frac{\mathrm{d}\delta}{\mathrm{d}t} = \omega_B(\omega - 1) \tag{8}$$

$$\frac{\mathrm{d}\Delta\omega}{\mathrm{d}t} = \frac{1}{M}\left[P_m - P_e(\delta) - P_{Smes} - D(\omega - 1)\right] \tag{9}$$

$$\frac{\mathrm{d}E'_q}{\mathrm{d}t} = \frac{1}{T'_{d0}}\left[-E'_q + (X_d - X'_d)I_d + E_{fd}\right]. \tag{10}$$

Where ω, δ are angular speed and power angle, P_m, P_e, P_{Smes} are the power input, electrical output and active power of the ASMES unit respectively E'_q is electromotive force of the synchronous machine, *M* and *D* stand for the inertia constant and the damping coefficient respectively .

Using elementary circuit theory, it can be shown that the *dq* axis, the line currents I_{Ld} and I_{Lq} are given by:

$$\begin{aligned} I_{Ld} &= C_{d1}\sin\delta + C_{d2}\cos\delta + C_{d3}E'_q \\ I_{Lq} &= C_{q1}\sin\delta + C_{q2}\cos\delta + C_{q3}E'_q. \end{aligned} \tag{11}$$

Where the parameters C_{ki} ($k = d$, q and $i = 1, 2, 3$) in Eq. (11) are determined by the external impedance. Line fault simulation is done by changing the values of C_k according to the phase of the fault sequence.

Clearly, the power system associated with ASMES is a class of time-varying nonlinear model. Hence nonlinear adaptive control theory is used to design a nonlinear stabilizing controller for such a system.

3 Fuzzy Controllers

Standard fuzzy control structure of ASMES aimed at improving power system stability proposed and discussed in [8], shows that the fuzzy control gives good results compared to conventional control. This standard structure, given in Fig. 3, uses both the angular speed ω and terminal voltage V_t control loops. The error $e=[e_1\ e_2]$ and change in error $c=[c_1\ c_2]$ are the inputs of corresponding fuzzy controllers. These controllers use the Min-Max operator (Mamdani implication) and the Center Of Gravity (COG) defuzzification method. The output of Fuzzy Speed Controller (FSC) is u_1, while u_2 is the output of Fuzzy Voltage Controller (FVC) [8, 9]. For both fuzzy controller designs, 5 fuzzy sets are defined for each controller input such that the membership functions are triangular-shaped (with base width of 1) and evenly distributed on appropriate universes of discourse (the outer-most membership functions are trapezoidal). Similarly, the normalizing controller gains for the error, change in error, and the controller output are chosen to be $g_e=[1/2\ \ 1/4]^{\mathrm{T}}$, $g_c=[1/5\ \ 1/5]^{\mathrm{T}}$ and $g_u=[5\ \ 7/2]^{\mathrm{T}}$ respectively. The fuzzy controllers sampling period was chosen to be $T=1$ ms.

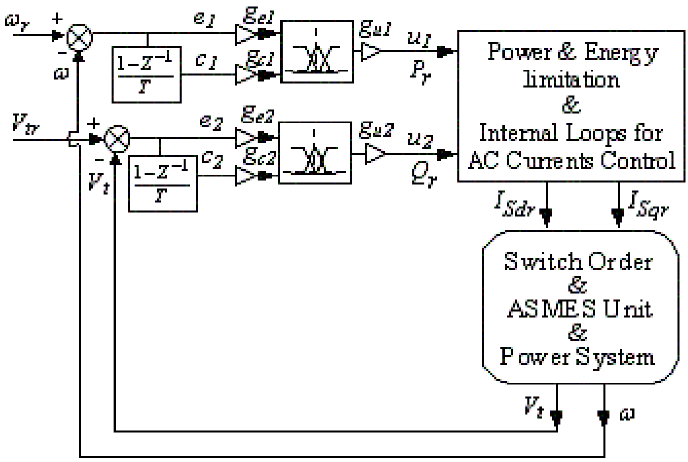


Fig. 3 – *Standard Fuzzy Control of* ASMES.

The control rules below are designed from an understanding of the desired effect of the controllers.

Rule (1): IF *e* is NB AND *c* is NB THEN *u* is PB

If the angular speed and terminal voltage exceed their references, then the ASMES is controlled in order to absorb the active and reactive powers so that the system finds its equilibrium point.

