ADVANCED HYBRID CONTROL TECHNIQUES APPLIED ON THE AVR-PSS TO ENHANCE DYNAMICS PERFORMANCES OF ELECTRICAL NETWORKS

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Abstract - *This paper present a comparative study between two advanced control techniques, applied on the AVR – PSS systems of the synchronous generators. The first method used the non-linear unified Neuro - Fuzzy PSS automated design, based on hybrid technology ANFIS (Adaptive Neuro-Fuzzy Inference System).This technology includes the transformation of fuzzy system into the adaptive network which has the property to train itself on a wide range of operating conditions. Using this technology, it is possible to get quality indexes, which are similar to the results achieved now with the use of conventional PSS, but having various gains of stabilization channels in different operating conditions. The second method, it is by using the robust linear H∞ Stabilizer, who was applied as a test control system in this work. The simplest "single machine–infinite Bus" (SMIB) system was used for evaluation of effectiveness of the proposed methods. Stabilizers suggested in this work have the same structure as the traditional Russian PSS. The simulation results show that a highs performances using the first regulation technique method (ANFIS), due to the physical initial (real) non-linear power system.*
Key words: Turbo-Alternator and Excitations, AVR and PSS, adaptive Neuro - fuzzy algorithms, Robust loop-shaping H∞ approach, linear and non-linear control.

. Introduction

Power system oscillations are damped by the introduction of a supplementary signal to the Automatic Voltage regulator (AVR) in power system. This is done through a regulator called Power System Stabilizer. Classical PSS rely on mathematical models that evolve quasi-continuously as load conditions vary. This inadequacy is somewhat countered by the use of news intellectual adaptive and robust generation of the PSS, and using numerical methods (fuzzy logic for examples) in modelling of the power system. Fuzzy logic power system stabilizer is a technique of incorporating expert knowledge in designing a controller. Past research of universal approximation theorem shown that any nonlinear function over a compact set with arbitrary accuracy can be approximated by a fuzzy system. There have been significant research efforts on adaptive fuzzy control for nonlinear system [16, 19, 22]. First generation of fuzzy regulators possessing the rather small knowledge base and including the simplest operations with fuzzy sets has been created and recognized as being perspective [1, 6]. The choice of membership functions of linguistic variables and formation of rule base for such a

regulator was made by a trial and error, which took a lot of time and was considered as non-effective. At the same time, the fuzzy regulator is shown to expand the areas of small signal stability in comparison with classical AVR-PSS.

The first regulator of the second generation, suggested in this paper, was developed on the basis of hybrid technologies combining the advantages of fuzzy logic and Adaptive networks [2,3]. The modern neuro - fuzzy systems (ANFIS [4], NEFCON [3], FuNe, GARIC, Fuzzy RuleNet) possess both adaptability of fuzzy methods and opportunity of training on the given data set. In order to train such a Neuro - Fuzzy PSS, the hybrid technology of Adaptive Neuro-Fuzzy Inference System (ANFIS) was chosen. This method in comparison with other ones has high speed of training, the most effective algorithm and simplicity of the software.

The second stabilizer of this new generation for the system AVR – PSS, aimed to improving power system stability, was suggested in this paper and applied as a controller test, was developed using the robust loop-shaping H∞ approach [14-15]. This has been advantage of maintaining constant terminal voltage and frequency irrespective of conditions variations in the system study. The closed loop is available for H∞ control. This loop is dedicated for regulating the terminal voltage of the Synchronous Generator to a set point by controlling the field voltage of the machine. The H∞ control design problem is described and formulated in standard form with emphasis on the selection of the weighting function that reflects robustness and performances goals [9]. The proposed system has the advantages of advantages of robustness against model uncertainty and external disturbances, fast response and the ability to reject noise.

Simulation results showed the evaluation of the proposed adaptive NL ANFIS and the robust linear H∞ stabilizers and make a comparative study between these two advanced generations of control techniques for AVR – PSS.

2. Adaptive Learning Fuzzy AVR – PSS Based on Hybrid Technology ANFIS

The development of the PSS automated designing methods using Neuro - Fuzzy identification algorithms is an important direction of automatic excitation control

perfection, which should provide high quality of transients in the wide operating conditions.

