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A GA-optimized Neuro-fuzzy Power System Stabilizer for Multi-machine System

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Abstract. The aim of this research is the design of a decentralized Power System Stabilizer (PSS) capable of performing well for a wide range of variations in system parameters and loading conditions. In addition, the designed PSS should provide effective damping of small/large disturbances and local/inter-area oscillations. The framework of the design is based on Fuzzy Logic Control (FLC). In particular, the neuro-fuzzy control rules are derived from training three classical PSSs; each is tuned using GA (Genetic Algorithms) so as to perform optimally at one operating point. The effectiveness and robustness of the designed stabilizer is investigated. The results of simulation prove that the proposed PSS offers a superior performance in comparison with the conventional stabilizer presently adopted by the industry.

1. Introduction

Power system stabilizers (PSSs) have been popularly used to damp out the low frequency oscillations in the system. The conventional PSS was mainly introduced as a lead-lag compensator (Concordia and de Mello, 1969). The parameters of a conventional PSS are normally fixed at values determined based on classical control theory in the frequency domain. This class of PSSs always suffers from a poor performance for a wide range of operating conditions. To mitigate the shortcomings of conventional PSS, many control strategies applying various techniques have been proposed over the last four decades. Examples of the applied techniques are: linear quadratic regulator (Davison and Rau, 1971), self-tuning regulator (Talaat and Moret, 1983), model reference adaptive control (Minh and Hoang, 1996), and robust control (Chen and Malik, 1995). More recently, the concepts of artificial intelligence (AI) techniques were applied in order to create a higher degree of robustness and adaptability. Three AI techniques were widely applied: Artificial Neural Networks (ANNs) (Chen *et al.*, 2006), Fuzzy Logic Control (FLC) (Ben-Abdennour and Lee, 1996), and Genetic Algorithms (GA) (Abdel-Magid and Abido, 2003). Merging more than one AI technique is also common in the literature (Fraile-Ardanuy and Zufiria, 2007; Dubey, 2008).

The evaluation of the performance of any of these techniques should be carried out in view of the design objectives of a PSS, which can be summarized into two main requirements. The first is the robustness, i.e. the PSS has to perform well against the wide domain of variations of both the system parameters and the loading conditions. Secondly, the design of the PSS should be multi-objective; it should provide effective damping of small/large disturbances and effective damping of local/inter-area oscillations.

This research aims at designing a decentralized PSS capable of satisfying the abovementioned requirements. The work has been divided into two phases. The current paper summarizes the results of the first phase of the work which represents the computer simulation results. In the next phase, the study will be extended to implement the designed stabilizers on a laboratory system. The framework of the design is based on FLC. The fuzzy control rules of the proposed PSS are derived from training three classical PSSs. Each classical PSS is tuned using GA so as to perform optimally at one operating point. The training process is carried out using Adaptive Neuro-based Fuzzy Inference (ANFIS) principles.

2. Study System

The multi-machine power system considered for laboratory simulation is depicted in Fig. 1. It is composed of three identical machines rated 1000 MVA each. The system does not include an infinite bus. The transmission network is composed of four lines, having different lengths, all rated 380 kV. The PSS under development, which is assumed to apply decentralized control concept, is installed at one of the machines, namely machine#2.

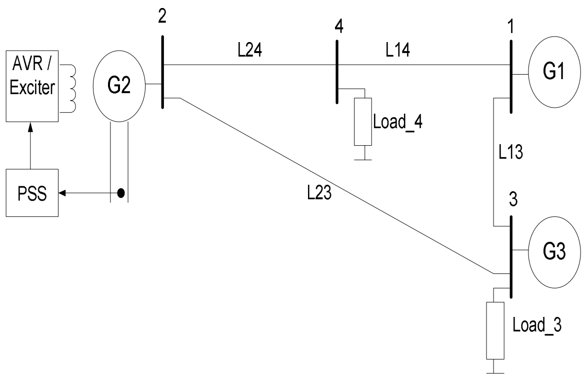

Fig. 1. The system under laboratory simulation.

The laboratory simulation uses scale 1:1000 for the voltage, 1:1000 for the current, thus, $1:10^6$ for the power. Therefore, each of the three machines has to be simulated by a laboratory 380 V, 1 kVA synchronous machine, where it is assumed that the step-up transformers (13.8/380 kV) are included within the machines.

