

Fuzzy Learning Control of Advanced Super-Conducting Magnetic Energy Storage to Improve Transient Power System Stability

H. Hamdaoui, A. Semmah, Y. Ramdani, and M. K. Fellah

Abstract—This paper proposes an Advanced structure of Super-conducting Magnetic Energy Storage using a PWM Current Source Inverter by adopting a robust method based on the fuzzy set theory for generate the modulation index and the shift angle, which allowed the active and reactive powers exchange control in the four quadrants. Two independent fuzzy controllers are assigned, one for the angular speed control and the other for the terminal voltage control. However, the fuzzy control methodology which has ever been reported has many problems, since structure and choosing of fuzzy rules, membership function and parameters in fuzzy controller are determined by trial and error depending on computer simulations and skilled person's intuition. In this paper, we introduce a learning control that is developed by synthesizing several basic ideas from fuzzy set and control theory, self-organizing control and conventional adaptive control. This provides the motivation for adaptive fuzzy control where the focus is on the automatic on-line synthesis and tuning of fuzzy controller parameters. Simulation results show that the proposed learning control is able to ensure the transient stability of power system under various fault conditions and significant disturbances.

Index Terms—Power system stability, CSI, ASMES, fuzzy learning control.

I. INTRODUCTION

THE INEVITABLE perturbations such as short circuit can affect the power system operation at any moment and lead it outside of its stability limit. Power System Stabilizers (PSS) and Automatic Voltage Regulators (AVR) are normally employed to damp out the electromechanical oscillations. However, in the event of large faults, the non-linearity of the power system becomes very severe, thereby putting limitations on the performances of PSS and AVR to respond effectively this type of faults [1].

The actual development of the power electronics and microelectronics allows the identification of rapid control systems called Flexible Alternating Current Transmission System (FACTS) to improve power system stability [2]. Several distinct models have been proposed to represent FACTS (i.e., SVC, TCR, TCSC, STATCOM, etc..) in static and dynamic analysis [3]. The STATCOM is a

structure which is based on a Voltage Source Inverter (VSI). It is a bi-directional converter whose characteristics enable it 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 angular speed control [5]. These studies showed that the use of the SMES permits to improve the transient stability of power systems compared to other structures of FACTS family. In many papers, this SMES is based on a conventional structure using thyristors firing angle control and requires the P-Q modulation for operating in the four quadrants [6], 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 [7], a new structure was proposed, it is a bi-directional Current Source Inverter (CSI), associated with Super-Conducting Magnetic Storage (SMES) unit. The idea behind this concept, called as Advanced-SMES (ASMES), is to consider 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 controllers, to improve voltage and angular speed stability. Detailed model of the proposed ASMES, that can be used to improve the transient power system stability is discussed in this paper.

The power system models for transient stability studies are nonlinear and complex. Their parameters change with time, 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 to improve the power system stability has been a topic of research for a long time. 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 obtained by using 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 a desired active and reactive powers to be absorbed or released by ASMES unit.

Manuscript received June 15, 2003; revised March 27, 2004.

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Publisher Item Identifier S 1682-0053(04)0215

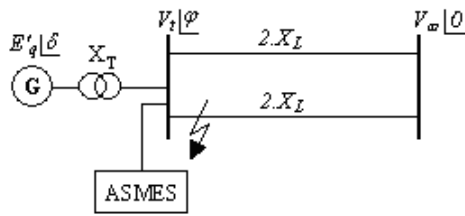


Fig. 1. Online diagram of power system with ASMES unit.

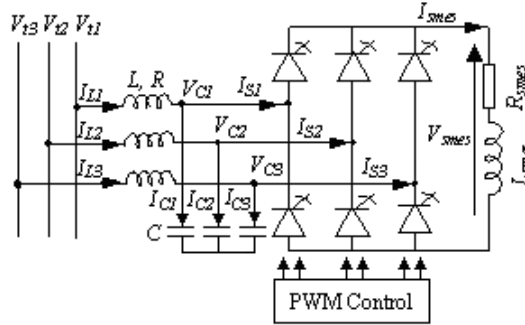


Fig. 2. General diagram of the ASMES unit.

