Applications of fuzzy logic control for damping power system oscillations

by Jie Lu

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering
Montana State University

Abstract:
This thesis is concerned with applications of fuzzy logic control to enhance the damping of low frequency electro-mechanical oscillations in electric power systems. The objective is to develop power system stabilizers and damping controllers with fuzzy logic control so that they can be improved over conventional stabilizers in terms of adaptiveness and robustness.

Two fuzzy adaptive control schemes are developed. One scheme is based on direct tuning of stabilizer parameters and the other is based on an optimal combination of damping signals. In the first scheme, the Prony method is used to identify linear models of the power system under study, and then a root locus method is used to design conventional stabilizers at various operating points. A genetic algorithm is then used to optimize the fuzzy parameter tuner so that damping ratios are maximized regardless of changes in the operating condition. In the second scheme, a frequency-domain phase compensation method is used to identify the optimal characteristics of stabilizers at different operating points and to design conventional stabilizers for two extremes of these points. Then a fuzzy signal synthesizer is developed to optimally blend damping signals from the two independent conventional stabilizers, and therefore the stabilizer/controller can retain optimality even when the operating point drifts.

These two schemes are applied to develop power system stabilizers and/or SVC damping controllers, and extensive simulations on several systems demonstrate the effectiveness of these two schemes and show better performance than conventional stabilizers/controllers.

APPLICATIONS OF FUZZY LOGIC CONTROL FOR DAMPING POWER SYSTEM OSCILLATIONS

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Jie Lu

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This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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ABSTRACT

This thesis is concerned with applications of fuzzy logic control to enhance the damping of low frequency electro-mechanical oscillations in electric power systems. The objective is to develop power system stabilizers and damping controllers with fuzzy logic control so that they can be improved over conventional stabilizers in terms of adaptiveness and robustness.

Two fuzzy adaptive control schemes are developed. One scheme is based on direct tuning of stabilizer parameters and the other is based on an optimal combination of damping signals. In the first scheme, the Prony method is used to identify linear models of the power system under study, and then a root locus method is used to design conventional stabilizers at various operating points. A genetic algorithm is then used to optimize the fuzzy parameter tuner so that damping ratios are maximized regardless of changes in the operating condition. In the second scheme, a frequency-domain phase compensation method is used to identify the optimal characteristics of stabilizers at different operating points and to design conventional stabilizers for two extremes of these points. Then a fuzzy signal synthesizer is developed to optimally blend damping signals from the two independent conventional stabilizers, and therefore the stabilizer/controller can retain optimality even when the operating point drifts.

These two schemes are applied to develop power system stabilizers and/or SVC damping controllers, and extensive simulations on several systems demonstrate the effectiveness of these two schemes and show better performance than conventional stabilizers/controllers.

CHAPTER 1

INTRODUCTION

Background

This thesis is concerned with the development of intelligent control strategies, and more specifically, fuzzy logic control to enhance the damping of low frequency electromechanical oscillations in electric power systems.

Within an interconnected power system, the power flow over a tie-line should be maintained near a constant level under normal conditions. However, low frequency electromechanical oscillations may occur spontaneously under certain circumstances. When such oscillations occur, electric power can be transmitted back and forth over the tie-line, demonstrating an active power fluctuation in a frequency range of 0.1 ~ 1 Hz. Accompanying this, generators within a regional system may swing against each other with a slightly higher frequency (up to 3 Hz), which also greatly disturbs the normal operation of a power system. Once such oscillations begin, they may die out by themselves after a short period, may persist for a long time until some condition changes, or may keep intensifying in magnitude, destabilizing the system, and may eventually break the interconnected system into regional islands.

The fundamental cause of this kind of oscillation is the generation of negative damping by some components, which cancels out the inherent positive damping of the system and therefore causes very light or even negative system damping. This phenomenon is more likely to happen in some specially structured systems, for example, a weak interconnection between two regional systems, or a power plant connected to a load center over a long geographical distance. Generally speaking, low frequency oscillations are associated with the dynamics of the turbine governors, excitation systems and automatic excitation regulators. Negative damping may be introduced when their parameters are improperly set.

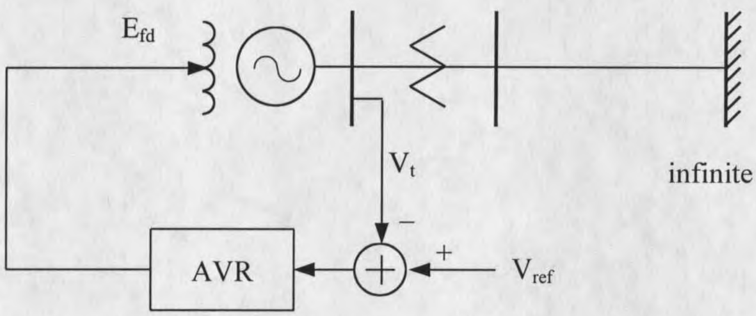
Undamped oscillations can result in great damage to interconnected systems, and they are very severe events in terms of economic loss. Power system engineers have been working on this important issue since the 1960's and have conducted numerous theoretical studies and field tests. However, research on this issue remains active because of the complexity of the problem and the advent of new control techniques and new fast-response devices not available when the problem was first studied. Among the former are intelligent (knowledge-based) control schemes such as fuzzy logic control (FLC) and digital control techniques that make logic-based control possible in industrial applications. Among the latter are Static VAR Compensators (SVC), Thyristor Controlled Series Compensators (TCSC), and other Flexible AC Transmission System (FACTS) devices, a common feature of which is short response time, which benefits control greatly.

The Nature of Low Frequency Oscillations

Prior to the actual design of a control scheme to suppress such low frequency oscillations, a full understanding of the nature of these oscillations is necessary. For precise mathematical analysis, a linearization followed by eigenvalue analysis is often desirable. However, for the purpose of understanding, a physical analysis on a one-machine system is more appealing, since it introduces useful physical concepts and reveals how the physical quantities interact with each other to develop negative damping. It is also useful in developing remedial measures against these negatively damped oscillations.

Consider the following simple system.

Figure 1. A simple system.



E_{fd}: excitation field voltage.
V_t: terminal voltage.
V_{ref}: reference voltage.
AVR: automatic voltage regulator.

Neglecting all minor details and assuming no immediate mechanical torque change following a small perturbation (which is justified by the slow response of turbine governors), linearized equations characterizing this system are as follows:

$$\frac{2H}{\omega_0}\Delta\dot{\omega} + D\Delta\omega = -\Delta T_e \quad (1.1)$$

$$\Delta\dot{\delta} = \Delta\omega \quad (1.2)$$

where

H is the inertia of the generator,

ω is the angular speed,

ω_0 is the nominal angular speed,

δ is the rotor angle,

D is the inherent damping, and

T_e is the electrical torque.

Since here we are talking about a linearized representation of the system, the electrical torque T_e can be further expressed as a linear combination of the other two variables ω and δ as follows:

$$\Delta T_e = K_S \cdot \Delta\delta + K_D \cdot \Delta\omega \tag{1.3}$$

where K_S and K_D are coefficients, which are highly sensitive of operating points, network parameters and excitation system parameters. The first term on the right-hand side of (1.3) is called synchronizing torque while the second term is called damping torque.

By substituting (1.2) and (1.3) into (1.1), we have

$$\frac{2H}{\omega_0}\Delta\ddot{\delta} + (D + K_D)\cdot\Delta\dot{\delta} + K_S \cdot \Delta\delta = 0 \tag{1.4}$$

For this second-order system to be stable, $(D+K_D)$ and K_S should both be positive. If the synchronizing torque is negative, the characteristic equation has (at least) one positive real root, and therefore the generator slips out of synchronism without any oscillation. If the damping coefficient $(D+K_D)$ is negative, the characteristic equation guarantees to have roots whose real parts are positive, which correspond to unstable modes. If the roots are complex, the system exhibits oscillations. Usually the synchronizing torque is safely large due to the action of the generator AVR, and therefore of less concern than the damping torque. On the other hand, it is exactly the same action of the AVR that under certain conditions could deteriorate the damping torque to such a degree that the generator becomes vulnerable to small disturbances in the system.