Rule (13): IF *e* is ZE AND *c* is ZE THEN *u* is ZE

This situation corresponds to an equilibrium operating point, therefore no exchange of active and reactive powers between the network and the ASMES is necessary.

Rule (25): IF *e* is PB AND *c* is PB THEN *u* is NB

This situation corresponds to the case where the angular speed and terminal voltage are small compared to their references therefore the active and reactive powers generation by the ASMES is necessary to stabilize the system.

These rules assume that the desired operating point will be reached soon after, and stabilization control is no longer needed. The complete set of control rules for both fuzzy controllers is shown in **Table 1** show each of the 25 control rules represents a desired controller response to a particular situation.

The control rules were designed to be symmetric under the assumption that, if necessary, any asymmetries could be best handled through scaling. In addition, adjacent regions in the rule table allow only nearest neighbor changes in the control output (NB to NS. NS to ZE and so on). This ensures that small changes in *e* and *c* result in small changes in *u*.

Table 1
The rule base matrix for both Fuzzy Controllers.

$c \backslash e$	NB	NS	ZE	PS	PB
NB	*PB*	*PB*	*PB*	*PS*	*ZE*
NS	*PB*	*PB*	*PS*	*ZE*	*NS*
ZE	*PB*	*PS*	*ZE*	*NS*	*NB*
PS	*PS*	*ZE*	*NS*	*NB*	*NB*
PB	*ZE*	*NS*	*NB*	*NB*	*NB*

4 Fuzzy Model Reference Learning Controllers

In this Section, we present a new learning control technique developed by extending some of the linguistic self-organizing control concepts presented by Procyk and Mamdani in [10] and by utilizing ideas from conventional Model Reference Adaptive Control (MRAC). The learning control technique, which is shown in Fig. 4, uses a learning mechanism that:

(i) observes data from a fuzzy control system, (ii) characterizes its current performance, and (iii) automatically synthesizes and/or adjusts the fuzzy control so that some pre-specified performance objectives are met. These performance objectives are characterized via the reference model shown in Fig. 4. In an analogous manner to conventional MRAC, the learning mechanism seeks to adjust the fuzzy controllers so that the closed-loop system (the map from ω_r to ω and V_{tr} to V_t) acts like a pre-specified reference model (the map from ω_r to ω_m and V_{tr} to V_{tm}). This control is named fuzzy learning control. Its unique approach to remembering the adjustments it makes, and according to the prevailing definition of learning [9, 10].

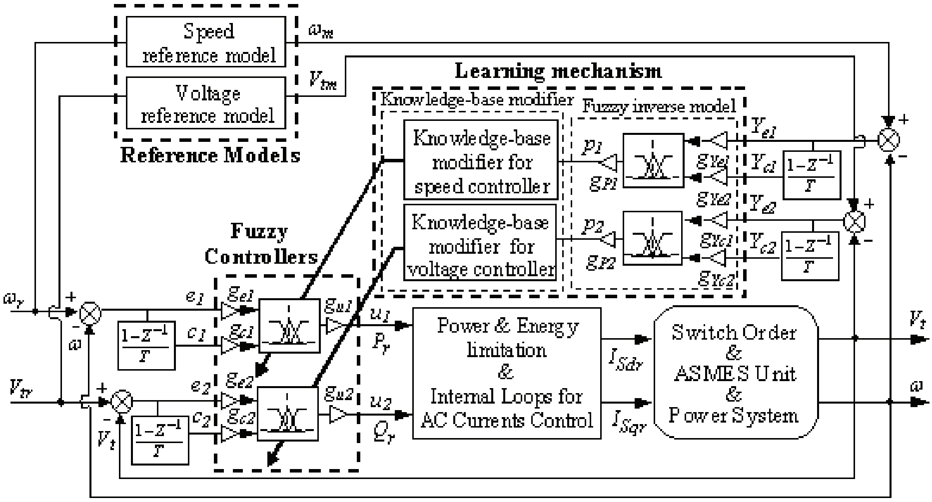


Fig. 4 – *Fuzzy Model Reference Control of ASMES.*

4.1 Reference model

The reference model provides a capability for quantifying the desired performance of the process. Given that the reference model characterizes design criteria such as stability, rise time, overshoot, settling time, etc. We would like the outputs ω and V_t to track desired reference values ω_m and V_{tm}, respectively, which are obtained from the reference model vector. It is easily verified that this system has a vector relative degree of $[3\ 2]^{\mathrm{T}}$. We want the outputs of the system to track the reference vector:

$$\left[\omega_m(s)\ V_{tm}(s)\right]^T = \left[\frac{15^3\omega_r(s)}{(s+15)^3},\ \frac{10^2 V_{tr}(s)}{(s+10)^2}\right]^T \qquad (12)$$

where $\omega_r(s) = £\{\omega_r(t)\}$ and $V_{tr}(s) = £\{V_{tr}(t)\}$, $£\{x(t)\}$ is the *Laplace* transform of temporal function $x(t)$ and s is the *Laplace* transform operator.