However, the fuzzy control methodology which has ever been reported has many problems, since structure and choosing of fuzzy rules, membership function and parameters in fuzzy controllers are determined by trial and error depending on computer simulations and skilled person's intuition. In this paper, we introduce a fuzzy learning control that is 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 ASMES and utilizing feedback information from the power system. In this case, we utilize a learning mechanism which observes the angular speed and the terminal angle and adjusts the knowledge-base in a fuzzy controllers when the power system parameters change due to faults.

II. PLANT MODEL

Consider a power system consisting of the synchronous machine connected through two (02) parallel transmission tie-lines, to a very large network that can be approximated by an infinite bus whose on-line diagram is shown in Fig. 1. The ASMES unit is located near the machine bus terminal to improve the dynamic performance of power system.

The synchronous machine is represented by one axis model [8]:

$$\frac{d\delta}{dt} = \omega_B \Delta\omega \quad (1)$$

$$\frac{d\Delta\omega}{dt} = \frac{1}{M} [P_m - P_e(\delta) - P_{smes} - D \cdot \Delta\omega] \quad (2)$$

$$\frac{dE'_q}{dt} = \frac{1}{T'_{d0}} [-E'_q + (X_d - X'_d)I_d + E_{fd}] \quad (3)$$

where $\Delta\omega$ and δ are angular speed deviation and power angle; P_m, P_e, P_{smes} are respectively the power input, electrical output and active power of the ASMES unit; E'_q

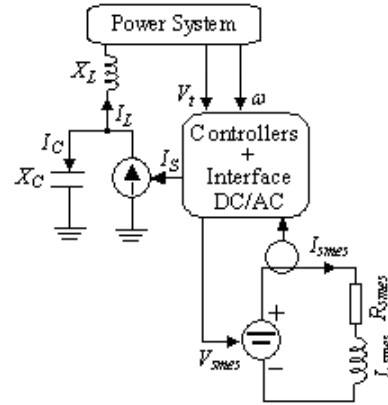


Fig. 3. Detailed diagram of the ASMES unit.

is electromotive force of the synchronous machine; M and D represent respectively the inertia constant and the damping coefficient.

III. ASMES UNIT

In this section, we propose a new structure called ASMES, which is based on Current Source Inverter (CSI). It is a bi-directional converter whose characteristics enable it to absorb sinusoidal network currents and exchange active and reactive powers with the network. The modeling and the control of this converter to enhance the transient stability of power system are studied. Fig. 2 represents the general diagram of the ASMES unit, it is about a current source inverter (CSI) made up of six GTO.

Taking into account the inductive nature of the network, the connection of such a converter must be inevitably carried out through a decoupling battery made up of capacitors between-phases. This interface permits to short-circuit the harmonic currents related to cutting high frequency of the switches so that they do not affect the line currents [7]-[9]. The detailed diagram of the ASMES unit associated with the power system is illustrated in Fig. 3.

The ASMES unit is modeled according to the dq axis by the differential equations in the AC side as follows:

$$L \frac{d}{dt} \begin{bmatrix} I_{Ld} \\ I_{Lq} \end{bmatrix} = \begin{bmatrix} -R & L\omega \\ -L\omega & -R \end{bmatrix} \begin{bmatrix} I_{Ld} \\ I_{Lq} \end{bmatrix} + \begin{bmatrix} V_{td} - V_{Cd} \\ V_{tq} - V_{Cq} \end{bmatrix} \quad (4)$$

and those of the inverter output voltage as:

$$C \frac{d}{dt} \begin{bmatrix} V_{Cd} \\ V_{Cq} \end{bmatrix} = \begin{bmatrix} 0 & C\omega \\ -C\omega & 0 \end{bmatrix} \begin{bmatrix} V_{Cd} \\ V_{Cq} \end{bmatrix} + \begin{bmatrix} I_{Ld} - I_{Sd} \\ I_{Lq} - I_{Sq} \end{bmatrix} \quad (5)$$

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

$$\begin{cases} I_{Sd} = S_d I_{smes} \\ I_{Sq} = S_q I_{smes} \end{cases} \quad (6)$$

where S_d and S_q are the switch orders in dq axis and I_{smes} is the current in super-conducting coil.