In the above analysis, we concentrated on the electrical torque and neglected the mechanical torque. In fact, the mechanical torque can be decomposed as synchronizing and damping torque as well. Therefore, similar analysis can also be carried out for the mechanical torque; the only difference is that the resultant coefficients would depend on different factors like turbine governor parameters rather than excitation system parameters. This is the reason that in some cases low frequency oscillations are due to improper mechanical subsystem settings.

The whole matter is much more complicated if more than one machine is involved; the order of the system is higher, and interactions between machines have to be considered. However, the physical nature of the oscillation remains the same. Hence some concepts developed with the single machine case are still applicable, and the control methodologies based on them may be extended to multi-machine systems.

Measures against Low Frequency Oscillations

There are two philosophies in developing power system stabilizers for improving system damping: one is based on control theories; and the other is to follow the understanding of the physical nature of low-frequency oscillations.

The underlying thought of the former is to view the problem from the perspective of control theories, where a mathematical model of the whole system is obtained and analyzed, and based on its characteristics appropriate control theories are applied to design a controller. In other words, the problem is put into a general frame of control problems, and an optimal solution is sought in that framework. One advantage of this approach is that so many control methodologies are readily available, among which some may fit well to the particular problem at hand. These control methodologies usually have well-defined procedures to follow in controller design. Classical examples include using root locus to develop stabilizers based on the zero-pole representation of the system and using linear quadratic regulation theory to design an optimal stabilizer based on the system state-space representation.

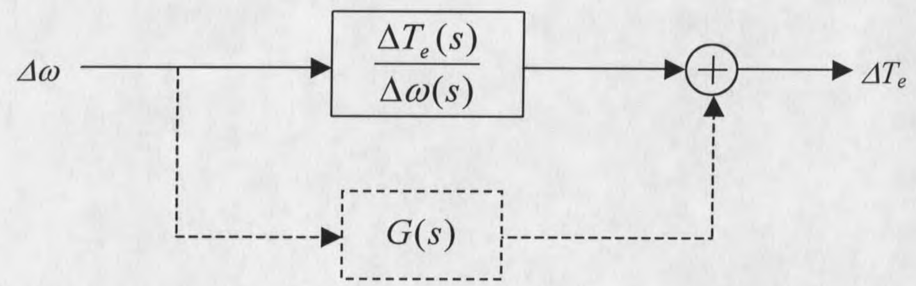
In contrast, the other category of approaches views the problem from a physical perspective, especially focuses on why and how oscillations develop, what is the key driving force behind the power oscillations, and what are physically suitable remedies. For example, after the interaction between the voltage regulation and the machine speed is unveiled, a heuristic controller might be designed to give supplementary control to the excitation system utilizing a phase-plane representation of the machine speed and acceleration.

In particular, a methodology for power system stabilizer design is worthy of mention since it serves as a basis of an adaptive controller, which a part of this thesis concerns. From (1.3) we can see that the coefficient K_D is actually defined as:

$$K_D = \frac{dT_e}{d\omega} \tag{1.5}$$

Equation (1.5) shows how much damping would be introduced in the electrical torque if a deviation of machine speed takes place. This implies that by adding a parallel compensatory signal path with a positive gain in addition to the inherent signal path from

Figure 2. Compensatory signal path added to improve damping.



ω to T_e, damping can be improved. This is illustrated in Fig. 2, where the dotted path is the added-in compensatory one.

By incorporating (1.2) and (1.3) and performing Laplace transformations, we obtain the following expression, assuming the oscillation of concern is sinusoidal:

$$F(j\Omega) \triangleq \frac{\Delta T_e(j\Omega)}{\Delta\omega(j\Omega)} = \frac{K_S}{j\Omega} + K_D \tag{1.6}$$

where Ω is the angular frequency of oscillation[1]. It follows that

$$K_D = \mathrm{Re}[F(j\Omega)] \tag{1.7}$$

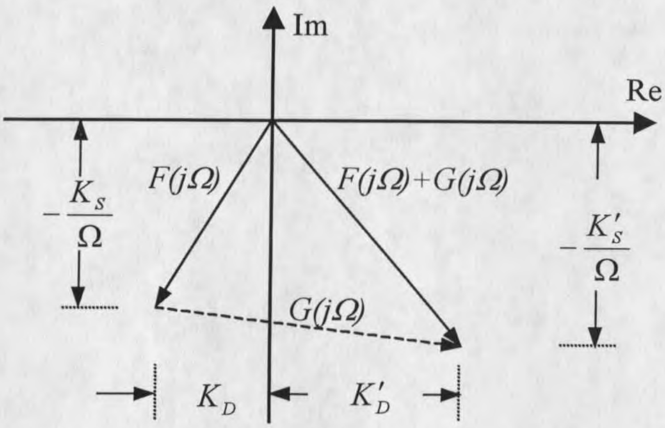
and

$$K_S = -\Omega\,\mathrm{Im}[F(j\Omega)] \tag{1.8}$$

where Re(·) and Im(·) denote the real and imaginary parts of a complex number respectively. Suppose the complex gain of the compensatory path is $G(j\Omega)$, then, as shown in the phasor diagram given in the Fig. 3, it is clear that the best angle of the $G(j\Omega)$ phasor should be negative and approaching zero, so that the damping is enhanced

[1] To avoid confusion, a capital Ω is used here to denote the angular oscillation frequency, since ω is already denoting the angular speed of the generator.

Figure 3. Phasor diagram of complex gains.



K'_D, K'_S: Coefficients after compensation

without having an undermining effect on synchronous torque. Here the compensatory path includes not only a controller but also some unalterable part of the system. Frequency domain methods are used to design the compensator so that the complex gain of the path is close to real.

Controllers have to be actually attached to physical devices such as a generator excitation unit, an SVC, a Static Synchronous Compensator (STATCOM), or a TCSC. These devices except the first one are categorized as FACTS devices. Controllers based on excitation units have the advantage of being a low-cost option, and they are applied most widely for the purpose of damping low-frequency oscillations. On the other hand, FACTS devices, which are high power electronic devices, have fast response time and potential to yield better control performance. They are expensive, and therefore it is generally infeasible to install them solely for the purpose of damping low frequency oscillations. However, if there are FACTS devices already in operation for other purposes like voltage support, supplementary controllers can be designed for them to enhance damping. In this thesis, consideration is given to excitation unit-based and SVC-based controllers, since these two are the most available options at present time.

Fuzzy Logic Control

Fuzzy logic control (FLC) is a powerful tool in modeling and controlling those imprecise systems that are difficult to represent in traditional mathematical models. It is based upon fuzzy set theory that mathematically establishes the definitions and manipulation rules of fuzzy sets representing imprecise objects or terms in real life. For example, the statement "if A is very high and B is medium, then C is moderately high," which might be impossible to translate into conventional mathematical languages, is expressible with the fuzzy set theory. With the definition of fuzzy terms and inference rules, just like the IF-THEN statement above, expertise given by a human being or experience learned by other means can be stored and applied by a computer.

In control applications, fuzzy logic is fairly flexible. In the statement above, if A and B are measurements, then C could be an output, or it could be a control signal. In the former case the rule is a part of a fuzzy model, and in the latter case it is a control law. The two forms can be (and usually are) used jointly in controller design: based on a model rule, a fuzzy control law is developed. A paradigm is as follows: if measurement A is very high, and measurement B is medium, then the output is moderately high and therefore the control effort should be moderately low.

There are two forms of fuzzy logic systems: Mamdani type and Takagi-Sugeno type. The difference between them is with the consequent (THEN) part of rules: in the former the output variable is specified with a fuzzy term, and it needs to be defuzzified to obtain a crisp value. In the latter type the output is given as a crisp (as opposed to fuzzy) linear combination of the input variables. The two forms both have their own advantages: the Mamdani type is easy to construct based on human language description of an object, whereas the Takagi-Sugeno type is useful when some traditional mathematical representation of an object is involved. With this type, a design pattern is often followed:

(1) Determine a proper division of state space so that in every subspace the object in study is linear or quasi-linear. For each subspace a rule is given to specify the subspace in the antecedent (IF) part and describe the linear relationship in the consequent part as follows:

If $\overline{X}$ is …, then $\overline{Y} = F(\overline{X})$, where $F(\cdot)$ is a linear function.