A. ANFIS Architecture

The parameter set of an adaptive network is the union of the parameter sets of each adaptive node. In order to achieve a desired input-output mapping, these parameters are updated according to given training data and a gradient-based learning procedure described below.

Suppose that a given adaptive network has L layers and the k-th layer has $\#(k)$ nodes. The node in the i-th position of the k-th layer can be denoted by $(k; i)$, and its node function (or node output) by O_i^k. Since a node output depends on its incoming signals and its parameter set, we have:

$$O_i^k = O_i^k(O_i^{k-1},...,O_{\#(k-1)}^k, a, b, c,...) \qquad (1)$$

Where a, b, c, etc… are the parameters pertaining to this node.

Assuming the given training data set has P entries, we can define the error measure for the p-th ($1 \leq p \leq P$) entry of training data entry as the sum of squared errors:

$$E_p = \sum_{m=1}^{\#(L)}(T_{m,p} - O_{m,p}^L)^2 \qquad (2)$$

where $T_{m,p}$, is the m-th component of p-th target output vector; and $O_{m,p}^L$ is the m-th component of actual output

vector produced by the presentation of p-th input vector. The overall error measure is: $E = \sum_{p=1}^{p} E_p$.

First we have to calculate *the error rate* $\dfrac{\partial E_p}{dO}$ for p-th training data and for each node output O. The error rate for the output node at $(L; i)$ can be calculated readily from equation (2):

$$\frac{\partial E_p}{dO_{i,p}^L} = -2(T_{i,p} - O_{i,p}^L) \qquad (3)$$

For the internal node at $(k; i)$ the error rate can be derived by the chain rule:

$$\frac{\partial E_p}{dO_{i,p}^k} = \sum_{m=1}^{\#(k+1)} \frac{\partial E_p}{\partial O_{m,p}^{k+1}} \cdot \frac{\partial O_{m,p}^{k+1}}{\partial O_{i,p}^k} \qquad (4)$$

Where $1 \leq k \leq L-1$. That is, the error rate of an internal node can be expressed as a linear combination of the error rates of the nodes in the next layer. Therefore for all $1 \leq k \leq L$ and $1 \leq i \leq \#(k)$ we can find $\dfrac{\partial E_p}{dO_{i,p}^k}$ by equations (3) and (4).

Actually, there are two learning paradigms for adaptive networks. With the *batch learning (off-line learning)*, the update action takes place only after the whole training data set has been presented. On the other hand, if we want the parameters to be updated immediately after each input-output pair has been presented, then it is referred to as the pattern learning (On-line learning).

Assume that the adaptive network has only one output:

$$output = F(\vec{I}, S) \qquad (5)$$

Where $\vec{I}$ is the set of input variables and S is the set of parameters. If there exists a function H such that the composite function $H \circ F$ is linear in some of the elements of S, then these elements can be identified by the least squares method. More formally, if the parameter set S can be decomposed into two sets: $S = S_1 \qquad (6)$

Such that $H \circ F$ is linear in the elements of S_2, then upon applying H to equation (5), we have:

$$H(output) = H \circ F(\vec{I}, S) \qquad (7)$$

Which is linear in the elements of S_2. Now given values of elements of S_1, we can plug P training data into equation (7) and obtain a matrix equation:

$$AX = B, \qquad (8)$$

Where X is an unknown vector whose elements are parameters in S_2. Let $|S_2| = M$, then the dimensions of A, X and B are $P \times M$, $M \times 1$, $P \times 1$, respectively. Since P (number of training data pairs) is usually greater than M (number of linear parameters), a least squares estimate of X, is sought to minimize the squared error $\|AX - B\|^2$.

We can now combine the gradient method and the least squares estimate to update the parameters in an adaptive network. Each epoch of this hybrid learning procedure is composed of a forward pass and a backward pass. In the forward pass, we supply input data and functional signals go forward to calculate each node output until the matrices A and B in equation (8) are obtained, and the parameters in $S2$ are identified by the least squares formulas. After identifying parameters in $S2$, the functional signals keep going forward till the error measure is calculated. In the backward pass, the error rates (equation (3) and (4)) propagate from the output end toward the input end, and the parameters in $S1$ are updated by the gradient method.