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

$$P_{smes} = V_{td} I_{Ld} + V_{tq} I_{Lq} \quad (7)$$

$$Q_{smes} = V_{td} I_{Lq} - V_{tq} I_{Ld} \quad (8)$$

In the DC side, the ASMES voltage is characterized by:

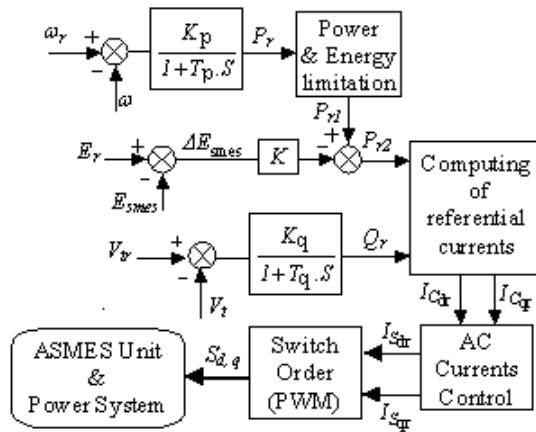


Fig. 4. Conventional control design of ASMES unit.

$$V_{smes} = S_d V_{Cd} + S_q V_{Cq}. \quad (9)$$

The current in the super-conducting coil is given by:

$$L_{smes} \frac{dI_{smes}}{dt} = V_{smes} - R_{smes} I_{smes} \quad (10)$$

and $I_{smes}(0) = I_{ref}$, where I_{ref} indicates the initial current and L_{smes} the inductance of the super-conducting coil which is normally charged on an energy level E_{ref} and does not output any active power. The connection losses are gathered in a resistance R_{smes} which, in practice, can be neglected. When the exchange of active power P_{smes} is imposed, the instantaneous value of the current I_{smes} in the coil dictates the voltage value V_{smes} . From a measurement of I_{smes} current, we can estimate the level of storage of the ASMES which is given by:

$$E_{smes} = \frac{1}{2} L_{smes} I_{smes}^2 \quad (11)$$

IV. CONTROLLER DESIGN

A. Conventional Control

The conventional control for the ASMES unit is shown in Fig. 4. It is based on two first order controllers and use both the angular speed ω and terminal voltage V_t control loops for computing a desired active and reactive powers to be absorbed or released by ASMES unit.

1) Power and Energy Limitation

When the storage E_{smes} of the coil is on a minimal level (E_{min}), the ASMES cannot generate the active power. Consequently, any request for additional generation of active power must be truncated to zero ($P_{smes} = 0$). In a symmetrical way, when the storage of the coil is at the maximal level (E_{max}), any additional consumption of the active power must be truncated to zero. However, the reactive power exchange is not affected by these two situations. If we indicate by P_r the power claimed by the controller and P_{rl} that granted by the limiting device of energy, the policy to be followed in any time [7], [9], [10] can be summarized as follows:

$$\begin{cases} P_{r1} = P_r & \text{if } (E_{min} < E_{smes} < E_{max}) \\ P_{r1} = 0 & \text{if } (E_{smes} < E_{min}) \wedge (P_r < 0) \\ & \text{or } (E_{smes} > E_{max}) \wedge (P_r > 0) \end{cases} \quad (12)$$

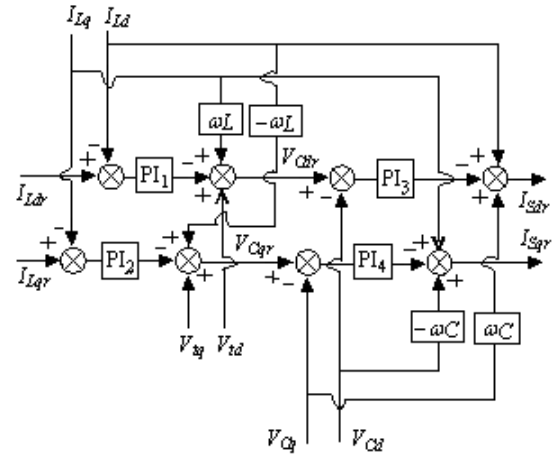


Fig. 5. AC currents control in dq axis.

2) Energy Feedback Control Loop

It is desirable to restore the energy E_{smes} of coil to its rated value as quickly as possible after disturbance, so that the ASMES unit can respond properly to any subsequent disturbance [11]. To archive this, the energy deviation is sensed and used as negative feedback control loop to archive quick restoration of energy level. In the case, the desired active power of ASMES unit can be determined by:

$$P_{r2} = P_{r1} - K \Delta E_{smes} \quad (13)$$

where K is the gain of energy deviation feedback.