(2) Based on the model rules given in (1), for every subspace a controller H is designed optimally in some sense.

(3) The control laws are then constructed, followed by any optimization (if necessary) of the fuzzy membership functions:

If $\overline{X}$ is …, then $H = H(\overline{X},\overline{Y})$, where $H(\cdot)$ is the control function.

This procedure is used in this thesis to develop adaptive stabilizers.

Literature Review on Control for System Damping

This section will review some published work on damping low frequency oscillations. Most of them are focused on intelligent control schemes for damping purposes, while some others are included due to their relevance to this thesis.

DeMello and Concordia [1] were among the first to analyze the nature and remedies of the low frequency electro-mechanical oscillations. In their paper, they presented, in the form of a block diagram, a linearized model of a synchronous generator and its excitation system connected to an infinite bus. Detailed explanations were given on parts of their diagram and on the physical significance of the constants appeared therein. They introduced the concepts of synchronous and damping torques, and pointed out that lack of adequate damping torque caused oscillation or instability. Using these concepts and the block diagram, the authors developed expressions for torques and thus revealed the effect of the excitation system on stability: under certain conditions, high voltage regulator gain jeopardized stability by lowering damping inadvertently when attempting to increase synchronizing torque. Based on this understanding, the authors used frequency domain methods to develop speed-based power system stabilizers (PSS) to compensate this negative impact on damping torque and demonstrated the effectiveness through analog simulations.

Kundur, et al., [2] described in detail analytical work and a design procedure to determine PSS parameters for a large power generation station. The frequency response method outlined in their paper is based on and is similar to the stabilizers proposed in [1], but the authors obtained the frequency characteristics with the model of a whole system instead of a single machine model. This created a more accurate representation of the generator of interest. The authors also put emphasis on simultaneous damping of inter-area and local modes and robustness of PSS design. It was pointed out by the authors that if the time constant of the washout filter was too small then damping was adversely affected on inter-area modes by over-compensation. In their paper, the effect of transient gain reduction was also discussed, and the authors showed that it did not provide any major benefit. As the authors reported, the frequency response method (that mainly aimed to compensate the lag from the excitation input to the electrical torque) was fairly robust. This meant that a PSS with proper frequency characteristics could be universal regardless of external conditions or mode of oscillations.

Trudnowski, et al., [3] presented an interesting identification method and a method of designing PSS other than frequency domain based ones. The authors used a pulse of a short time period as the excitation to a generator in a multi-machine system to obtain a response, and based on this input-output relationship, generated a transfer function that was optimal in the sense of least-squares error of time domain fit. A root locus method together with a decentralized sequential control technique was used to demonstrate the procedure to use transfer functions acquired above for damping controller design. The authors clearly showed the effectiveness of their design method by presenting simulation results, FFT analysis on those and a root locus plot for a 16-machine 27-bus test system.

Hsu and Cheng [4] proposed a PSS based on fuzzy set theory. This paper attempted to use a classical Mamdani type fuzzy system to build a mapping relationship from measurement inputs to control output. The authors chose the normalized values of speed deviation $\Delta\omega$ and its derivative as two inputs to a fuzzy logic inference machine, which gave a fuzzy value of PSS control signal. A seven-by-seven rule table was employed, and the authors determined all the membership functions based on their design experience and no optimization on these membership functions was intended or mentioned in their paper. A two-machine nine-bus system including an infinite bus was used as the test system to simulate a three-phase fault. The results reported showed good damping as compared with a conventional lead-lag PSS.

Hiyama published a series of papers on applying rule-based and fuzzy logic controllers to stabilize power systems. He proposed [5] the following control scheme: First, the speed deviation is selected as the input signal, and then a phase plane is constructed based on speed deviation and its first-order derivative, i.e., the acceleration of the generator. The phase plane is divided into six sectors, which respectively represent different speed and acceleration combination states and therefore demand for different control strategies: strong accelerating control, slight accelerating control, slight decelerating control, and strong decelerating control. Dividing lines are defined to divide the phase plane, and the positioning of these lines are parameterized and subject to subsequent optimizations. Naturally the sign of the control reflects whether it was an accelerating or decelerating control. Two gain levels, high and low, were used to implement "strong" and "slight" controls respectively. The gain of the controller is also dependent of how far the state is from the origin of the phase plane, which represents the equilibrium point of the generator: the gain is proportional to the distance from the origin within a given threshold, and is a constant beyond that. This threshold is also subject to optimizations. To achieve optimal performance, all the parameters including those mentioned above undergo an optimization to determine the optimal setting. A time-domain summation of squared errors is used as the performance index, and the parameters are optimized sequentially. Simulations showed impressive damping improvement over conventional stabilizers. In [6] the same design was extended into multi-machine cases and it also showed good results.

In [7] Hiyama presented a modified version of the rule-based stabilizers. Use of the phase plane, with speed deviation as the input signal, and the concepts of strong or slight controls, accelerating or decelerating controls remained the same. However, instead of using two gain levels and sign of the control signal to realize the control strategy as reported above, he introduced a fuzzy logic scheme to describe the transition of different controls. Two terms were defined to represent strong positive and strong negative control respectively, and their respective trapezoidal membership functions complemented each other and determined the control signal in states that are between the two extreme ones. The same sequential optimization technique was again used to get a minimal oscillation, though the parameters to be optimized were slightly different. The author also presented in detail his implementation in an experimental system using digital control, and showed that the approach yielded good performances. In [8], the author discussed the application of this approach to a multi-machine system, and based on the simulation results, it was claimed that the approach was robust over a wide range of operating conditions, though no theoretical analysis was presented. In [9] the author reported inferior performances or even instability associated with a condition where the acceleration and speed deviation were close to zero while the phase was not at its steady-state value. To correct this situation, further modifications were made to his scheme: the phase information or the integration of the speed deviation was introduced (hence the name PID Type stabilizer since an integration was involved) and the origin of the phase plane was moved leftward or rightward depending on the sign of the integral. This shift was to force the phase integration to zero by applying accelerating or decelerating controls when the integration drifted from zero towards negative or positive sides respectively. The author did both simulations and experiments to demonstrate the effectiveness of the modification on correcting this problem. Overall, Hiyama's heuristic based approach showed success in his series of research works. However, without a sound theoretical foundation backing it, the author failed to show that parameters optimized in his method are reasonably insensitive to external condition changes. In other words, before any further research is carried out, this approach should be considered robust only in the cases that were considered in his design.

Hassan and Malik also looked at the application of fuzzy logic in stabilizing power oscillations. They [10] developed a similar control scheme to Hiyama's [7], which uses the same concepts of phase plane, accelerating and decelerating controls, and quadratic optimization based parameter tuning. However, they used standard B-spline membership functions instead of trapezoidal ones. Although the authors mentioned the use of trapezoidal membership functions in other papers, they did not elaborate on how their choice of membership functions was superior. The parameter optimization was based on a quadratic performance index in the time domain, and simulations on a single machine system were given to show the effectiveness of the stabilizer. In a later development [11], they advanced the stabilizer by introducing a self-tuning mechanism. They set the initial threshold (see the review given above on [5]) to a non-machine-specific and very small value, and during the transient process set the threshold slightly larger than the maximum magnitude of state deviation from the origin detected in the current disturbance. In this way, stabilizers would be able to maintain a high gain during the very beginning of a disturbance, which was known to help secure transient stability. This was a fairly simple adaptive measure, and was not self-tuning in a strict sense, because self-tuning generally involves a varying plant model and corresponding controller modification based on that model. Although the authors gave a rationale for their self-tuning scheme, they did not clearly establish the advantages of their scheme over fixed fuzzy logic stabilizers by comparing their performances.