Let consider the fuzzy inference system has two inputs x and y and one output z.

Suppose that the rule base contains two fuzzy if-the n rules of Takagi and *Sugeno's* type:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1$x+q_1y+r_1;
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2$x+q_2y+r_2:

Then the type-3 fuzzy reasoning is illustrated in Figure 3(a), and the corresponding equivalent ANFIS architecture is shown in Figure 3(b).

Layer 1: Every node i in this layer is an adaptive node with a node function: $O_i^1 = \mu_{A_i}(x) \qquad (9)$

For $i = 1$-2, or $O_i^l = \mu_{B_{i-2}}(y)$ for $i = 3$-4, where x (or y) is the input to node i, and A_i (or B_{i-2}) is the linguistic label (*small*, *large*, etc.) associated with this node function. Here, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function, In this paper, generalized Gaussian membership function is taken as follows:

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \qquad (10)$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. Parameters in this layer are referred to as *premise parameters*.

Layer 2: Every node in this layer is a fixed node which multiplies the incoming signals and sends the product out. For instance,

$$O_i^2 = \omega_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \qquad i = 1,2. \qquad (11)$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \qquad i = 1,2. \qquad (12)$$

Outputs of this layer will be called *normalized firing strengths*.

Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_{iy} + r_i), \qquad (13)$$

where $\overline{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as *consequent parameters*.

Layer 5: The single node in this layer is a fixed node that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \qquad (14)$$

It is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. The output f in Figure 4 can be rewritten as:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 = \overline{\omega}_1 f_1 + \overline{\omega}_2 f_2 = \qquad (15)$$

$$= (\overline{\omega}_1 x)p_1 + (\overline{\omega}_1 y)q_1 + (\overline{\omega}_1)r_1 + (\overline{\omega}_2 x)p_2 + (\overline{\omega}_2 y)q_2 + (\overline{\omega}_2)r_2$$

Which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. As a result, we have S being a set of total parameters, S_1 being a set of premise parameters and S_2 being a set of consequent parameters in equation (6); $H(.)$ and $F(.,.)$ are the identity function and the function of the fuzzy inference system, respectively. Therefore the hybrid learning algorithm described above can be applied without any modification. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent.

B. Design of ANFIS Based AVR and PSS

A step-by-step method of designing ANFIS-based AVR is first presented as follows:

a. Choice of input variable: In this step it is decided which state variables representative of system dynamic performance must be taken as the input signals to the controller. In this paper, deviation of terminal voltage (*e*) and its derivative ($\dot{e} = \frac{de}{dt}$) are taken as input signals of the ANFIS based AVR.

b. Choice of linguistic variables: The linguistic values may be viewed as labels of fuzzy sets [10]. In this paper, seven linguistic variables for each of the input variables are used to describe them. These are, LP (Large Positive), MP (Medium Positive), SP (Small Positive), ZE (Zero), SN (Small Negative), MN (Medium Negative), LN (Large Negative).
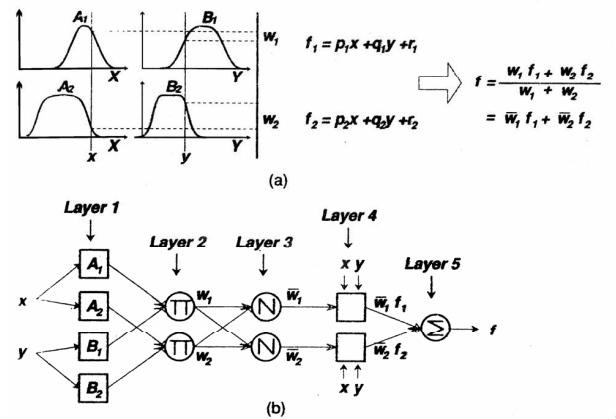