3) AC Currents Control in dq Axis

Once the requests P_{r2} and Q_r are calculated, they must now be converted into active I_{Ldr} and reactive I_{Lqr} referential currents which will be used as inputs for currents control in dq axis (Fig. 5). These referential currents are given by:

$$\begin{cases} I_{Ldr} = \frac{P_{r2} V_{td} - Q_r V_{tq}}{V_{td}^2 + V_{tq}^2} \\ I_{Lqr} = \frac{P_{r2} V_{tq} + Q_r V_{td}}{V_{td}^2 + V_{tq}^2} \end{cases} \quad (14)$$

B. Fuzzy Learning Control

In this Section, we present a new learning control technique that was developed by extending some of the linguistic self-organizing control concepts presented by Procyk and Mamdani in [12] and by utilizing ideas from conventional Model Reference Adaptive Control (MRAC).

The learning control technique, which is shown in Fig. 6, 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. 6. 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,

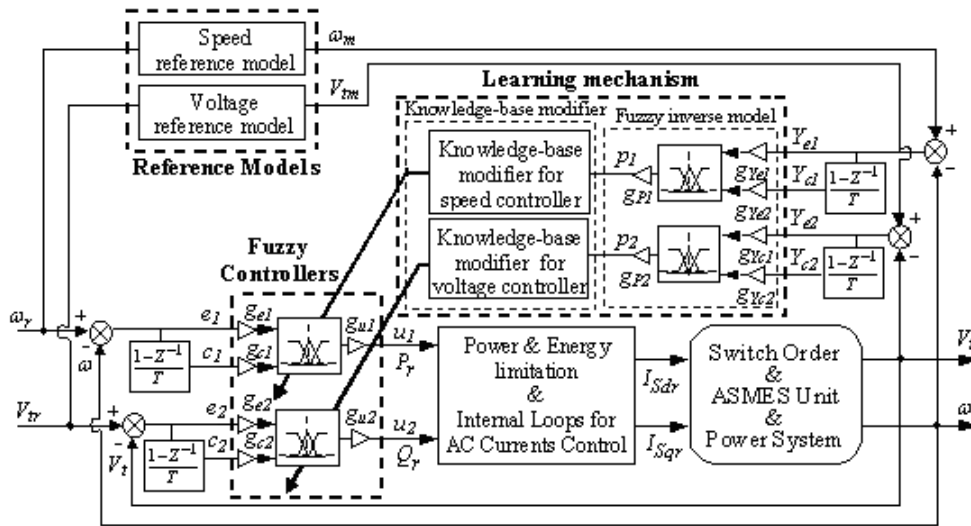


Fig. 6. Fuzzy control design of ASMES unit.

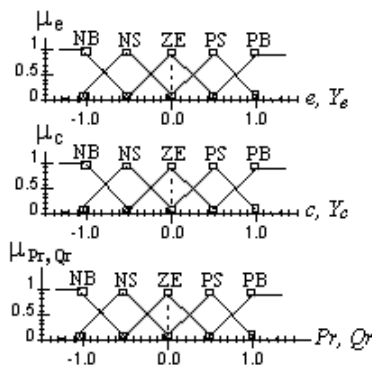


Fig. 7. The membership functions for both controllers.

TABLE I
THE RULE BASE MATRIX FOR BOTH FUZZY CONTROLLERS

$e \backslash c$	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

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, then the active and reactive powers generation by The ASMES is necessary to stabilize the system.

These rules anticipate that the desired operating point will be reached soon and stabilization control is no longer needed. The complete set of control rules for both fuzzy controllers is shown in Table I. 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 .

2) 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 that the outputs ω and V_t follow desired reference values ω_m and V_m , respectively, which are obtained from the reference model vector. It is easily

and according to the prevailing definition of learning [13].

1) Fuzzy Controller:

The proposed fuzzy controller along with ASMES unit (obtained by replacing the first order conventional controllers in Fig. 4 by two fuzzy controllers) use 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 (Fig. 6). These controllers use Min-Max operator (Mamdani implication) and 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) [7], [14], [15]. For both fuzzy controller designs, five 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). Also, the normalizing controller gains for the error, change in error, and the controller output are chosen to be $g_e = [1/2 \ 1/4]^T$, $g_c = [1/5 \ 1/5]^T$, and $g_u = [5 \ 7/2]^T$, respectively. The fuzzy controllers sampling period was chosen to be $T = 1$ milliseconds.

Fig. 7 shows the membership functions of inputs and their respective output variable, for both controllers.