Hoang and Tomsovic [12] developed and evaluated a fuzzy stabilizer similar to the one presented in [4]. Fuzzy logic control applications including this paper and [4] have been often based on a standard paradigm as could be found in many fuzzy logic control textbooks [13]. This means any performance improvement would depend on other parameters in the controller such as scaling factors. As the authors correctly pointed out, many applications demanded heuristic tuning of parameters, which was time-consuming, error-prone and could not guarantee a robust solution. In this paper, a procedure was proposed for selecting the input and output scaling factors. The basic idea was to set all the factors to their maximum possible values and then adjust the two factors associated with the input variables (speed deviation and its derivative) based on eigenvalue analysis to achieve maximum damping. It was difficult to conduct small-signal analysis on such a system containing a non-differentiable fuzzy logic inference machine. However, the authors viewed the fuzzy logic controller as a zero-memory nonlinearity and used numerical linear approximation around an operating point to circumvent this difficulty. Apparently, linear analysis is far less time-consuming than time-domain performance evaluation, and is equally convenient to observe effects of controllers, and the authors used it in their design and showed stability improvement as indicated by considerable leftward movement of eigenvalues. Critical clearing times were also presented as a proof of correctness of their analysis and the effectiveness of the controller as they coincided with the result of eigenvalue analysis.

Dash, Mishra and Liew [14] presented a different fuzzy logic stabilizer. Like other fuzzy logic stabilizers, their proposed stabilizer took the speed deviation and acceleration as two input signals to the fuzzy logic controller. Five linguistic labels for each input, and therefore twenty-five rules, were used in the stabilizer. Scaling factors were chosen so the input would fall into a range of −1 to 1. Their stabilizer differed from others in that every rule took a form of PI controller, namely, the output is a linear combination of two scaled inputs. Likewise the overall output was in fact a linear combination of two scaled inputs, with the weighting factors varying to adapt to the changing state. An interesting feature presented with the proposed controller was that another compensatory control was present to give more robustness against possible large system changes. This compensatory control was actually an additional and independent self-tuning control. It used a second-order auto regressive moving average (ARMA) model to formulate the relationship between the machine speed and the control signal, identified the parameters of this model with the recursive least squares algorithm in real-time, generated a proper control signal based on that, and applied it to the exciter of the generator. With two controllers in place, the authors simulated fault or other disturbance cases and showed good damping against oscillations.

In a following development [15], the same authors proposed using a PID stabilizer and a fuzzy logic mechanism to do gain scheduling for the PID controller. Firstly they prescribed two ranges to which the proportional gain and the derivative gain are confined respectively. The actual values of these gains would be determined in real-time by two coefficients which would vary to adapt to the changing state. The integral gain was then determined using the Zeigler-Nichols PID tuning rule, which contains a linear parameter α to be optimized. Two coefficients associated with proportional and derivative gains were determined using a fuzzy logic mechanism, which took speed deviation and acceleration as inputs. The parameter α can also be determined in this fashion, but it can also be a pre-optimized constant. The coefficients had two linguistic labels, namely large and small, and the membership indices of the coefficients were determined in such a way that good transient and steady-state characteristics were achieved: when in transient, the integral and proportional gains should be large and the derivative gain should be small, and when in steady-state, the opposite held true. The authors simulated fault cases in both a single machine system and a multi-machine system, and were able to show some improvement over conventional stabilizers.

In another interesting development, Hariri and Malik [16] attempted to merge artificial neural network and fuzzy logic control to develop a new type of fuzzy stabilizer, one that could acquire good damping ability by learning in the manner of an artificial neural network. First the authors represented a fuzzy logic system as a functionally equivalent five-layered network called Adaptive Network, where nodes in each layer executed different functions like calculating membership functions or figuring out the truth-values or firing strengths of rules. Rules of the Takagi-Sugeno [17] type were employed because such rules could be expressed with fewer parameters. Naturally the membership functions and rules were expressed in the form of parameters in nodes, so tuning the fuzzy logic mechanism was equivalent to letting the network learn. To get the network learning, a goal controller (pole-shifting controller in the paper) and various scenarios were selected, so the fuzzy stabilizer could learn to emulate the behaviors of the goal controller in those scenarios. The authors tested a single machine system under different disturbance cases, and the resultant stabilizer reportedly showed much improvement over conventional stabilizers. Viewed from another perspective, the learning procedure was in fact an optimization procedure; what the authors achieved was to use already-matured neural network optimization algorithms, like the back propagation algorithm, to automatically optimize fuzzy rule based stabilizers.

In [18], Hariri and Malik presented a problem associated with the approach in [16]: while the learning was highly automatic, controller designers still needed to select the total number of rules, which is a tedious trial and error procedure. The authors took the challenge by utilizing a Genetic Algorithm (GA) [19]. They first set the range of variables and the shape of membership functions. Based on that all the membership functions could be represented simply as a string of binary values. Then the actual learning procedure was as follows: first a certain number of candidates of membership functions were generated, based on which the optimization method mentioned in [16] was performed to obtain optimal rules; after that, the performance indices were calculated for every candidate, and a "survival of the better" strategy was used to pick those better candidates to produce next generation of candidates; this new generation would go through the same path as their parents did; eventually, the membership functions and rules were both optimized and the learning ended. This kind of optimization further improved the performance of their fuzzy logic stabilizer as shown in the simulation of a single machine system in the paper. While this approach sounds very appealing, some parts of it still need a human being to be involved, like the selection of a goal controller and the selection of scenarios. Also, this iterative optimization would be very slow since both neural-network learning and genetic algorithm execution, especially the former, are notoriously computationally intensive and time-consuming. For a large system, this might be so slow that it becomes infeasible.

In the same way as Hariri and Malik used GA to improve an existing algorithm, M. A. Abido [20] used GA to replace the manual iterative optimization procedure described in [5]. This was fairly straightforward: the design in [5] was to manually optimize a function that mapped parameters to a time-domain performance index, and the application of GA did not only eliminate the involvement of any human being, but also ensured to a large degree the global optimality of the solutions. All the parameters including dividing line positions and the threshold were encoded as a binary string fed into GA, and for every generation of candidates, decoding, evaluation, elimination and reproduction were performed. In the paper, the author demonstrated the effectiveness of this optimization by simulating a single-machine system and two multi-machine systems. Again, the main drawback of this approach was its demanding computational effort due to so many time-domain simulations and the slow nature of GA.

Another attempt by Abido to take advantage of a neural network in fuzzy stabilizer design was presented in [21]. Similar to the work done in [16], a neural network named Fuzzy Basis Function Network (FBFN) was used to express the operation of a fuzzy system. The network was slightly different from the one used in [16]. However, unlike [16], where a gradient descent algorithm was adopted to optimize the parameters, a classical Gram-Schmidt orthogonal least squares algorithm was used, which was known to be much faster. Another difference was that in [16] a goal controller had to be chosen for the network to learn, while in [21] a damping coefficient was used as the optimization objective. This was reasonable and avoided time-domain simulation, though another lengthy computation, eigenvalue analysis was implied.

Yet another research effort on this topic was presented in [22] by Hosseinzadeh and Kalam. In their work, they did not use a network to express a fuzzy system. Instead, they still used the fuzzy structure introduced in [4], but applied neural network training as an optimization technique to optimize the scaling factors of two input signals to their fuzzy controller. As mentioned before, these parameters were deciding factors affecting performance. A more traditional three-layer network was adopted and three measurements or parameters, namely, the active and reactive power and the external reactance were used as the inputs to the neural network, and the two scaling factors were the output. A time-domain summation of absolute error acted as a performance index. A Levenberg-Marquardt method was used in an effort to speed up the learning. Simulations were done on a single machine system, and the reason why the author did not use a multi-machine system would possibly be the heavy computational burden imposed by performance index calculation, which involved time-domain simulation.

Objective of This Thesis and Organization of Remaining Chapters

As could be seen in the reviews, fuzzy logic control shows great potential in damping power oscillations. However, it often suffers from lack of a systematic way to build a good knowledge base. Unlike some other control problems, the problem of damping low frequency oscillations can be largely formulated into mathematical models, and there are numerous studies on this problem and mature techniques are available. The objective of this thesis is to integrate traditional techniques and FLC, so fuzzy logic applications can be improved by learning from other mature techniques. In particular, FLC will be used in PSS design and in controlling of SVC for enhancing damping of power system low frequency oscillations.

The following pages are organized into four chapters. Chapter 2 introduces a fuzzy stabilizer, which is designed with a root-locus method and genetic algorithms. A fuzzy stabilizer for multi-machine systems is presented in Chapter 3, which is based on traditional frequency domain techniques. In Chapter 4, a similar approach is applied to design SVC damping controllers. Chapter 5 is the conclusion and discussion of aspects worthy of future work.

