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Abstract—The aim of this research is the design and implementation 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 so as to perform optimally at one operating point. The effectiveness and robustness of the designed stabilizer, after implementing it to the laboratory model, is investigated. The results of real-time implementation prove that the proposed PSS offers a superior performance in comparison with the conventional stabilizer presently adopted by the industry.

Index Terms—Distributed Control, Fuzzy Neural Networks, Genetic Algorithms, Power System Stability.

I. 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 [1]. 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 [2], self-tuning regulator [3], model reference adaptive control [4], and robust control [5]. More recently, the concepts of artificial intelligence (AI) techniques were applied in order to create higher degree of robustness and adaptability.

Three AI techniques were widely applied: Artificial Neural Networks (ANNs) [6], Fuzzy Logic Control (FLC) [7] and Genetic Algorithms (GA) [8]. Merging more than one AI technique is also common in the literature [9],[10].

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.

The evaluation of any proposed PSS should not consider “How recent the applied technique is?” but instead “to what extent did the application use the full capability of the selected technique?”

With respect to the environment of evaluation, most of the researches in the literature rely on computer simulation of a single-machine-infinite-bus system to test their design. However, this environment is not adequate for two reasons. First, it simulates only local oscillations and, second, it does not consider practical constraints and/or considerations. Nevertheless, the studies which implemented a proposed PSS on a laboratory multi-machine system are rare [11].

This research aims at: firstly designing and implementing a decentralized PSS capable of satisfying the abovementioned requirements and, secondly, investigating its performance experimentally on an environment similar to that of a real power 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.

To achieve the project objectives, four major steps were undertaken: i- construction of the laboratory multi-machine model, ii- modeling, simulation and model validation of the setup, iii- design and preliminary evaluation of the proposed stabilizer via computer simulation, and iv- real-time implementation and testing of the designed stabilizer on the laboratory setup.
II. LABORATORY MULTI-MACHINE SYSTEM

A. Study System

The multi-machine power system considered for laboratory simulation, Fig. 1, is composed of three identical machines rated 1000 MVA each. The transmission network is composed of four lines of different lengths, all rated 380 kV. The PSS under development, which is assumed to apply a decentralized control concept, is installed at machine#2. Lines parameters are listed in the Appendix.

B. Main Components

Each power plant of the studied system is represented by a dc motor simulating prime-mover, coupled to a micro-synchronous machine simulating the generator. Each set is equipped with two power converters; one for supplying DC power to the DC motor for both the armature and the field winding, and the other for supplying DC power to the field winding of the synchronous generator, which is considered as the machine exciter. The transmission line simulators are constructed as π-circuits. Three-phase resistive and inductive load simulators are used to simulate the system loading.

A voltage control loop has been constructed, Fig. 2, for the machine under control. It incorporates a voltage transducer, an amplifier, a damping feedback block, a firing circuit and a full-wave thyristor bridge. The electronic components of the AVR are implemented on a Printed Circuit Board (PCB) using operational amplifiers.

C. Digital Equipment

The Speed/Angle transducer is composed of two parts; a shaft encoder, which is coupled to the machine under control, generating 2048 pulse per revolution and a PCB for processing the pulses with two outputs: the rotor angle and the rotor speed. The starting of transducer function is controlled by a logic signal.

A controlled circuit breaker is adapted to operate as a fault application unit. The fault unit can be used to apply any type of short circuits with a controlled duration at the bus connected to the unit.

The data acquisition system used in this study is a 12-bit resolution Analog Input/Analog Output card having 8 differential/16 single-ended Analog Input channels, 2 Analog Output channels, and 24 Digital Input/output channels. The data acquisition card connections to the study system are shown in Fig. 3.

D. Computer Simulation

A comprehensive computer model is developed for the laboratory set-up. This model is considered as the computational environment required for the design, testing and evaluation of various forms of PSSs. The three machines of the system are assumed to be identical. The dynamic parameters of the machine are obtained from on-line measurements under different conditions through applying a parameter estimation algorithm. Two main obstacles have been observed during the course of this stage; the highly nonlinear characteristics of the lab system, and the high noise contents superimposed on the signals. The set of parameters that yield the best fit to the recorded responses are listed in the Appendix.

III. CONTROL STRATEGY

A. General

The control strategy employed in this project follows the following three basic steps:
1. Selection of a very simple control structure such as a first order linear compensator for each of the operating points chosen for design (here, three points are selected: light load, medium load, and heavy load),
3. 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.

B. 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 [12].

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

\[ U_{stab} = \frac{K(s + z)}{(s + p)} \Delta \omega \]  

(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, and
- 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:

\[ \text{fitness} = \frac{1}{W_\delta \text{sse}(\delta) + W_\Delta \text{sse}(\Delta \omega) + W_u \text{sse}(u)} \]  

(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 \( W_\delta \), \( W_\Delta \) 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: \( 10^{-4}, 1 \) and \( 10^{-2} \), respectively.

The GA tuning of the stabilizer in this study is multi-objective in a sense that it inherently optimizes two types of oscillations; namely local and inter-area, corresponding to two sizes of disturbances; small and large disturbances.

C. 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 [13]:

Rule 1: if \((x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then } (f_1 = p_1 \times x + q_1 \times y + r_1)\)

Rule 2: if \((x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then } (f_2 = p_2 \times x + q_2 \times y + r_2)\)

These two rules give

\[ \begin{cases} f_1 = p_1 \times x + q_1 \times y + r_1 \\ f_2 = p_2 \times x + q_2 \times y + r_2 \end{cases} \Rightarrow f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = w_1 f_1 + w_2 f_2 \]  

(4)

A possible ANFIS architecture is to implement these two rules as shown in Fig. 4.