4.2 Learning mechanism

As previously mentioned, the learning mechanism performs the function of modifying the knowledge-base of a fuzzy controller so that the closed-loop system behaves like the reference model. These knowledge-base modifications are made based on observing data from the controlled process, the reference model, and the fuzzy controller. The learning mechanism consists of two parts: a *fuzzy inverse model* and a *knowledge-base modifier*.

The fuzzy inverse model performs the function of mapping necessary changes in the process output, as expressed by $Y_e=[Y_{e1}\ Y_{e2}]^T$, to the relative changes into process inputs (denoted by $P=[P_1\ P_2]^T$) necessary to achieve these process output changes. The knowledge-base modifier performs the function of modifying the fuzzy controller's knowledge-base to affect the needed changes in the process inputs.

For this Fuzzy Model Reference Learning Control (FMRLC) design, two fuzzy inverse models are needed, one for each fuzzy controller. In general, both process inputs will affect both process outputs. However, for these fuzzy inverse models design we will assume that the cross-coupling between the inputs is negligible. As a result, the inputs to a given fuzzy inverse models includes the errors and change in errors between the associated reference model outputs and process outputs. Therefore, for the both fuzzy inverse model, the inputs are $Y_e=[Y_{e1}\ Y_{e2}]^T$ and $Y_c=[Y_{c1}\ Y_{c2}]^T$ respectively and the output is $p=[p_1\ p_2]^T$. For these inputs and outputs, 5 fuzzy sets are defined with triangular shaped membership functions which are evenly distributed on the appropriate universe of discourse.

The normalizing fuzzy system gains associated with Y_e, Y_c and P are chosen to be $g_{Ye}=[1/2\ 1/2]^T$, $g_{Yc}=[1\ 1/2]^T$, and $g_P=[100\ 25]^T$, respectively. Consequently, the knowledge-base array, shown in **Table 2**, is used for both fuzzy inverse models.

Table 2

The rule base matrix for both Fuzzy Inverse Models.

$Y_c \backslash Y_e$	NB	NS	ZE	PS	PB
NB	*NB*	*NB*	*NB*	*NS*	*ZE*
NS	*NB*	*NB*	*NS*	*ZE*	*PS*
ZE	*NB*	*NS*	*ZE*	*PS*	*PB*
PS	*NS*	*ZE*	*PS*	*PB*	*PB*
PB	*ZE*	*PS*	*PB*	*PB*	*PB*

The fuzzy inverse model rule base matrix, shown in **Table 1** was designed to take advantage of the damping feature described above. In considering the following rules:

Rule (1): IF Y_e is NB AND Y_c is NB THEN P is NB

This rule corresponds to the case where the process output $Y=[\omega\ V_t]^T$ is greater than the reference model output $Y_m=[\omega_m\ V_{tm}]^T$ and Y continues to increase over Y_m, then the fuzzy inverse models output $P=[P_1\ P_2]^T$ characterizes that a negative increment should be added to the process input to insure that Y will not continue to increase.

Rule (13): IF Y_e is ZE AND Y_c is ZE THEN P is ZE

In this situation, the fuzzy inverse models indicate that no change in the inputs process is required to force $Y=Y_m$ since this equality is already achieved.