To perform a simulation study of the multi-machine laboratory system, the system parameters should be supplied to the simulation model. The parameters of the static components of the system, i.e. lines and loads can be obtained from direct measurements. However, the parameters of the machines are more difficult to obtain. It is more practical to obtain the parameters of the machines from online measurements under different conditions through applying a parameter estimation algorithm. The three machines of the system are assumed to be identical. The rotor angle and rotor speed responses of machine#2 obtained from applying three-phase fault to its terminals under the considered loading conditions are recorded.

The set of parameters that yield the best fit to the recorded responses are then estimated. The estimated parameters are listed in Table 1.

Table 1. Estimated parameters of the synchronous generator

Parameter	R p.u.	X_l p.u.	X_d p.u.	X_d' p.u.	X_d'' p.u.
Estimated Value	0.07	0.08	0.68	0.28	0.15
Parameter	X_q p.u.	X_q'' p.u.	T_d' s	T_d'' s	T_q'' s
Estimated Value	0.62	0.15	0.019	0.009	0.009

3. Control Strategy

3.1. General

The control strategy employed in this project follows the following three basic steps:

a) Selection of a very simple control structure such as a first order linear compensator for each of the operating points chosen for design. Three points have been selected: light load, medium load, and heavy load.
b) Optimal tuning of the compensators' parameters using Genetic Algorithms (GA). The simulation environment used for this purpose is the SimPowerSystem model developed during this study.
c) Obtain a single neuro-fuzzy PSS that replaces the optimal compensators designed in the previous step. This PSS is trained with the control actions generated by the optimized compensators. The resulting stabilizer should capture the performance of the single compensators while offering even a better performance due to its nonlinear structure.

3.2. GA Tuning of the compensators

GA is an attractive derivative-free optimization tool capable of attaining optimal solutions even when the search space is large. Multi-objective performance measures can also be incorporated with ease. The GA used here is similar to what is now called the classical GA and which can be found in the standard literature in the subject (Goldberg, 1989).

The PSS structure implemented with the system at hand is described by:

$$U_{stab} = \frac{K(s+z)}{(s+p)} \Delta\omega \tag{1}$$

where, U_{stab} is the PSS output, $\Delta\omega$ is the angular speed deviation, and K, z and p are the parameters of the stabilizer. The objective is to tune the three parameters with the following requirements:

- Optimal dynamic performance of rotor speed (max damping, min settling time, min overshoot, …).
- Optimal dynamic performance of load angle.

- Minimal control action.

The fitness function used by the GA should reflect all the above requirements. One choice of such function is based on the sum of the squared error (*sse*), where error here means the deviation in the variable. The fitness function is given by:

$$fitness = \frac{1}{W_\delta \; sse(\delta) + W_\omega \; sse(\Delta\omega) + W_u \; sse(u)} \tag{2}$$

The first and second terms of the denominator express the deviation of the load angle and the angular speed respectively, while the third term is used to minimize the stabilizer output. The coefficients W_δ, W_ω and W_u are used to weigh the importance of each of the three quantities and to balance these terms to more or less the same order of magnitude. In this work these coefficients are selected as: 10^{-5}, 1 and 10^{-2}, respectively.

The GA tuning of the stabilizer in this study is multi- objective in a sense that it inherently optimizes different types of oscillations resulting from changing the size and location of the disturbance.

3.3. Architecture of the neuro-fuzzy PSS

Once the classical PSSs are optimized for the selected operating conditions, they should be “blended” in a single neuro-fuzzy PSS that not only captures their performances, but also brings up the advantage of its nonlinearity in generalizing the optimal performance of each single classical PSS. By the end of this step, we will end up with only one PSS capable of performing hopefully well for a wide range of operating conditions. To achieve this step, we resort to a system called Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes the design of a neuro-fuzzy PSS more systematic and less relying on expert knowledge.

To present the ANFIS architecture, let’s consider two fuzzy if-then rules based on a first order fuzzy Sugeno model (Jang, 1993):

Rule 1: if (x is A_1) and (y is B_1) then ($f_1 = p_1 x + q_1 y + r_1$)
Rule 2: if (x is A_2) and (y is B_2) then ($f_2 = p_2 x + q_2 y + r_2$) (3)

These two rules give

$$\begin{cases} f_1 = p_1 x + q_1 y + r_1 \\ f_2 = p_2 x + q_2 y + r_2 \end{cases} \Rightarrow f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \overline{w}_1 f_1 + \overline{w}_2 f_2 \tag{4}$$

A possible ANFIS architecture is to implement these two rules as given below.