![Fig. 4. ANFIS Architecture for a Two-rule Fuzzy System](image-url)

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

\[ \mu_{ai}(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i}\right)^2} \]  

\( i = 1,2 \)  

(5)

Where \( a_i, b_i, c_i \) 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, 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):

\[ \tilde{w}_i f_i = \tilde{w}_i (p_i x + q_i y + r_i) \]  

\( i = 1,2 \)  

(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 \((a_i, b_i, \text{ and } c_i)\) pertaining to the input MFs. These parameters are called premise parameters. Layer 4 has also three modifiable parameters \((p_i, q_i, \text{ and } r_i)\) pertaining to the first order polynomial. These parameters are called consequent parameters.

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

D. Training of the Neuro-Fuzzy PSS

The structure of the neuro-fuzzy stabilizer adopted here is shown in Fig 5. This stabilizer has two inputs. The first input (input 1) is the angular speed and the second input (input 2) is the angular acceleration. The latter is obtained using an approximate derivative instead of a pure differentiator. This choice is made for two reasons. The first is to avoid 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:

\[
H(s) = \frac{s}{(1+0.01s)}
\]  

(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 computer 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. This fuzzy decision surface, shown in Fig 6, plots the fuzzy output versus the two inputs.

IV. EXPERIMENTAL INVESTIGATIONS

The performance of the Fuzzy-based PSS developed in the previous section is to be tested in an environment similar to the real power system. The lab power system, which has been built specially for this project, is used as a simulation environment. The performance of the stabilizer under design is evaluated under various loading conditions and/or disturbance type.

A. Applied Stabilizers

The input to the PSS, irrespective of the strategy of the design, is the angular speed deviation of the machine under control. The output of the stabilizer is fed to a limiter of \pm 0.15 per unit. The stabilizing signal is added to the reference of the automatic voltage regulator of machine#2.

To provide a fair base of comparison, a conventional type PSS should be designed to perform optimally at one of the operating conditions. A simple first-order compensator in the form of equation (7) has been used.

\[
G_{PSS}(s) = \frac{K_s(s + Z)}{(s + P)}
\]  

(7)

The extensive testing of the conventional PSS leads to the best parameters: \(K_s = 1, Z = 6\) and \(P = 3\).

The second stabilizer to be tested is the Neuro-Fuzzy (simply Fuzzy) PSS, which is the subject of this research. The dynamic performance of the lab power system has been compared for three control case studies: without PSS, with conventional PSS and with Fuzzy PSS. To provide a fair comparison, and since the system is subject to continuous
variations, the three control cases are always compared under the same experiment before any significant variations to the system variables take place.

B. Loading Conditions

Three loading conditions are applied for the experimental investigations: light, medium and heavy loading. Table I lists the average values of the two system-loads at different loading conditions. The word "average" here refers to the nature of the operation of the three-machine lab system where it is difficult to operate the system under fixed operational variables.

<table>
<thead>
<tr>
<th>Loading Condition</th>
<th>Load at bus#3</th>
<th>Load at bus#4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P (pu)</td>
<td>Q (pu)</td>
</tr>
<tr>
<td>Light</td>
<td>0.34</td>
<td>0.24</td>
</tr>
<tr>
<td>Medium</td>
<td>0.68</td>
<td>0.35</td>
</tr>
<tr>
<td>Heavy</td>
<td>1.18</td>
<td>0.48</td>
</tr>
</tbody>
</table>

C. Responses to a 3-cycle Three-Phase Fault

A 3-cycle three-phase short circuit was applied to the terminals of the machine under control (bus#2) for the medium loading condition, under three control cases. The rotor angle deviation, rotor speed deviation and stabilizing signal responses are given in Fig. 7. The rotor angle deviations for the light and heavy loading conditions are given in Fig. 8 and Fig. 9 respectively. The performance of the stabilizers under this fault condition is better than that of the system without stabilizers for both the maximum overshoot and the damping characteristic. For instance, the developed Fuzzy stabilizer exhibited superior performance having the lowest overshoot and highest damping for the three loading conditions. It is interesting here to mention that the investigators have experienced the excellent performance of the adopted PSS from just hearing the sound resulting from the machine upon applying short circuit to its terminals. The Fuzzy PSS absorbs the disturbance such that the resulting sound is the softest. The robustness of the designed Fuzzy PSS has been proved through extensive testing under different operating conditions where its response is always better than that of the conventional PSS.

D. Responses to a 6-cycle Three-Phase Fault

A larger disturbance is applied by increasing the duration of the short circuit to bus#2 to 6 cycles, under medium loading. The corresponding responses are given in Fig. 10. The Neuro-Fuzzy PSS is still offering better responses characterized by higher damping and lower overshoot.
V. CONCLUSION

The lab power system, which was developed using micro-synchronous machines having low inertia constants, exhibits modes of oscillations that are comparable to those exist in real multi-machine systems. In the process of developing the proposed PSS, a comprehensive approach empowered by experimentation schemes, mathematical methods, analysis techniques, and simulation tools was employed. This stabilizer offered a superior performance, characterized by higher damping and lower overshoot, in comparison with the conventional stabilizer 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. In light of the achieved results and the experience gained over the course of this project the investigators are convinced that the proposed approach enjoys a great deal of qualities making it stand as an excellent control strategy for the problem at hand.

REFERENCES


Fig. 10. Responses to a 6-cycle Fault at bus#2 - Medium Loading