Similar statements hold for the remaining elements in **Table 2**. The knowledge-base modifier performs the function of modifying the fuzzy controller so that better performance is achieved. Given the information about the necessary changes in the inputs as expressed by the vector $P=[P_1\ P_2]^T$ from the fuzzy inverse models, the knowledge-base modifier changes the knowledge-base of the fuzzy controllers so that the previously applied control action is modified by the amount P. Therefore, previously computed control action contributed to the present quality of the system performance. Note that $e=[e_1\ e_2]^T$ and $c=[c_1\ c_2]^T$ would have been the process errors and change in errors, respectively, at that time. Likewise, $u=[u_1\ u_2]^T$ would have been the controller output at that time. The controller output which would have been desired is expressed by [13]-[14]:

$$\bar{u}(KT-T)=u(KT-T)+P(KT) \tag{13}$$

5 Simulation Results

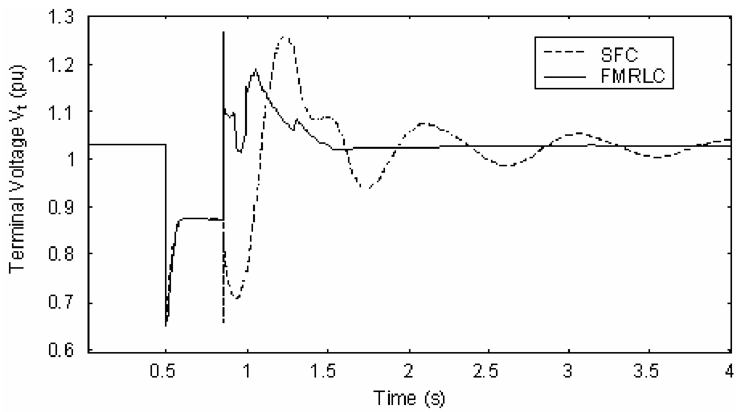
In order to evaluate the usefulness of the proposed ASMES structure with fuzzy learning control, we perform the computer simulation for a single machine infinite bus system. The critical fault time of the non-compensated machine (i.e., without ASMES) is t_{cd}=0.14 s.

We suppose that the fault appearance time is 0.5 s and the re-close interval is t_f=1s (50 cycles). The power system stability can be judged by the fault duration therefore two cases are considered in this simulation.

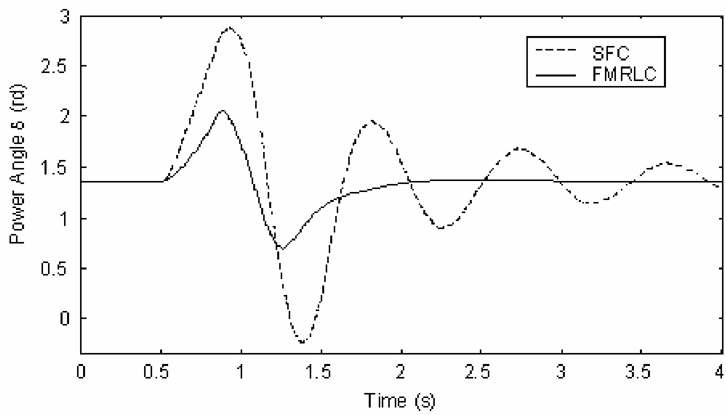
The first fault time is t_d=0.32 s and the second one corresponds to t_d=0.43 s. Fig. 5 depicts the nonlinear behavior of terminal voltage V_t, angular speed ω and power angle δ , after a sudden three-phase fault applied at the terminal machine node. In Fig. 5, we can see that for a fault duration t_d=0.32 s, when we introduce the ASMES unit with the Standard Fuzzy Control (SFC), the system finds its operating equilibrium point after fault elimination. In these same curves, we can notice the presence of a transient operating mode witch must be reduced in order to improve power system stability.

The improvement of transient stability is increasingly significant, when the SFC is replaced by the Fuzzy Model Reference Learning Control (FMLC), we can notice that the transient mode is reduced, the system finds its equilibrium point exactly after fault elimination, the peak and the response time are significantly minimized.

The effectiveness of the FMLC proposed in this paper is more validated through the simulation results presented in Fig. 6. When the fault time is increased (e.g., t_d=0.43 s), the Fig. 6 shows that the compensated machine with SFC loses completely its stability, this is due to the nonlinear nature of the power system whose parameters are variable during great disturbances. But the application of the FMLC allowed the system to find its equilibrium operating point.