CHAPTER 2

A FUZZY LOGIC SELF-TUNING POWER SYSTEM STABILIZER

Introduction

In this chapter, a fuzzy logic-based control strategy to implement a self-tuning PSS is introduced, where the PSS parameters are adjusted by a fuzzy parameter tuner according to on-line measurements. The underlying idea is straightforward: since we can design a linear stabilizer, which has satisfactory performance at a particular operating point, we can do this at many different operating points; it is then possible to develop a synthetic scheme incorporating these individual stabilizers which can track and respond to varying operating conditions with excellent performance. This is done by tuning the parameters of the stabilizer on-line according to the knowledge of the individual stabilizers.

Unlike most other fuzzy logic applications, where rules are generated based on operator's experience or general knowledge of the system in a heuristic way, in this application an optimization technique is used for selecting both individual rules and membership functions. Therefore, a sound knowledge base can be guaranteed. The implementation includes three main parts: plant identification (i.e. obtaining linear models), individual stabilizer design, and membership function optimization. Identification involves obtaining linear models for the generator over a wide range of operating points. Prony-based analysis [3] is used to obtain such linear models. Among the operating points some, distributed uniformly over a grid, are selected as "pivot points" to design conventional stabilizers on, and the others are used to optimize the membership functions. If the generator happens to operate at a pivot point, the PSS parameters are tuned exactly to the values acquired. Otherwise, the stabilizer parameter settings are obtained using knowledge of neighboring pivot points and fuzzy logic operations. The performance of such a stabilizer at a non-pivot point depends on the membership functions, which determine the relative weights of the neighboring pivot points' influence on the current operating point. To optimize the shape of these membership functions, an objective function for the overall performance of the fuzzy PSS over these non-pivot points is extremized with respect to the shape of the membership functions using a genetic algorithm (GA).

The relevant concepts and techniques used in this chapter are introduced in the next section. Following that section, the stabilizer design is discussed in detail. Simulation results are presented to demonstrate the effectiveness of the proposed stabilizer.

Fuzzy Logic and Genetic Algorithms

In this section, a brief discussion of fuzzy logic and genetic algorithms is given. Detailed information on these subjects is readily available in subject-related textbooks, i.e. [19], [23]. The application of a GA to optimize fuzzy logic-based controller performance is not new, i.e. [24]. In this study, fuzzy logic is used for online reasoning and the GA is used for optimization of the membership functions in the off line design phase, as described in the following section.

Fuzzy logic involves three procedures: fuzzification, inference, and defuzzification. Fuzzification converts crisp input values into fuzzy linguistic terms with their corresponding memberships. The inference procedure is reasoning using fuzzy linguistic rules, which are based on some knowledge acquired by experience or other knowledge extraction means. Defuzzification converts the results of the reasoning procedure back into crisp values. In cases where the output of fuzzy reasoning is crisp, defuzzification is unnecessary. While rules play an essential role in the inference procedure, membership functions are also important in obtaining a proper output from the fuzzy controller. Unlike rules which are in linguistic form, membership functions can often be defined by mathematical functions, which means that it is possible to use a numerical technique to optimize them to improve the performance of the fuzzy controller. In particular, triangular and trapezoidal membership functions can be characterized by several numbers, i.e. their corner points. A stochastic optimization algorithm such as a GA can then be used to optimize the membership functions and improve the performance of the fuzzy logic controller.

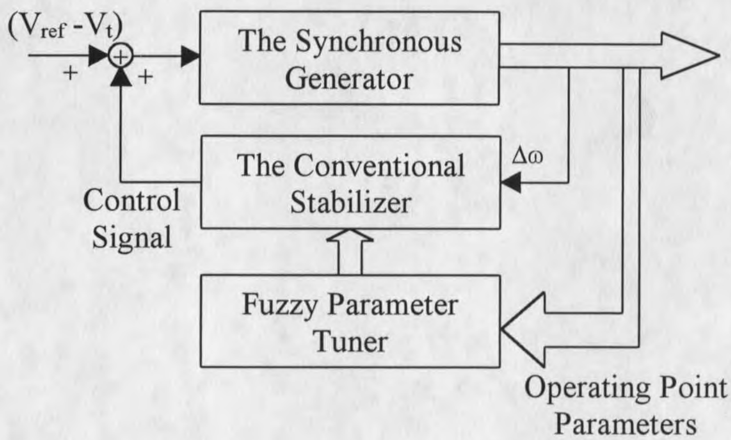
Genetic algorithms are stochastic optimization algorithms which have proved to be effective in various applications. A given GA emulates the process of evolution and natural selection, which is based on an idea that the force driving species to evolve can be imitated in an artificial context. A typical GA maintains a population of solutions and implements a "survival of the fittest" strategy in the search for better solutions. It has been shown to be capable of finding global optima in complex problems by exploring virtually all regions of the state space and exploiting promising areas through mutation, crossover and selection operations applied to individuals in the populations. In this study a GA is used to obtain proper corner points for a set of trapezoidal membership functions.

The Proposed Stabilizer

The Structure of the Stabilizer

The proposed fuzzy logic stabilizer consists of a conventional power system stabilizer (CPSS) and a fuzzy logic-based parameter tuner. Using the knowledge from a rule base, prepared off line, the fuzzy tuner adjusts the parameters of the CPSS according to the real-time operating information. Fig. 4 illustrates the structure of the stabilizer. All the rules for the fuzzy tuner and the shape of the membership functions are obtained through a genetic algorithm based optimization method, as will be explained later.

Figure 4. The structure of the proposed stabilizer.



The transfer function of the CPSS used is as follows:

$$H(s) = K \cdot \frac{sT_w}{1 + sT_w} \cdot \frac{1 + sT_1}{1 + sT_2} \cdot \frac{1 + sT_3}{1 + sT_4} \tag{2.1}$$

where K is the PSS gain, and T_1 through T_4 are the stabilizer time constants, all of which are determined by the fuzzy parameter tuner. T_w is the time constant of a washout filter which is set to 5 seconds in this study.

Let vector $\overline{p}$ denote the CPSS parameter set, i.e.

$$\overline{p} = [K\ T_1\ T_2\ T_3\ T_4]^T . \tag{2.2}$$

The dimension of $\overline{p}$ is reduced in case some time constants are identical, or if they are designated as constants.

Assuming there are only two real-time measured operating parameters as input to the fuzzy tuner, the rules take the following form:

Rule (i,j): If (input 1) is $LT1_i$, and (input 2) is $LT2_j$, Then $\overline{p}$ is set to $\overline{p}_{ij}^*$, where i=1…m and j=1…n.

Here $LT1_i$ and $LT2_j$ are the linguistic terms for the two input variables to the fuzzy tuner, respectively. The structure of the rule base is shown in Table 1. Variables i and j are the indices of the linguistic terms and m and n are the total number of linguistic terms for the input variables. $\overline{p}_{ij}^*$ denotes the optimal CPSS parameter setting corresponding to the particular operating condition defined by the two input variables. The CPSS design methodology used will be explained in a later subsection. The input variables may be chosen from various measurements such as voltages, active and reactive powers. Proper selection of these variables will determine the steady state condition or operating point of the generator uniquely.

Table 1. Structure of the rule base.

			input 2			
		ling. terms	$LT2_1$	$LT2_2$	…	$LT2_n$
	ling. terms		j = 1	2	…	n
input 1	$LT1_1$	i=1	rule (1,1)	rule (1,2)	…	rule (1,n)
	$LT1_2$	2	rule (2,1)	rule (2,2)	…	rule (2,n)
	…	…	…	…	…	…
	$LT1_m$	m	rule (m,1)	rule (m,2)	…	rule (m,n)

The output of an individual rule is a crisp vector $\overline{p}_{ij}^*$ instead of a fuzzy linguistic term that needs defuzzification. In turn, the output of the fuzzy tuner is the weighted sum of the outputs of all applicable rules, where the input variables together with their corresponding membership functions determine the weights, each of which shows truth value or 'degree of applicability' of one rule.