The control rules are designed from an understanding of the desired effect of the controllers. For example, consider the rules:

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

verified that this system has a vector relative degree of $[3 \ 4]^T$. We want the outputs of the system to track the reference vector:

$$[\omega_m(s), V_{tm}(s)]^T = \left[\frac{0.75^3 \omega_r(s)}{(s+0.75)^3}, \frac{0.75^4 V_{tr}(s)}{(s+0.75)^4} \right]^T, \quad (15)$$

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

3) The 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*.

i) Fuzzy Inverse Model

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 Learning Control (FLC) 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 model 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, five 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 $g_{Y_e} = [1/2 \ 1/2]^T$, $g_{Y_c} = [1 \ 1/2]^T$, and $g_P = [100 \ 25]^T$, respectively. Consequently, the knowledge-base array, shown in Table II, is used for both fuzzy inverse models.

The fuzzy inverse model rule base matrix, shown in Table II, 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

TABLE II
THE RULE BASE MATRIX FOR BOTH FUZZY INVERSE MODELS

$\begin{matrix} Y_e \\ Y_c \end{matrix}$	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

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 II.

ii) The Knowledge-Base Modifier

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 will be modified by the amount P .

Therefore, consider the previously computed control action, which contributed to the present good/bad 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:

$$\bar{u}(KT - T) = u(KT - T) + P(KT). \quad (16)$$

V. 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 $t_{cd} = 0.14$ sec. We suppose that the fault appearance time is 0.5 sec and the re-close interval is $t_f = 1$ sec (50 cycles).

The power system stability can be judged by the fault duration, for that, two cases are considered in this simulation. The first fault time is $t_d = 0.15$ sec and the second one corresponds to $t_d = 0.26$ sec. Fig. 8 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. We can see that for a fault duration $t_d = 0.15$ sec, the non-compensated machine loses completely its stability, and when we introduce the ASMES unit with the Conventional Control (CC), 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 conventional control is replaced by the Fuzzy Learning Control (FLC), 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.

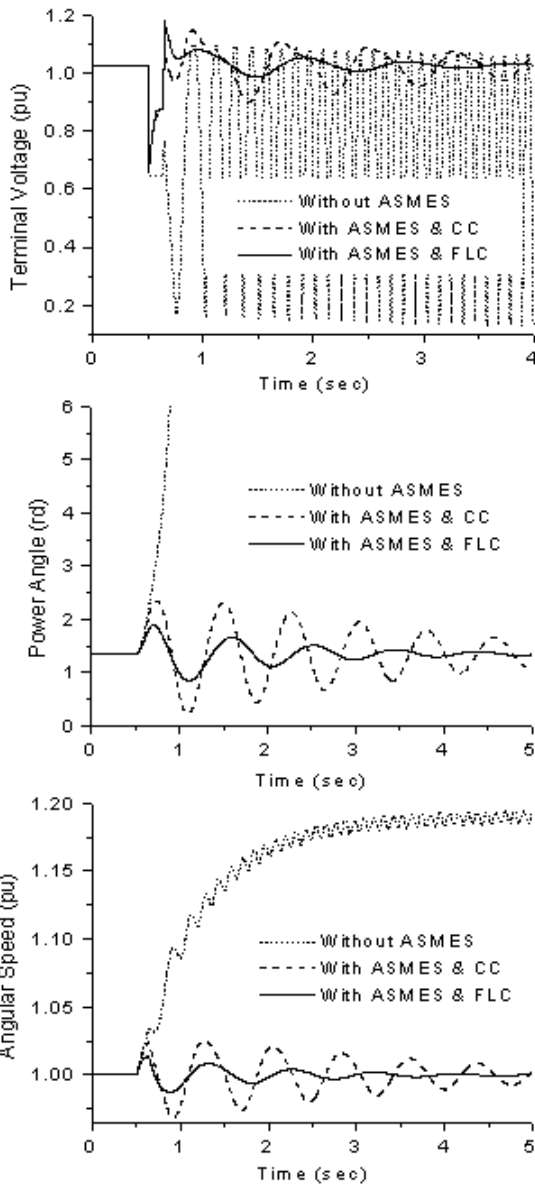


Fig. 8. Simulation results for three-phase fault of duration $t_d = 0.15$ sec.