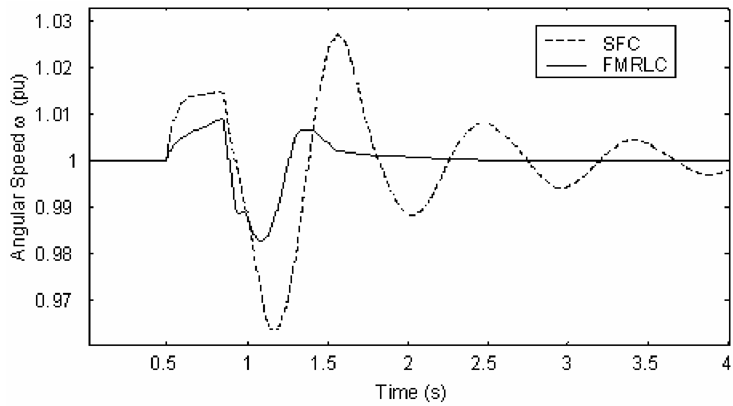


(a) Terminal Voltage V_t (pu)

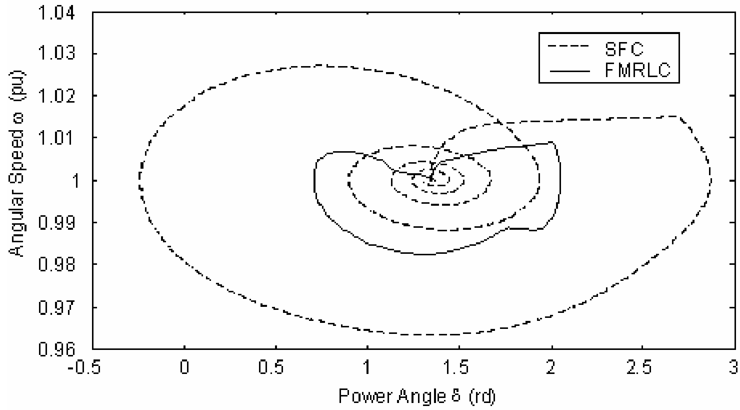


(b) Power Angle δ (rd)

Fig. 5(a-b) – *Simulation results for three-phase fault of duration* t_d = 0.32 s.

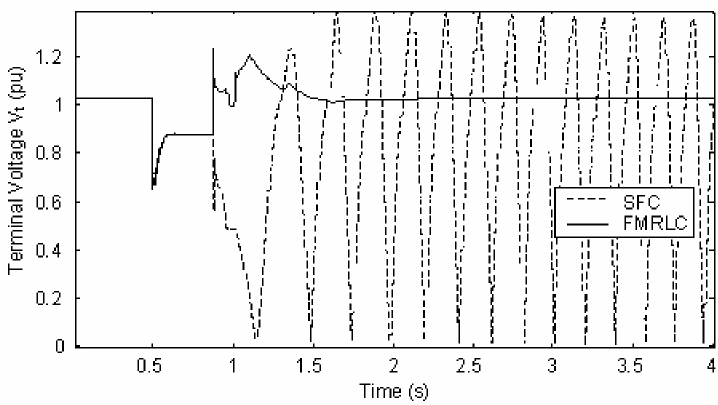


(c) Angular Speed ω (pu)



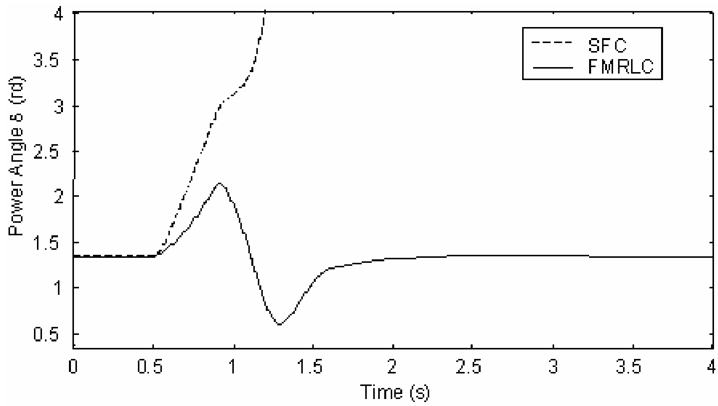
(d) Angular Speed-Power Angle characteristic

Fig. 5(c-d) – *Simulation results for three-phase fault of duration* $t_d = 0.32$ s.