Fig. 3. (a) type-3 fuzzy reasoning,
(b) Equivalent ANFIS [9]

c. Choice of membership functions: In this design, Gaussian membership functions are used to define the degree of membership of the input variables.
d. Choice of fuzzy model: A zero order *Sugeno* fuzzy model is chosen for ANFIS-based AVR.
e. Preparation of training data pair: In preparing the training data pair, the data should be representative of different kinds of disturbance situations, such that the

designed AVR can be used for highest flexibility and robustness. In this paper, the input and output training data pair for the ANFIS-based AVR are prepared by simulating the power system with conventional AVR under a broad range of small and large disturbances and for each run the

Conventional AVR is tuned to give best performance.

f. Optimization of unknown parameters: Using the training data matrix, the unknown parameters of the Gaussian input membership functions (center (c_i) and spread (a_i)) and the output parameters of each rule of zero order *Sugeno* fuzzy model are optimized. Initially, it is assumed that the input membership functions are symmetrically spaced over the entire universe of discourse. Accordingly some initial values for the center and the spread of each input membership function are assumed, whereas, in case of output for each rule, all initial values are assumed to be zero. Then, the input parameters are optimized by error back-propagation algorithm and the output constants are optimized by least square method. The tuned AVR thus obtained is used in the test systems to obtain a stable output.

Now, in case of design of ANFIS based PSS, the same procedure is adopted except the following differences:

- The input variables are rotor speed deviation ($\Delta\omega$) and acceleration ($\omega = \dfrac{d\omega}{dt}$) respectively and the output is a voltage signal V_{PSS}. Speed deviation and accelerating power deviation can also be chosen as input signal [11].

- Unlike AVR model, the PSS model is a first order *Sugeno* fuzzy model where p_i and q_i are non-zero.

3 The Robust Loop – Shaping H∞ Synthesis of Power System Stabilizer

Advanced control techniques have been proposed for stabilizing the voltage and frequency of power generation systems. These include output and state feedback control [20], variable structure and neural network control [21], fuzzy logic control [1,6, 19], Robust H2 (linear quadratic Gaussian with KALMAN filter) and robust H∞ control [8,15].

H∞ approach is particularly appropriate for the stabilization of plants with unstructured uncertainty [15]. In which case the only information required in the initial design stage is an upper band on the magnitude of the modelling error. Whenever the disturbance lies in a particular frequency range but is otherwise unknown, then the well known LQG (Linear Quadratic Gaussian) method would require knowledge of the disturbance model [8]. However, H∞ controller could be constructed through, the maximum gain of the frequency response

characteristic without a need to approximate the disturbance model. The design of robust loop – shaping H∞ controllers based on a polynomial system philosophy has been introduced by Kwakernaak [10] and Grimbel [11].

H∞ synthesis is carried out in two phases. The first phase is the H∞ formulation procedure. The robustness to modelling errors and weighting the appropriate input – output transfer functions reflects usually the performance requirements. The weights and the dynamic model of the power system are then augmented into an H∞ standard plant. The second phase is the H∞ solution. In this phase the standard plant is programmed by computer design software such as MATLAB [12-13], and then the weights are iteratively modified until an optimal controller that satisfies the H∞ optimization problem is found [9].

Time response simulations are used to validate the results obtained and illustrate the dynamic system response to state disturbances. The effectiveness of such controllers is examined and compared with using the Non-linear adaptive Neuro – Fuzzy PSS at different operating conditions. The advantages of the proposed linear robust controller are addresses stability and sensitivity, exact loop shaping, direct one-step procedure and close-loop always stable [8].

The H∞ theory provides a direct, reliable procedure for synthesizing a controller which optimally satisfies singular value loop shaping specifications [7-9]. The standard setup of the control problem consist of finding a static or dynamic feedback controller such that the H∞ norm (a uncertainty) of the closed loop transfer function is les than a given positive number under constraint that the closed loop system is internally stable.