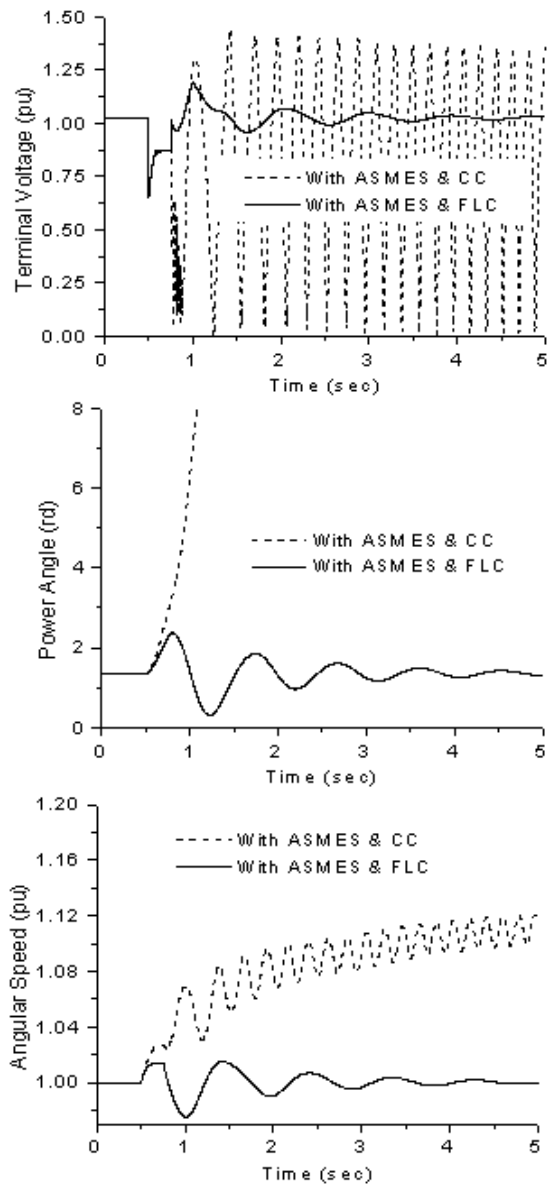


Fig. 9. Simulation results for three-phase fault of duration $t_d = 0.26$ sec.

The effectiveness of the FLC proposed in this paper is more validated through the simulation results presented in Fig. 9. When the fault time is increased (e.g., $t_d = 0.26$ sec), Fig. 9 shows that the compensated machine with CC 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 FLC allowed the system to find its equilibrium operating point.

This application clearly illustrates the effectiveness of the fuzzy learning algorithm for controlling a nonlinear time varying process. Once again the fuzzy learning control provide 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 $t_d = 0.26$ sec, are illustrated by Fig. 10. Noting that nonzero values of P_1 or P_2 indicate the knowledge-base adaptation for fuzzy controllers.

The control surface provides a 3-dimensional view of the relationship between two inputs and output variables of the fuzzy controller. Fig. 11 checks the output behavior across

the entire range of possible inputs combinations using the knowledge-base array illustrated by Table I. Before learning control, this knowledge-base is fixed and the control surface, shown in Fig. 11, for both controllers is linear without bumps.

When the fault occurs, the power system parameters change rapidly, for that 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).

During the fault phase, Figs. 12 and 13 show the control surfaces for both Fuzzy Controllers, exactly at 0,57 sec. 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. 12, is moved downward. The control surface of Fuzzy Voltage Controller, illustrated in

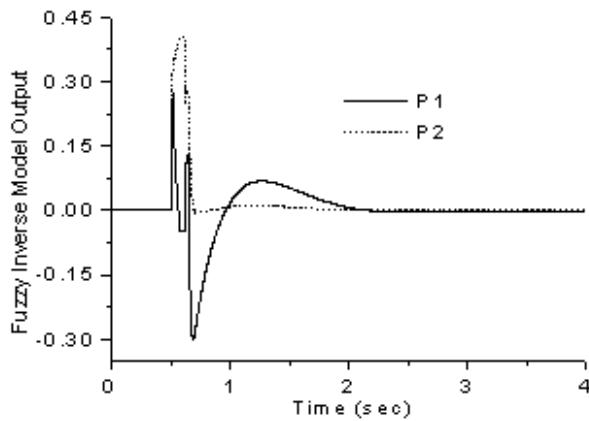


Fig. 10. The signal output for both fuzzy inverse model.