Layer 1: All the nodes in this layer are adaptive nodes. The output of each node is the degree of membership of the input to the fuzzy membership function (MF) represented by the node. If the bell MF is used then the degree of membership is

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}, \; i = 1,2 \tag{5}$$

where a_i, b_i and c_i are the parameters for the MF.

Layer 2: The nodes in this layer are fixed (not adaptive). They are labeled M to indicate that they play the role of a simple multiplier. The output of each node in this layer represents the firing strength of the rule.

Layer 3: The nodes in this layer, which are also fixed, and are labeled N to indicate that they perform a normalization of the firing strength from the previous layer.

Layer 4: All the nodes in this layer are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for first order Sugeno model):

$$\overline{w}_i f_i = \overline{w}_i \left(p_i x + q_i y + r_i\right) \qquad i = 1,2 \tag{6}$$

Layer 5: This layer has only one node labeled S to indicate that it performs the function of a simple summer.

The ANFIS architecture is not unique. Some layers can be combined and still produce the same output. Architectures for the Mamdani fuzzy model are also available but are not adopted in this project.

In this ANFIS architecture, there are two adaptive layers (Layers 1 and 4). Layer 1 has three modifiable parameters (a_i, b_i and c_i) pertaining to the input MFs. These parameters are called premise parameters. Layer 4 has also three modifiable parameters (p_i, q_i and r_i) pertaining to the first order polynomial. These parameters are called consequent parameters.

The task of the training or leaning algorithm for this architecture boils down to tuning all the modifiable parameters to make the ANFIS output match the training data.

3.4. Training of the neuro-fuzzy PSS

The structure of the neuro-fuzzy stabilizer adopted here has two inputs. The first input (Input 1) is the angular speed and the second input (Input 2) is the angular acceleration. The acceleration is obtained from the speed using an approximate derivative instead of a pure differentiator. This choice is made for two reasons. The first is to avoid the differentiation of high frequency noise typically existing in the speed signal, and the second is to avoid unnecessarily long simulation time caused by small integration steps employed by the variable-step integration algorithm. The acceleration is synthesized using the following transfer function:

$$H(s) = \frac{s}{(1+0.01s)} \tag{7}$$

Each of the two inputs is represented by seven fuzzy membership functions, resulting in a total of 49 fuzzy rules. The system has a single output representing the stabilizing signal.

To train this network, the angular speed, the angular acceleration, and the corresponding control action are collected through running the SimPowerSystem model with the GA-optimized compensators for the three operating conditions. The collected data are used to train ANFIS with the objective of automatically generating the fuzzy rules that match a corresponding output for each given pair of inputs. Since this fuzzy model is of the Sugeno type, unlike the Mamdani model, the output is crisp rather than fuzzy. Therefore, there will be an output value for each of the 49 fuzzy rules generated by the ANFIS structure instead of fuzzy output membership functions. However, the fuzzy decision surface is concisely represented here in a three-dimensional space to examine the degree of nonlinearity that this fuzzy stabilizer is capable of capturing.

4. Design Results

The control strategy presented in Section 3 is implemented here. The essence of the strategy is twofold. The objective of the first phase of the design is to optimize the three classical compensators using genetic algorithms. Then, as a second phase, the optimized compensators are used to train a single fuzzy controller to serve later a single stabilizer for all operating conditions. The subsequent subsections highlight the main steps of the design process.

4.1. Results of the GA optimization of classical controllers

A classical genetic algorithm is implemented with the following parameters:

- Mutation rate = 0.75
- Crossover rate = 0.75
- Population size = 12
- Generation size = 10

It is worth noting here that the population and generation sizes could have been chosen much larger. However, due to the large simulation time taken by Simulink, this was not possible. During the optimization of the controller, the initial parameters are selected randomly, which could yield an unstable performance, causing the simulation to take too long due to the small integration step adaptively chosen by Simulink running with a variable step integration option. While this problem ceases with the improvement in the controller, offered by GA over the iterations, it still affects the total simulation time. Note here that even with the relatively small population and generation sizes chosen in this case, (12 and 10, respectively) running the system for the three operation conditions requires 360 runs of the Simulink model. However, to ensure that the GA search converges fast enough, we chose a relatively high crossover and mutation rates.