Next we define a matrix P to be used in the 'then' part of the rule base, i.e.,

$$\mathbf{P} = [\overline{p}_{11}^* \ \overline{p}_{12}^* \cdots \overline{p}_{1n}^* \ \overline{p}_{21}^* \ \overline{p}_{22}^* \cdots \overline{p}_{2n}^* \cdots \overline{p}_{m1}^* \ \overline{p}_{m2}^* \cdots \overline{p}_{mn}^*]. \tag{2.3}$$

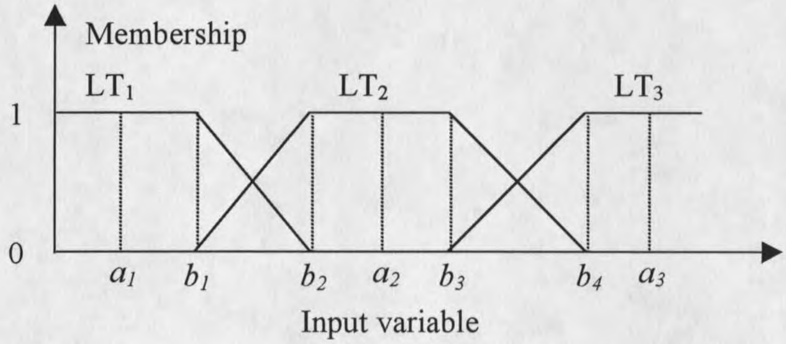
Assume the current crisp input to the fuzzy tuner is (OP1, OP2). The value OP1 is then evaluated to determine its degree of membership w_{1i} in $LT1_i$, for i=1, 2, …, m; similarly, OP2 is then evaluated to determine its degree of membership w_{2j} in $LT2_j$, for j=1, 2, …, n. Weights w_{ij} are then assigned using w_{ij} = min (w_{1i}, w_{2j}). Each w_{ij} is an element of a weight vector $\bar{w}$ which yields the fuzzy tuner output when multiplied by **P**, as shown below,

$$\overline{w} = [w_{11} \ w_{12} \ldots w_{1n} \ w_{21} \ w_{22} \ldots w_{2n} \ldots w_{m1} \ w_{m2} \ldots w_{mn}]^{\mathrm{T}} \tag{2.4}$$

$$\overline{p} = \mathbf{P} \cdot \overline{w}. \tag{2.5}$$

Typical shapes of the membership functions for the input variables are shown in Fig. 5. One characteristic of this type of membership functions is that for any crisp input only one or two linguistic terms are involved, and in the latter case, the sum of the memberships corresponding to the two terms is unity. Therefore, the shapes of the membership functions can be completely described with a set of boundaries that determine the interval of overlap of the two linguistic terms. For example, for the three linguistic terms (shown in Fig. 5), boundary points b_1, b_2, b_3 and b_4 are enough to specify the membership functions.

Figure 5. The membership functions.



Individual Rules

The rule base consists of a group of individual rules, which are obtained based on the linear models of the system at various operating points. The 'if' part of each rule has several fuzzy linguistic terms covering the ranges of the input variables. For every rule, a crisp operating point (named pivot point in this chapter) must be selected to obtain the crisp stabilizer parameter vector $\bar{p}_{ij}^*$. A convenient way to achieve this is to choose "center" values within the range of linguistic terms for every input variable and then designate all possible combinations of these center values (one for each input variable in every combination) as "pivot points". As shown in Fig. 5, a_1, a_2 and a_3 might be chosen as center values of LT_1, LT_2 and LT_3, respectively. The selection of the "center" values is heuristic and somewhat arbitrary. However, the optimization of membership functions will compensate for this arbitrariness.

For example, suppose we use active power and terminal voltage as the operating parameters. Then, we define light, medium and heavy output for active power as 0~0.5 p.u., 0.5~0.9 p.u. and 0.9~1.2 p.u., respectively. Also, we define low and high voltage as 0.8~1.05 p.u. and 1.05~1.3 p.u. respectively. Then, we may choose 0.3, 0.7 and 1.0 to be associated with the three power linguistic terms and 0.9 and 1.2 to be associated with the two voltage terms, respectively. The pivot points will be (0.3, 0.9), (0.3, 1.2), (0.7, 0.9), (0.7, 1.2), (1.0, 0.9) and (1.0, 1.2). We then design individual linear stabilizers for these pivot points to obtain $\overline{p}_{ij}^*$.

CPSS Design Methodology

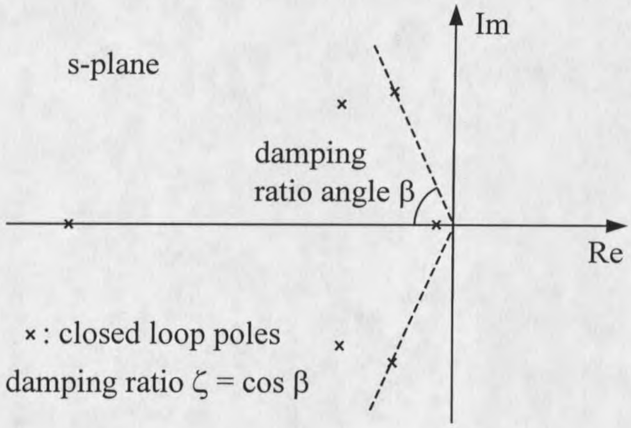
As explained in the preceding two subsections, every rule actually contains a CPSS for a particular operating condition. Therefore, a CPSS design methodology is required. Several different methods exist for designing CPSS. In this study Prony analysis is used to obtain linear transfer functions for the nonlinear system at different operating points [3]. Then, the dominating poles of the transfer function are chosen and an optimization algorithm, described in the next subsection, is used to maximize the damping ratio of these controlling modes with respect to the stabilizer parameters. Details follow:

Suppose the transfer function of the linearized system is $G(s)$ and that of the stabilizer to be optimized is $H(s)$ as given by (2.1). The stabilizer parameters K, T_1, T_2, T_3 and T_4 are to be chosen. Noticing that the feedback of the stabilizer into the exciter is positive rather than negative, as shown in Fig. 4, the closed loop transfer function is

$$\frac{G(s)}{1-G(s)H(s)}=\sum_i \frac{a_i+jb_i}{s-(c_i+jd_i)} \tag{2.6}$$

In (2.6) a_i, b_i, c_i and d_i are real numbers and j is the unity imaginary number. For a term in the summation that has $b_i = d_i = 0$, the time domain counterpart is $a_i e^{c_i t}$. For a complex pole pair in the summation, the time domain expression becomes $\sqrt{a_i^2+b_i^2}\cdot e^{c_i t}\cdot\cos(d_i t+\theta_i)$, which is obtained by performing the inverse Laplace transformation on the corresponding partial fraction terms of the poles. The term $\sqrt{a_i^2+b_i^2}$ reflects the magnitude of the mode and should be taken into consideration when choosing the dominating modes. This will prevent some trivial modes with very small magnitudes from being weighted excessively in the performance index. After eliminating these modes and the modes lying far left in the s-plane, the remaining ones are the dominating modes to be taken into account in CPSS design.. The objective function used, which is to be maximized, is the smallest one among all damping ratios of the controlling modes. An equivalent description is to minimize the largest damping ratio angle β, as illustrated in Fig. 6.

Figure 6. Optimization criterion.