The robust H∞ synthesis is carried in two stages:

i. *Formulation*: Weighting the appropriate input – output transfer functions with proper weighting functions. This would provide robustness to modelling errors and achieve the performance requirements. The weights and the dynamic model of the system are hen augmented into H∞ standard plant.

ii. *Solution:* The weights are iteratively modified until an optimal controller that satisfies the H∞ optimization problem is found.

Figure 5 shows the general setup of the design problem where:

P(s): is the transfer function of the augmented plant (nominal Plant G(s) plus the weighting functions that reflect the design specifications and goals),

u2: is the exogenous input vector; typically consists of command signals, disturbance, and measurement noises,

u1: is the control signal,

y2: is the output to be controlled, its components typically being tracking errors, filtered actuator signals,
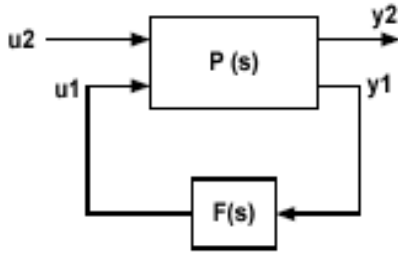
y1: is the measured output.

Fig. 5 General setup of the loop-shaping H∞ design

The objective is to design a controller F(s) for the augmented plant P(s) such that the input / output transfer characteristics from the external input vector u2 to the external output vector y2 is desirable. The H∞ design problem can be formulated as finding a stabilizing feedback control law u1(s)-F(s).y1(s) such that the norm of the closed loop transfer function is minimized.

In the power generation system including H∞ controller, two feedback loops are designed; one for adjusting the terminal voltage and the other for regulating the system angular speed as shown on fig. 6. The nominal system G(s) is augmented with weighting transfer function $W_1(s)$, $W_2(s)$, and $W_3(s)$ penalizing the error signals, control signals, and output signals respectively. The choice proper weighting function is the essence of H∞ control. A bad choice of weights will certainly lead to a system with poor performance and stability characteristics, and can even prevent the existence of solution to the H∞ problem.
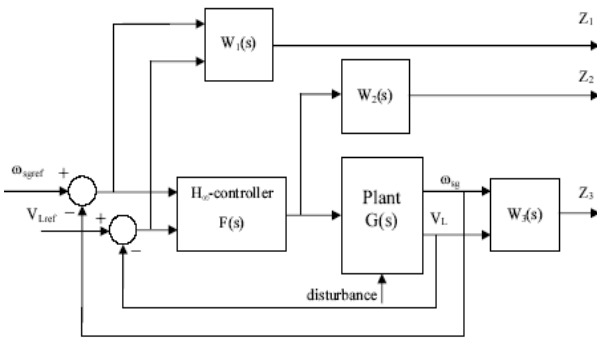

Fig. 6 Simplified block diagram of the augmented plant including H∞ controller

The control system design method by means of modern neuro - fuzzy identification algorithms is supposed to have some linear H∞ test regulator. It is possible to collect various optimal adjustment of such a regulator in different operating conditions into some database. Robust H∞ technique was used in this work as a test system, which enables to trade off regulation performance, robustness of control effort and to take into account process and measurement noise [8].

4. Dynamic Power System Model

In this paper the dynamic model of an IEEE - standard of power system, namely, a single machine connected to an infinite bus system (SMIB) was considered [1]. It consists of a single synchronous generator (turbo-Alternator) connected through a parallel transmission line to a very large network approximated by an infinite bus as shown in figure 7.
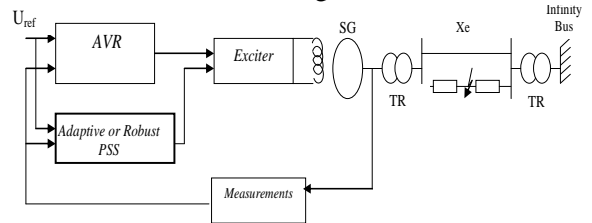

Fig. 7 Block schematic diagram of the used Standard - IEEE type SMIB Power system

Let the state variable of interest be the machine's rotor speed variation and the power system acceleration:

$$x_1 = \Delta\omega$$
$$x_2 = \Delta P = P_m - P_e \tag{17}$$

Where x_1 is the speed deviation and x_2 is accelerating power, Pm and Pe represents respectively the mechanical and electrical power. It is possible to represent the power system in the following form [16].