The fitness function previously given by (2) is selected here as follows:

$$fitness = \frac{100}{10^{-5}(fit_{\delta}) + (fit_{\omega}) + 10^{-2}(fit_{u})} \tag{8}$$

These values are obtained after the examination of the sum of the squared error (sse) of the three variables. The weighting coefficients are chosen to balance these values to more or less the same order of magnitude. The GA-optimized controllers for the three operating conditions are given in Table 2.

Table 2. GA-optimized classical controllers

Light Load	Medium Load	Heavy Load
$\frac{1.06(s+4.5)}{(s+0.9)}$	$\frac{2.9(s+4.2)}{(s+.85)}$	$\frac{2.1(s+4.7)}{(s+3.6)}$

To evaluate these controllers, their performance is compared to the generic PSS discussed in the previous section, in addition to the case when the system operates without external stabilization. These three different control strategies will be referred to as “without PSS”, “generic-PSS”, and “GA-PSS”.

The performance of the load angle and the angular speed in response to a three-cycle-three-phase short circuit for the three different operating conditions are depicted in Figs. 2 to 4. To examine that the GA-optimized controllers do not exert unrealistic control efforts, their control action is depicted in Fig. 5.

From these results, it is clear that the GA-optimized compensators offer impressive performance despite their simplicity. However, while these results are what a designer hopes for, they are still no more than simulation results. Two more hurdles do still exist in this design problem. These are:

- Can a single fuzzy controller capture the desirable performance of these three optimized compensators?
- Can this single controller perform with the real system as in the simulation scenario?

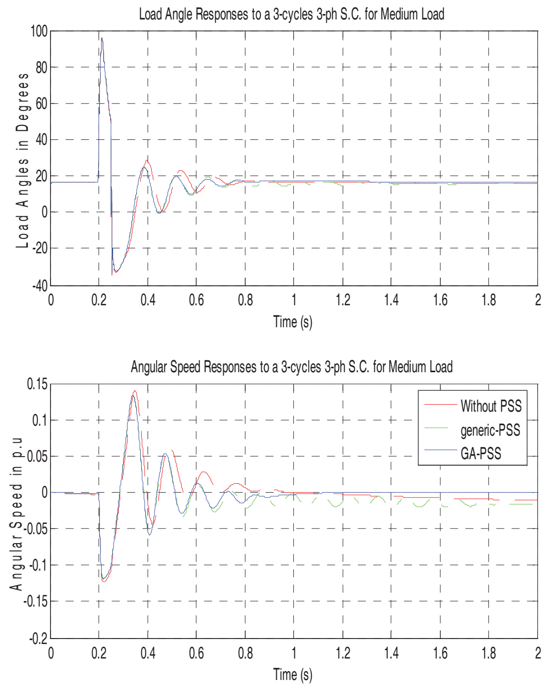

Fig. 3. GA-PSS performance for medium load.

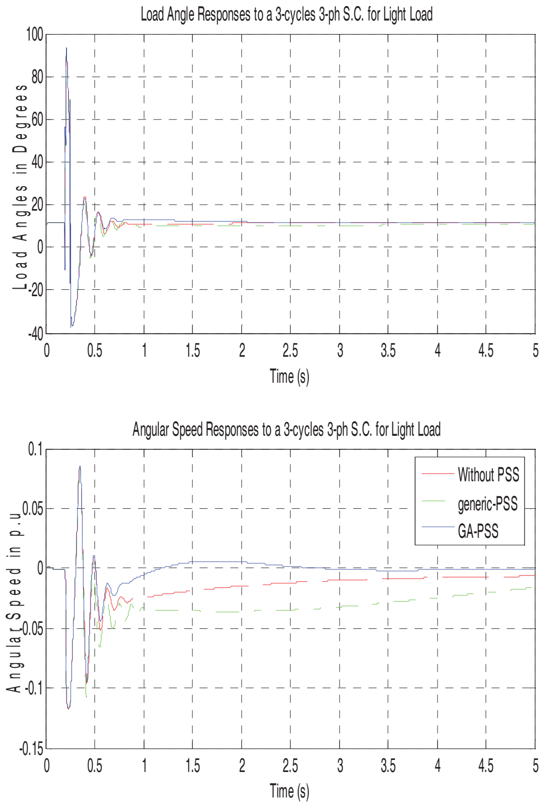

Fig. 2. GA-PSS performance for light load.