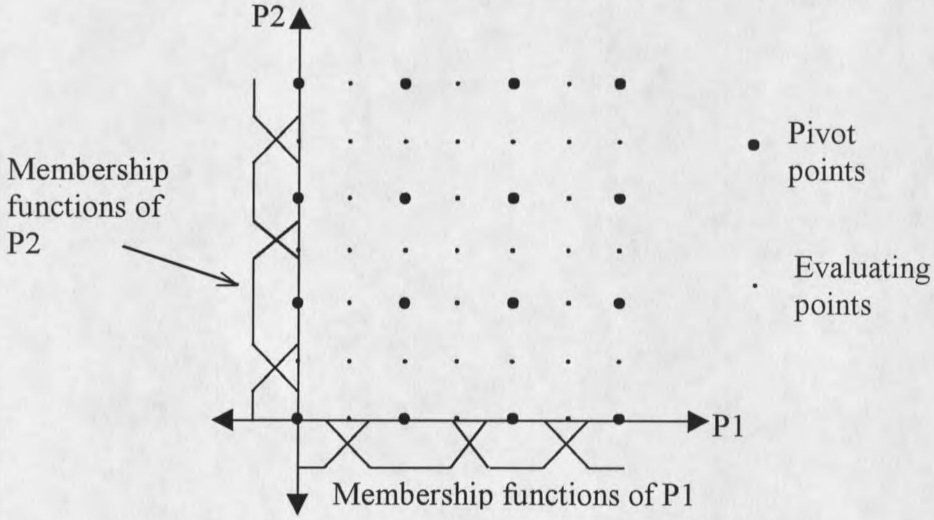


Optimization of the Membership Functions

As discussed in the beginning of this section, the membership functions can be represented by a set of boundary points shown in Fig. 5. Hence, it is possible to use a numerical optimization technique to optimize the performance of the fuzzy tuner with respect to the membership functions. Every optimization method requires an objective function, which is to be extremized. Therefore, a key issue is to formulate the performance index into an explicit expression in terms of the membership functions, which are actually a set of real numbers. A properly chosen performance index expression should reflect the performance of the fuzzy tuner accurately. Once the performance index is formulated the membership functions can be obtained using an appropriate optimization method.

Previously we developed an evaluation function to assess the performance of a stabilizer parameter setting at a particular operating point. We use that evaluation function to construct a single objective function for the fuzzy parameter tuner over a full range of operating points. For evaluation purpose, we choose a selection of evenly distributed operating points (evaluating points) at which the performance is evaluated. At these evaluating points, Prony analysis is again applied to obtain linear models of the nonlinear system. An example of a combined view of the pivot points and evaluating points, together with the membership functions for two input variables P_1 and P_2, is shown in Fig. 7.

Figure 7. Combined view of pivot and evaluating points and membership functions.



We evaluate the performance of a set of membership functions by the following procedure:

1) obtaining stabilizer parameter settings over the evaluating points by using the membership functions and the already available stabilizer parameter settings for pivot points;

2) obtaining the performance indices for individual evaluating points using the linear (Prony-based) models obtained at these points; and

3) adding the indices obtained in step 2) to obtain a single index. The above steps can be formulated in the following form:

$$PI(MF) = \sum_{p \in EP} \min_{q \in CP(p,H(p,MF))} \zeta(q) \tag{2.7}$$

where, the abbreviations are:

PI: performance index,

MF: membership functions,

EP: the set of all the evaluating points,

H(p,MF): the resulting CPSS transfer function based on operating point and membership functions,

CP(p,H): the set of controlling modes at an operating point p, with a given transfer function (H) for the CPSS, and

ζ(q): the damping ratio for an oscillation mode q.

With the performance index being defined, then a numerical optimization technique can be applied to optimize the membership functions for the input variables. Here we used a genetic algorithm for this purpose [19]. This searching algorithm is chosen because the function mapping relationship from the membership function to the overall performance index is irregular and demands a robust algorithm to achieve the optimum. A floating point version of the algorithm is used, as solutions in this problem are not discrete. In the first step, an initial solution population having a pre-set size is generated randomly. Then, the selection procedure is applied, using the GA crossover operators, to choose "good" individual solutions, which will be parents to produce the next "generation". Mutation operators are also applied to alter individual solutions with the hope to obtain better solutions by chance. This selection and reproduction procedure continues until certain termination criteria are met. In this study, the population size is set to 30, the algorithm stops after 50 generations, and various genetic operators are used [25].

Simulation Results

The performance of the proposed fuzzy power system stabilizer was evaluated in simulation studies of a one-machine infinite-bus system, parameters of which are given in the appendix. The generator in the study is equipped with a voltage regulator to maintain its terminal voltage at a desired level. Various measurements can be used as input signals to the fuzzy tuner; in this study we used the steady state value of active power (P), which can be obtained by filtering instantaneous electric power, and the reactance (X) from the generator terminal to the infinite bus.

System identification (Prony analysis) was performed to obtain linear models of the system under various operating conditions with active power evenly ranging from 0.2 p.u. to 1.0 p.u. and reactance from 0.2 to 0.7 p.u., both in steps of 0.1 p.u. We used five linguistic terms for active power and three for reactance. For active power, the center crisp values which represent the five linguistic terms are 0.2, 0.4, 0.6, 0.8 and 1.0 p.u., and for reactance, they are 0.2, 0.4 and 0.6 p.u. Then, individual stabilizers are designed for the pivot points. After that, the membership functions are optimized as explained in last section.

A three-phase short-circuit fault was applied at the remote end of the transmission line and cleared after 0.1 seconds. Simulation results were obtained under various operating conditions to evaluate the performance and robustness of the stabilizer. The post-fault line reactance may or may not change, depending on whether the line is tripped or reclosed successfully. For evaluation purposes, the performance of the system with the proposed fuzzy stabilizer was compared with that when a conventional stabilizer was used and when there was no stabilizer.

Figs. 8-10 show the machine angular speed as a function of time for three loading conditions, light, medium, and heavy, respectively. In these figures, P denotes active power and X_0 and X_{pf} are the transmission line pre-fault and post-fault reactances. All the units unspecified are per unit. It is clear from these figures that in all cases the damping of the electromechanical oscillations has been improved significantly with the proposed PSS as compared with using a conventional PSS or no PSS.

It was noticed that in some cases, although the oscillations damped out quickly, the DC component decayed at a lower speed. This situation can be alleviated by taking into consideration the poles on the left half of the real axis of the s-plane when attempt is being made to maximize the damping ratio.

Figure 8. Machine angular speed vs. time, light loading.
($P = 3.5$, $X_0=0.25$, $X_{pf}=0.5$)

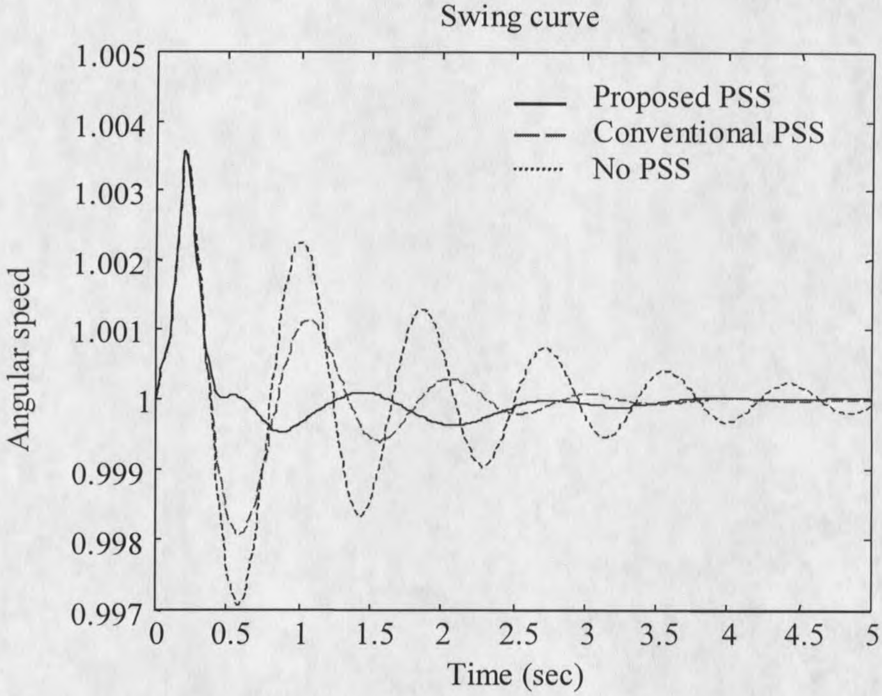


Figure 9. Machine angular speed vs. time, medium loading.
(P = 0.6, X0 = 0.25, Xpf = 0.5)