$$x_1 = \alpha x_2$$
$$\alpha \dot{x}_2 = f(x_1, x_2) + g(x_1, x_2)u \tag{18}$$
$$y = x_1$$

Where $\alpha = 1/2H$ and H is the per unit inertia constant of the machine. $x=[x_1\ x_2]$ is the state vector of the system and $f(x_1,x_2)$ and $g(x_1,x_2)$ are nonlinear functions and u is the *PSS* (Power System Stabilizer) control signal to be designed. We need to express f and g as function of active power P and reactive power Q.

The governor time constant is large compared to the time constants of synchronous machine and its exciter, the power system can be easily be put in the form (18) for a transient period after a major disturbance has occurred in the system.

Figure 8, shows the proposed regulated excitation system (AVR and PSS) under Simulink – Matlab [7].
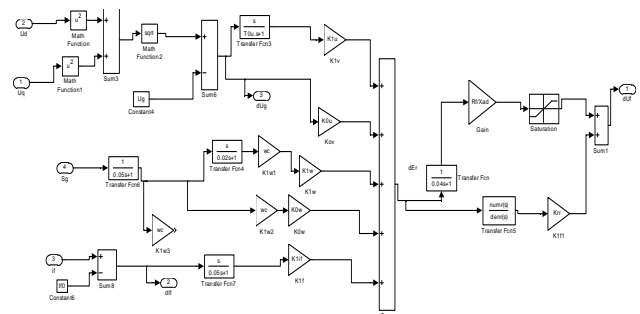

Fig. 8 The regulation System (controller AVR and the stabilizer PSS) under Simulink - Matlab.

On the basis of investigation carried out, the main points of adaptive Neuro – Fuzzy and robust H∞ PSS automated design methods were formulated [1, 6]. The nonlinear model of power system can be represented by the set of different linearized models [7-9]. For such models, the robust linear H∞ and Adaptive Non-linear ANFIS compensators can be synthesis and calculated by means of MATLAB Software [12, 13].

The family of test regulators is transformed into united fuzzy knowledge base with the help of hybrid learning procedure. In order to solve the main problem of the rule base design, which called "the curse of dimensionality", and decrease the rule base size the scatter partition method [2] was used. In this case, every rule from the knowledge base is associated with some optimal gain set. The advantage of this method is the practically unlimited expansion of rule base. It can be probably needed for some new operating conditions, which are not provided during learning process.

5 Simulation Results and Discussion

In the system study type 'SMIB' (Single Machine Infinite bus system), based on "Synchronous generator–transmission line–infinite bus" the main attention was devoted to receive adaptive Neuro – Fuzzy Control Power System Stabilizer 'NFCPSS' (based on Hybrid technology ANFIS) and robust H∞ PSS 'HinfPSS', working in the wide spectrum of operating conditions. The change of operating conditions corresponds to the variation of transmission line parameters (X_e) and the powers of the generator (P_G, Q_G). Certain attention was devoted to the problem of the reactive power consumption (under - excitation modes), which is very important for all electric power systems. The illustration with using conventional PSS (Russian PSS with Strong Action AVR-SA [1,7]), and with the proposed Robust linear H∞ controller and Adaptive Non-linear Neuro - fuzzy PSS method opportunities is given in Table 1 on the basis of the damping coefficient α comparison. Adaptive Neuro - Fuzzy regulator allows receiving the same performance quality as the application of robust linear compensator, but without resetting optimal gain of the regulator.
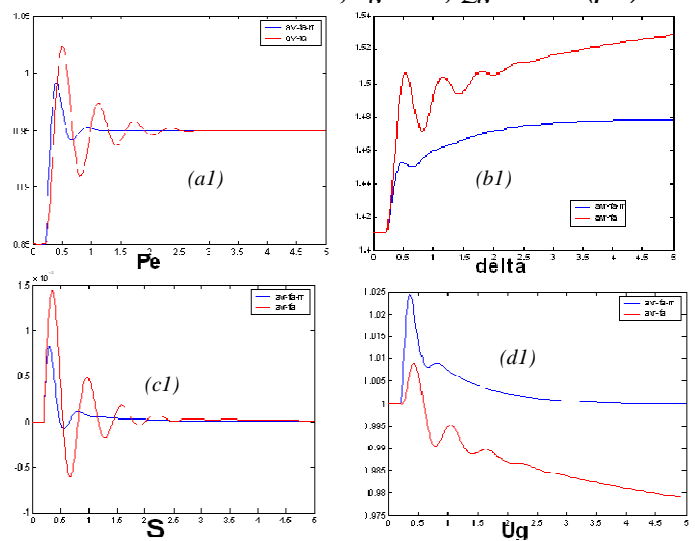
The electromechanical damping oscillations of the parameters of the SG under different operating mode in controllable power system, equipped by HinfPSS (Red) and NFCPSS (Blue) are given in Figures 9 (a, b, c, d). Results of time domain simulations confirm both a high effectiveness of test robust H∞ Regulator, which has various adjustments of regulation channels in different operating