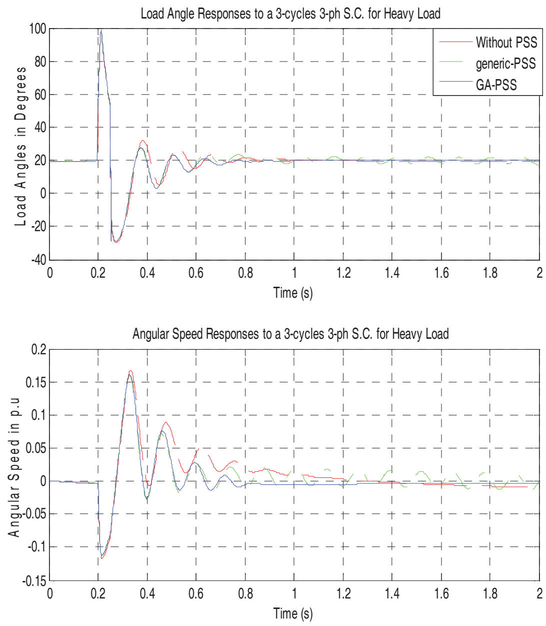

Fig. 4. GA-PSS performance for heavy load.

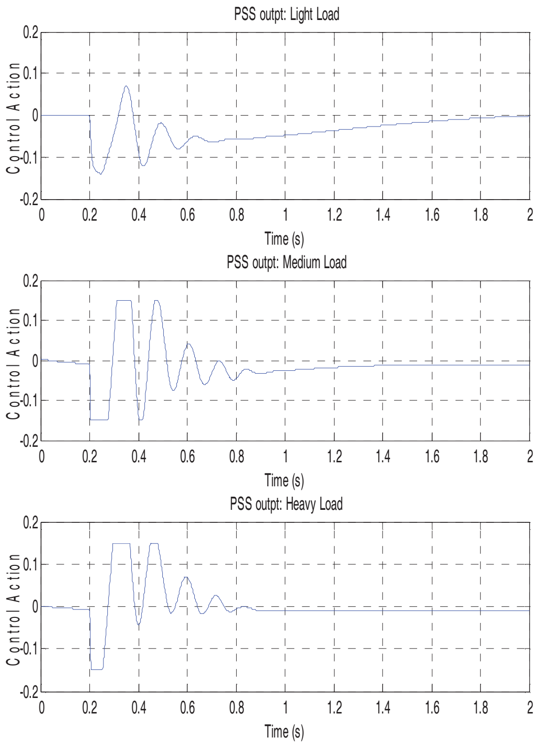

Fig. 5. GA-PSS control actions.

4.2. Results of the fuzzy-logic stabilizer design

With the availability of the three GA-optimized compensators, the task now is to design a single fuzzy controller that hopefully captures the desirable performance provided by these three compensators. The structure of the fuzzy stabilizer is shown in Fig. 6. This stabilizer has two inputs. The first input (Input 1) is the angular speed and the second input (Input 2) is the angular acceleration. Each of these inputs is represented by seven fuzzy membership functions, resulting in a total of 49 fuzzy rules. The system has a single output representing the stabilizing signal. The ANFIS structure is shown in Fig. 7, and the fuzzy membership function for each of the two inputs are depicted in Fig. 8.

The training of the network is carried out using the way explained before in Subsection 3.4. The obtained fuzzy decision surface, shown in Fig. 9, plots the fuzzy output versus the two inputs.

To evaluate the designed fuzzy stabilizer, its performance is compared to the generic PSS, in addition to the case when the system operates without external stabilization. These three different control strategies will be referred to as "without PSS", "generic-PSS", and "FUZZY-PSS".

The performance of the load angle and the angular speed in response to a three-cycle-three-phase short circuit for the three different operating conditions are depicted in Figs. 10 to 12. To examine that the fuzzy stabilizing signals do not exert unrealistic actions, they are plotted in Fig. 13. From these results, it is clear that the fuzzy stabilizer offers as impressive performance as the GA-optimized compensators with almost identical response. The gained objective here is that we have only one single stabilizer instead of three. This stabilizer is nonlinear (unlike the three classical compensators) which promises that it has more to offer in terms of robustness. The robustness feature is particularly important when the stabilizer is implemented with the real system. Needless to say that the real situation is very likely to be different from the idealistic simulation scenario and we hope that the fuzzy compensator succeeds in accommodating these differences.