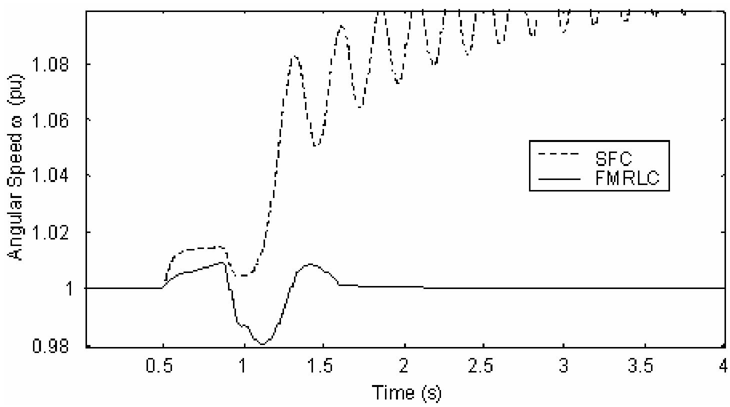


(a) Terminal Voltage V_t (pu)

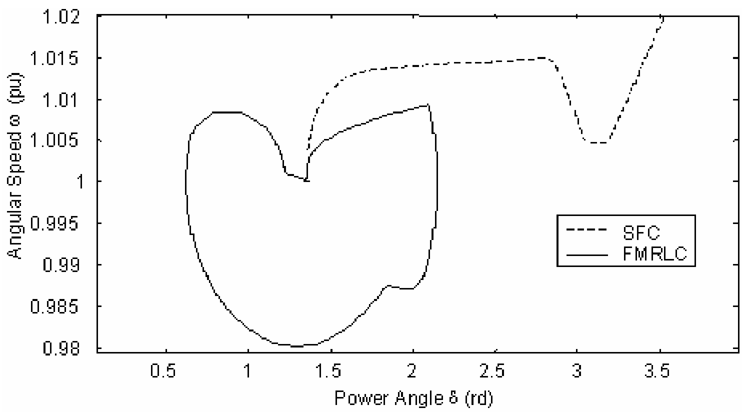
Fig. 6a – *Simulation results for three-phase fault of duration* $t_d = 0.43$ s.



(b) Power Angle δ (rd)



(c) Angular Speed ω (pu)



(d) Angular Speed-Power Angle characteristic

Fig.6(b-d) – *Simulation results for three-phase fault of duration* t_d = 0.43 s.

This application clearly illustrates the effectiveness of the fuzzy learning algorithm for controlling a nonlinear time varying process. Once again the fuzzy learning control provides good system tracking with respect to the reference model. As a result, the system exhibits good steady state and transient response.

The fuzzy inverse models outputs (P_1, P_2) for fault time t_d=0.32 s, are illustrated by Fig. 7. The nonzero values of P_1 or P_2 indicate the knowledge-base adaptation for fuzzy controllers.

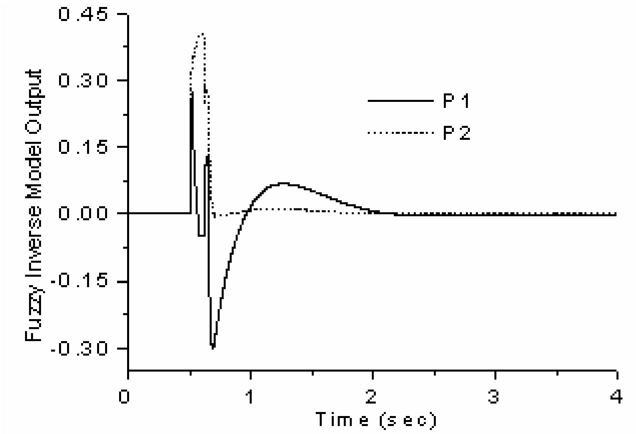


Fig. 7 – *The signals outputs for both fuzzy inverse model.*

The control surface provides a 3-dimensional view of the relationship between two inputs and output variables of the fuzzy controller. The Fig. 8 checks the output behavior across the entire range of possible inputs combinations using the knowledge-base array illustrated by **Table 1**.

Before learning control, this knowledge-base is fixed and the control surface, shown in Fig. 8, for both controllers is linear without bumps.

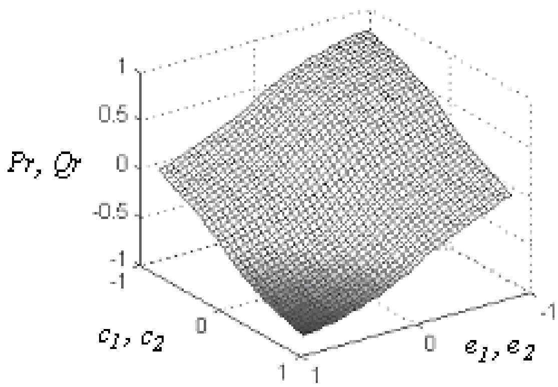


Fig. 8 – *The control surfaces before learning for both controllers.*

When the fault occurs, the power system parameters change rapidly therefore the angular speed ω and the terminal voltage V_t escape from their desired reference model values. In this case the learning mechanism seeks to adjust the fuzzy rules of the controllers (i.e., knowledge-base modifications).