conditions, but more large degree of performances and much more robustness of the dynamic of power system are improving and obtained by using the adaptive ANFIS PSS (figures 9 (b) and (d), due to the initial non-linear system study. After appearance of the real non-linear properties of the power system, especially in the under - excitation mode (2), the PSShinf quickly loses his effectiveness under condition of uncertainties.

Table 1: *Damping coefficients 'α' in the Close Loop system with AVR, HinfPSS and NFCPSS in different operating Conditions of power system*

Xe (p.u)	Pg (p.u)	Qg (p.u)	α (AVR-SA)	α (HinfPSS)	α (NFCPSS)
0.5	0.85	0.20	-0.78	-2.18	-2.60
0.5	0.85	0.65	-0.48	-2.10	-2.38
0.5	0.85	-0.25	-0.89	-2.62	-2.85
0.5	1	0.25	-0.99	-2.51	-2.60
0.4	0.85	0.15	-0.72	-2.46	-2.50
0.4	0.85	0.6	-0.48	-2.05	-2.10
0.4	0.85	-0.25	-0.84	-2.14	-2.20
0.4	1	0.20	-0.86	-2.42	-2.50
0.3	0.85	0.15	-0.66	-2.2	-2.30
0.3	0.85	0.65	-0.52	-1.78	-1.90
0.3	0.85	-0.25	-0.79	-1.85	-2.00
0.3	1	0.20	-0.76	-2.26	-2.30
0.2	0.85	0.15	-0.65	-2.10	-2.10
0.2	0.85	0.60	-0.55	-1.69	-1.70
0.2	0.85	-0.20	-0.76	-1.88	-1.90
0.2	1	0.20	-0.70	-1.90	-2.00
0.1	0.85	0.20	-0.68	-1.57	-1.60
0.1	0.85	0.55	-0.62	-1.30	-1.40
0.1	0.85	-0.25	-0.77	-1.25	-1.35
0.1	1	0.20	-0.69	-1.50	-1.53

1. Nominal mode: Xe=0.5, Pg=0.85, Qg=0.1865 (p.u)

2. Under-excited mode: Xe=0.5, Pg=0.85, Qg=-0.245 (p.u)

(a2) Pe   *(b2)* delta

(c2) S   *(d2)* Ug
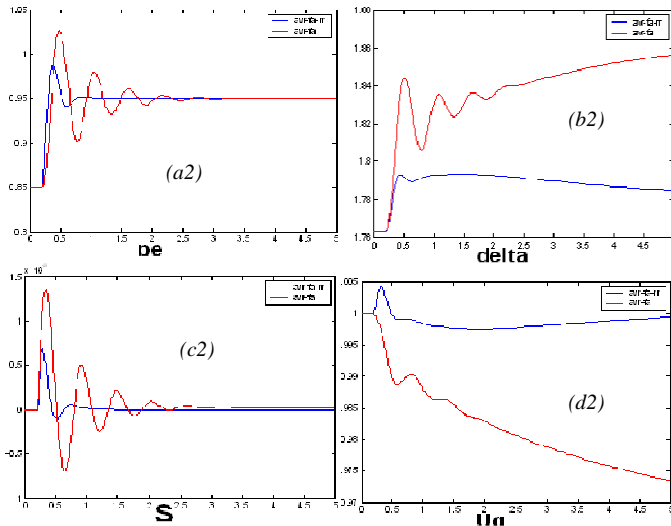
3.Over-excited mode: Xe=0.5, Pg=0.85, Qg=0.635 (p.u)