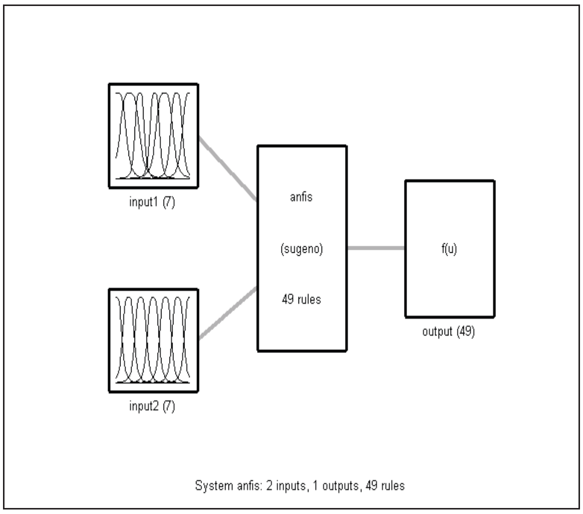

Fig. 6. Structure of the fuzzy stabilizer.

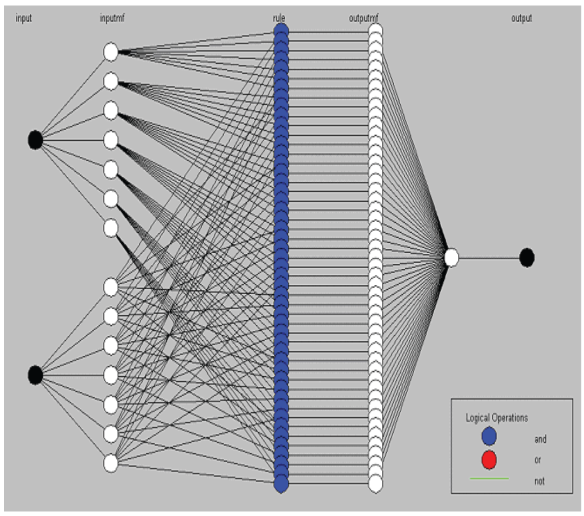

Fig. 7. ANFIS structure.

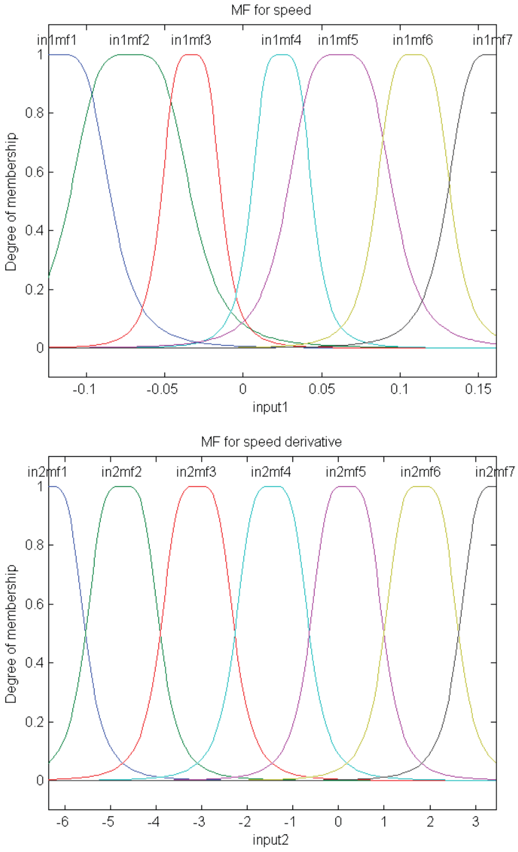

Fig. 8. Input membership functions.

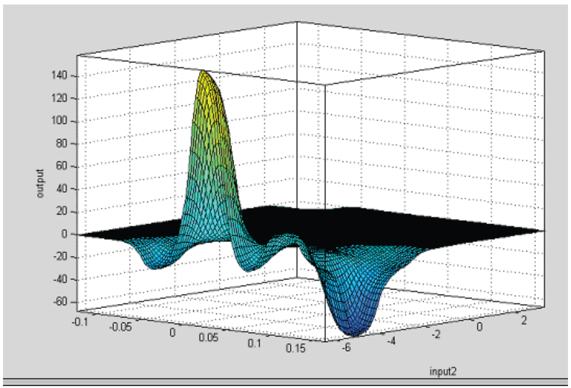

Fig. 9. Fuzzy decision space.