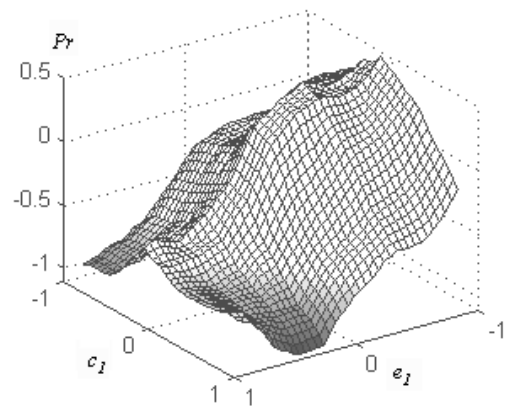


Fig. 12. Control surface of fuzzy speed controller.

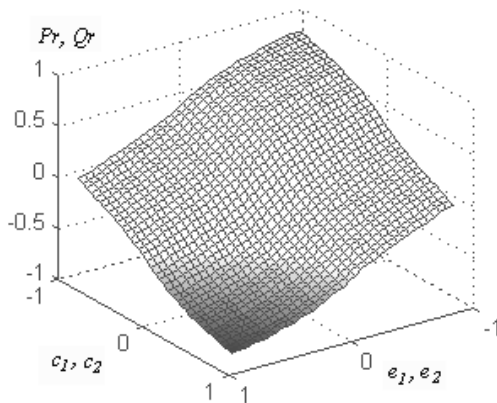


Fig. 11. The control surfaces before learning for both controllers.

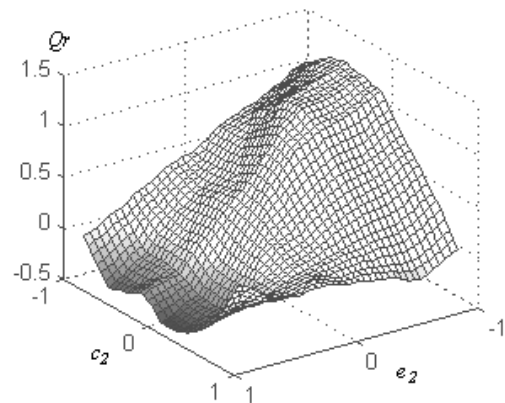


Fig. 13. Control surface of fuzzy voltage controller.

Fig. 13, is shifted upward, this is due to P_2 which was assigned a positive value so that V_{im} attracts V_t .

For both controllers, these control surfaces which are initially linear form (Fig. 11), have more bumps. 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.)

VI. CONCLUSION

This paper proposes a non-linear control method applied on ASMES to improve 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 to accurately and reliably carry out transient stability study of power system and its controllers for voltage and speed 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 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.

APPENDIX

Power system parameters:

$$\begin{aligned} x_d &= 1.030 \text{ pu}, & x_q &= 0.618 \text{ pu}, & x'_d &= 0.326 \text{ pu}, \\ T'_{d0} &= 6.5 \text{ s}, & D &= 8, & X_T &= 0.200 \text{ pu}, & X_L &= 0.170 \text{ pu}, \\ R_L &= 0.073 \text{ pu}, & \omega_B &= 100\pi \text{ rad/s}, & M &= 5.59 \text{ s}, \\ E_{fd} &= 2.15 \text{ pu}, & P_m &= 0.8 \text{ pu}, & V_{tr} &= 1.05 \text{ pu}, & \omega_r &= 1 \text{ pu}. \end{aligned}$$

ASMES parameters:

$$\begin{aligned} R &= 0.08 \text{ pu}, & L &= 2.5 \text{ mH}, & C &= 800 \text{ }\mu\text{F}, & L_{smes} &= 0.5 \text{ H}, \\ R_{smes} &= 0 \text{ }\Omega, & I_{smes}(0) &= I_{ref} = 0.9 \text{ pu}. \end{aligned}$$

Conventional control parameters:

$$K_P = 80, T_p = 0.010, K_Q = 100, T_Q = 0.015.$$

AC current control parameters:

$$\begin{aligned} PI_1, PI_2 : k_{pd} &= 1.5, k_{id} = 175. \\ PI_3, PI_4 : k_{pd} &= 0.1, k_{id} = 67. \end{aligned}$$

ACKNOWLEDGMENT

The authors would like to thank the Editor-In-Chief and the reviewers for their helpful comments and suggestions.

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