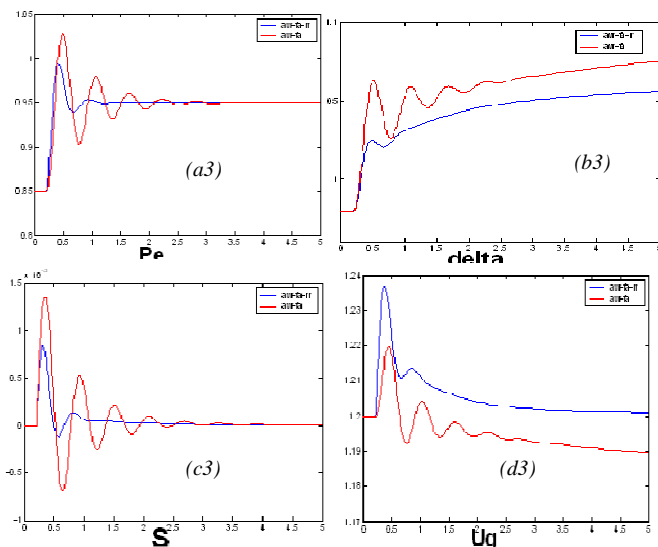*(a3)* Pe   *(b3)* delta

(c3) S   *(d3)* Ug

Fig. 9 Electromechanical damping oscillations of SG under different operating mode With HinfPSS (Red) and NFCPSS (Blue): (a) Active Power, (b) Interior angle, (c) Speed deviation,(d) Stator terminal voltage of SG Responses

6 Conclusion

This paper proposes two control methods: an adaptive non-linear stabilizer based on hybrid technology ANFIS and an optimal robust linear controller based on the loop-shaping H∞ approach, applied on system AVR - PSS of the synchronous generator, to improve transient stability of a single machine-infinite bus system (SMIB). This concept allows accurately and reliably 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 and robustness of the Neuro - Fuzzy Controller, in comparison with using robust H∞ Controller, 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. The results proved also that good performance and more robustness in face of uncertainties with the Non - Linear adaptive stabilizer (NFCPSS), in comparison with using linear robust H∞ controller, due to the initial non-linear power system.

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$$\dot{\delta} = \omega_0 \Delta\omega$$

$$\dot{\omega} = (P_{m-}P_e)/M$$

$$\dot{E_q'} = (E_{fd} - (x_d - x_d')i_d - E_q')/T_{do}'$$

$$\dot{E}_{fd} = \frac{1}{T_A}(K_A(V_{ref} - V_t + V_{PSS}) - E_{fe})$$

$$V_d = V_s \sin\delta + R_e i_d - x_e i_q$$

$$V_q = V_s \cos\delta + R_e i_q + x_e i_d$$

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

$$T_e = E_q' i_q - (x_d' - x_q)i_d i_q$$

▪ *Parameters of power system study:*

X_d=2.56 pu, X_0= 2.56, R_f= 8.44 10^{-4} pu, X_f=2.458 pu, X'_d=0.3361, X''_d=0.3423, X''_q=0.3316, T_{d0}'=4.14 sec, H=6s, X_T=0.12 pu, V_{bus}=1 pu, Uf0= 9.6523 10^{-4} pu.

▪ *AVR and PSS parameters:*

T_A= 0.05, K_A= 50, f= 50Hz, $-1.5.Ef0 \le E_{fd} \le 3.Ef0$

$-0.2\,pu \le U_{PSS} \le 0.2\,pu$,

Appendix

▪ *the used Power System model:*