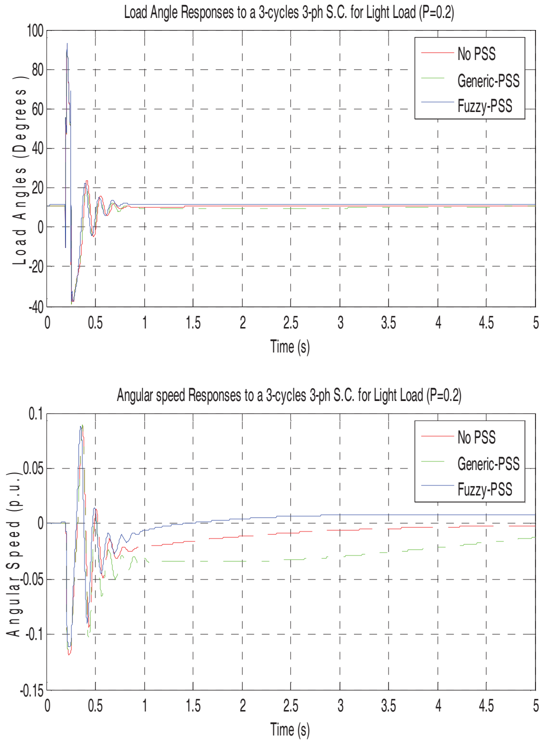

Fig. 10. Fuzzy-PSS performance for light load.

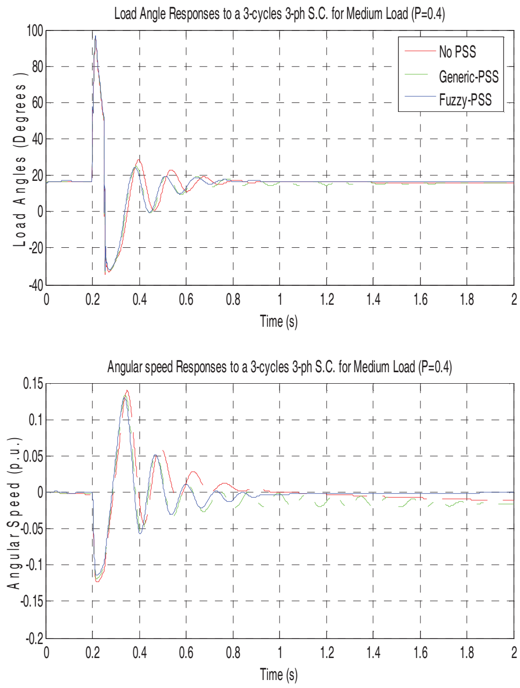

Fig. 11. Fuzzy-PSS performance for medium load.

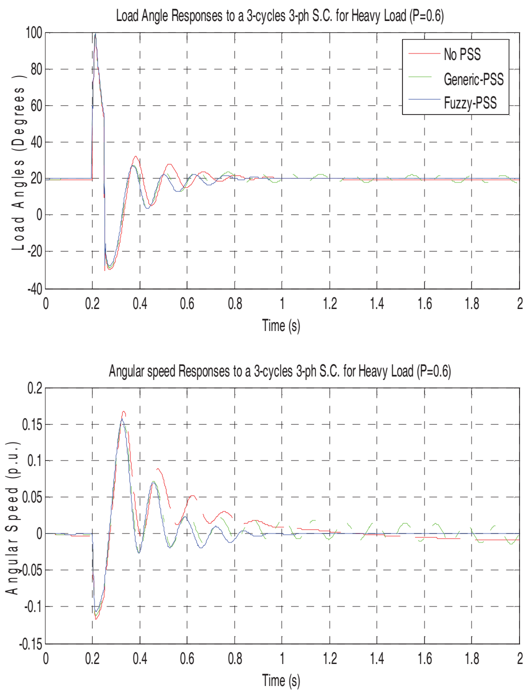

Fig. 12. Fuzzy-PSS performance for heavy load.