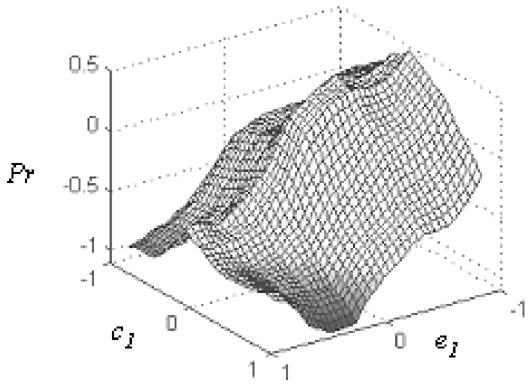


Fig. 9 – *Control surface of Fuzzy Speed Controller.*

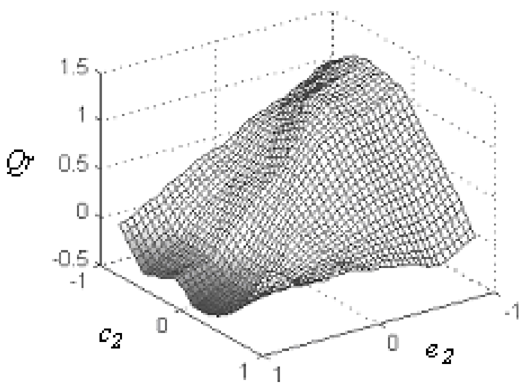


Fig. 10 – *Control surface of Fuzzy Voltage Controller.*

During the fault phase, Figs. 9 and 10 show the control surfaces for both Fuzzy Controllers, exactly at 0.57 s. At this time, the angular speed ω increases over the desired speed reference model output ω_m, while the terminal voltage V_t decreases below V_{tm}. For that, the fuzzy inverse model output P_1 must be negative so that the membership functions are shifted leftward (i.e., the modification of knowledge-base), to insure that ω reaches ω_m. For this reason, the control surface of Fuzzy Speed Controller, shown in Fig. 9, is moved downward. The control surface of Fuzzy Voltage Controller, illustrated in Fig. 10, is shifted upward. This is due to P_2 which was assigned a positive value so that V_{tm} attracts V_t.

For both controllers, these control surfaces which are initially linear form have more bumps, Fig. 8. This allows the controllers to have a nonlinear characteristic and consequently they get large changes in outputs when there are small changes in inputs, in order to improve the rapidness and robustness of the system response and drive rapidly the system outputs to their desired ones.

The knowledge-base modifications for both controllers are not similar. This is due to the fact that each fuzzy controller improve its performance by interaction with its environment which depends on reference model parameters (i.e., rise time, overshoot, settling time, etc.).

6 Conclusion

This paper proposes a non-linear control method applied on ASMES aimed at improving transient stability of a single machine-infinite bus system. The ASMES is placed at the point where the fault intervenes (i.e. with the node of the machine). This concept allows accurate and reliable carrying out transient stability study of power system and its controllers for voltage and speeding stability analyses. It considerably increases the power transfer level via the improvement of the transient stability limit.

The computer simulation results have proved the efficiency of the Fuzzy Model Reference Learning Control, showing stable system responses almost insensitive to large parameter variations. This learning control possesses the capability to improve its performance over time by interaction with its environment.

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Appendix

Electric Machine and Power System parameters:

$\omega_B = 100\pi$ rad/s, $x_d = 1.030$ pu, $x_q = 1.030$ pu, $x'_d = 0.326$ pu, $T'_{d0} = 6.5$ s,

$D = 8$, $V_\infty = 1.0$ pu, $X_T = 0.2$ pu, $X_L = 0.17$ pu, $R_L = 0.073$ pu,

$V_{ref} = 1.05$ pu, $E_{fd} = 1.05$ pu, $P_m = 0.8$ pu.

ASMES parameters:

$R = 0.5$ pu, $L = 2.5$ mH, $C = 1000$ μF, $R_{smes} = 0$ pu, $L_{smes} = 0.5$ H.