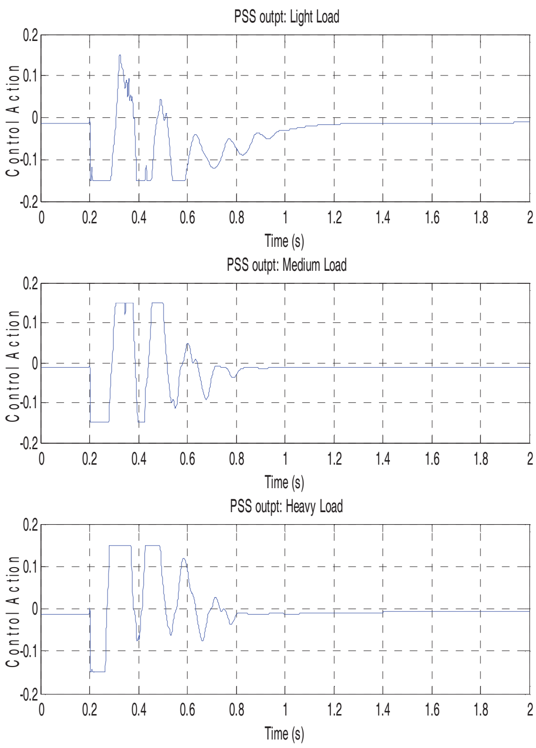

Fig. 13. Fuzzy-PSS control actions.

5. Conclusion

The main objective of this project was the design of a fuzzy-logic-based stabilizer for a laboratory-scale power system in order to provide adequate damping of system oscillations. The importance of this objective stems from the fact that oscillations can drive the system performance away from the stringent requirement of security usually imposed by the power industry. This paper summarizes the first phase of the project, namely; the computer simulation study. With the simulation environment being half-way between theory and reality, the outcomes of this project should give insights on the likelihood of success with real systems, especially that the simulation used captures most of the significant complications of real systems (e.g., multi-machine interconnection, long transmission lines, realistic disturbances, etc.). To achieve the project objective, two major steps were taken through the course of the research. These steps are: theoretical modeling of the constructed setup and validation, the design of the stabilizer and preliminary evaluation via simulation.

In the process of developing the fuzzy stabilizer, a comprehensive approach empowered by mathematical methods, analysis techniques, and simulation tools was employed. This stabilizer offered a superior performance in comparison with the generic alternatives presently adopted by the industry. Aside from its desirable performance, this stabilizer possesses impressive features such as robustness to changes in operating condition, capabilities in accommodating model variations and external disturbances, and simplicity of real-time implementation. The inherent nonlinearity of this stabilizer has the advantage of capturing the performance of many linear stabilizers of the type typically used in real systems. Its smoothness is particularly remarkable and has noticeable effect even in reducing the sound produced by the machines due to severe disturbances.

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الموازن العصبي–المبهم المؤمثل بالخوارزمات الوراثية لمنظومات القوى الكهربائية ذات الماكينات المتعددة

حسام الدين طلعت، وعادل عبدالنور، وعبدالعزيز السليمان

قسم الهندسة الكهربائية ، كلية الهندسة ، جامعة الملك سعود ،

ص ب ٨٠٠ ، الرياض ١١٤٢١ ، المملكة العربية السعودية

(قدم للنشر في ٢٠٠٨/٧/٢م ؛ وقبل للنشر في ٢٠٠٩/٧/١٨م)

الكلمات المفتاحية: التحكم الموزع ، الشبكات الاصطناعية المبهمة ، الخوارزميات الوراثية ، استقرارية منظومات القوى الكهربائية.

ملخص البحث. الهدف من هذا البحث هو تصميم موازن لا مركزي لمنظومات القوى الكهربائية ذات الماكينات المتعددة ، بحيث يكون أداء الموازن جيداً على نطاق واسع من التغيرات في كلٍّ من معالم المنظومة وأحوال التحميل. علاوة على ذلك ، فإن الموازن المصمم يستطيع توفير إخماد فعال للاضطرابات صغيرها وكبيرها وللاهتزازات بنوعيها المحلية والمناطقية. اعتمد أسلوب التصميم المستخدم هنا على التحكم المبني على المنطق الغامض ، وبالتحديد فإن قواعد التحكم العصبية/الغامضة تم اشتقاقها من تدريب ثلاثة موازنات تقليدية ، كل منها تم ضبطه باستخدام الخوارزميات الوراثية بحيث يكون أداؤه مثالياً عند إحدى نقاط التشغيل. وتم فحص الفعالية والمتانة للموازن المصمم. أثبتت نتائج المحاكاة أن أداء الموازن المقترح أفضل من الموازن التقليدي المستخدم حالياً في التطبيقات الصناعية.