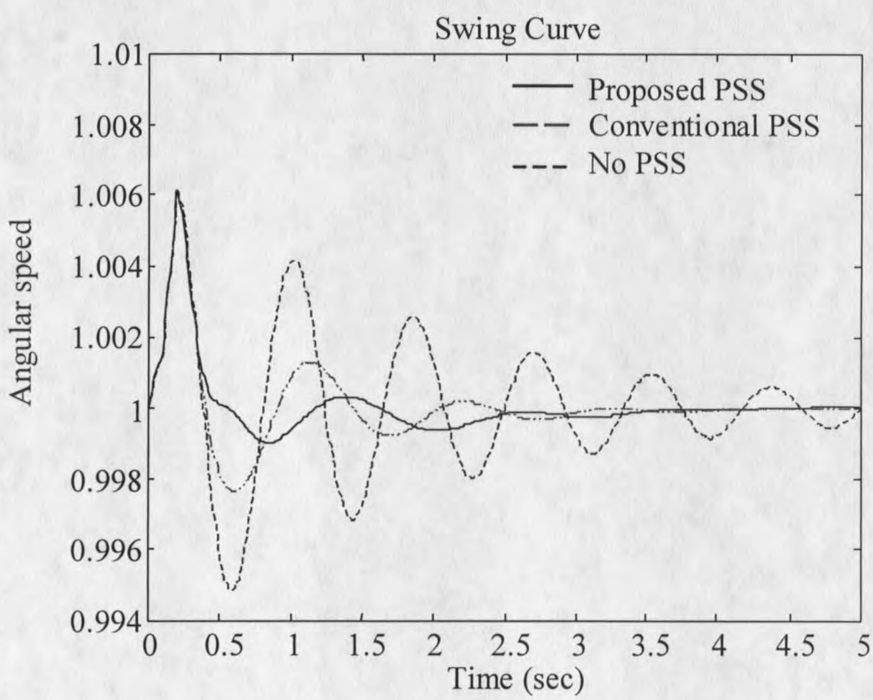
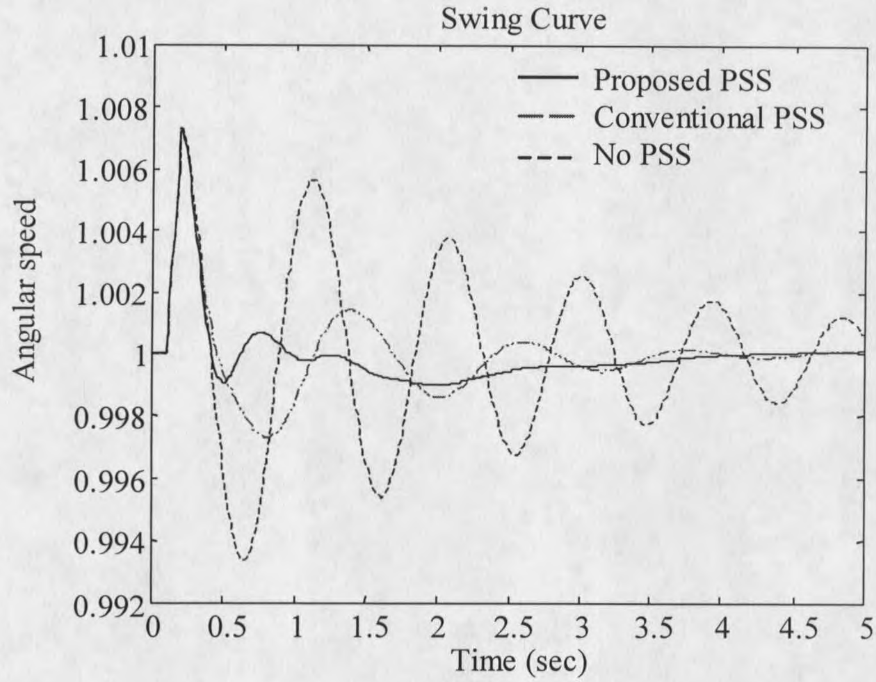


Figure 10. Machine angular speed vs. time, heavy loading.
(P = 0.95, X0 = Xpf = 0.6)



CHAPTER 3

A FUZZY ADAPTIVE POWER SYSTEM STABILIZER FOR MULTI-MACHINE SYSTEMS

Introduction

As discussed in Chapter 1, a frequency domain method, based on classical control theory, is widely viewed as a simple and robust methodology. In this approach, transfer functions are identified for a part of the excitation-generation system, namely, transfer functions between the voltage reference point and the electric torque. From these transfer functions, the frequency domain responses of the system are obtained. To contribute sufficient damping to the modes of interest in the system without causing adverse effects on other modes, the stabilizer should have a characteristic that is close to the inverses of the identified transfer functions. Therefore a linear compensator is manually designed to approximate the desired compensation characteristic. Conventional power system stabilizers designed with this philosophy work well, especially at the operating points for which they are designed. However, an adaptive stabilizer can perform better if it is capable of tracking and responding to the changing operating condition by providing a better match of the desired stabilizer characteristics, which may be affected by the operating condition.

In our proposed approach, a Takagi-Sugeno type fuzzy model [17] is used to develop the PSS. Firstly, two linear stabilizers are manually designed to accommodate two extreme loading cases, i.e. a heavy and a light condition. At any intermediate operating point, the output of the proposed stabilizer is formed from a weighted combination of the outputs of the two stabilizers. A least squares error criterion is used to determine weighting coefficients for the stabilizer characteristic to approach an ideal one. The two weighting coefficients reveal how close a particular operating point is to each extreme point. Assigning linguistic terms to the extreme points and considering the weighting coefficients as membership grades for the operating point, fuzzy logic is used to describe the relationship between intermediate points and the two extreme points. By applying this procedure for a series of pre-chosen operating points and using interpolation, two membership curves are obtained. When used in real time, the two stabilizers (for extreme cases) work simultaneously and independently providing two stabilizing signals. Fuzzy reasoning is then applied to determine how the two stabilizing signals are to be mixed to generate one output signal for the operating condition at that time. As a result, a higher-order adaptive stabilizer is achieved.

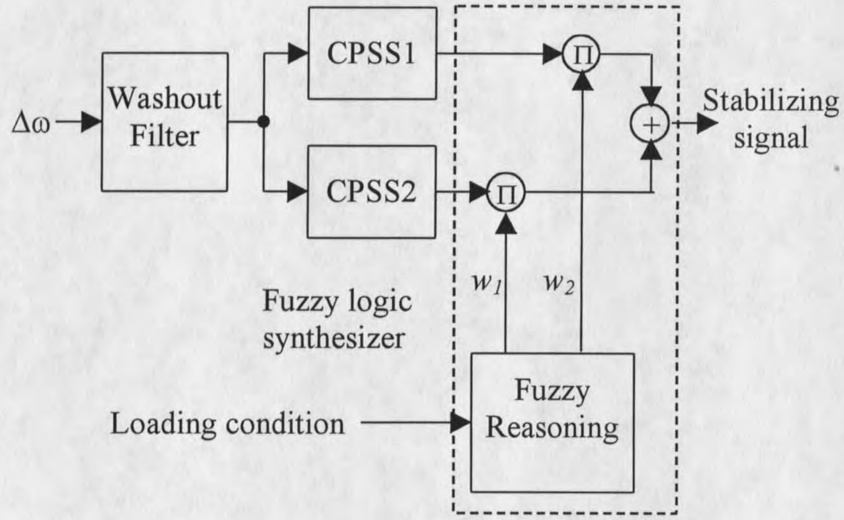
A detailed description of the proposed design procedure is given in the following section. Simulation results are given for a single-machine-infinite-bus system, a 4-machine 13-bus system and a 16-machine 68-bus system [26] to demonstrate the effectiveness of the proposed method.

Proposed Stabilizer

The Structure of the Stabilizer

The proposed fuzzy logic PSS consists of two conventional linear stabilizers and a fuzzy logic-based signal synthesizer. These two stabilizers are designed for extreme (heavy and light) loading conditions, and therefore they generate stabilizing signals working best under those extreme conditions. It is intuitive to assume that a proper combination of them would work best for the conditions between these extreme ones. How far away the current condition is from each extreme case determines how much the respective stabilizing signal is weighed in the output of the synthesizer. The synthesizer combines the two individual signals in such a way that the signal fits the loading condition optimally. Fig. 11 illustrates the structure of the stabilizer.

Figure 11. The overall structure of the proposed stabilizer.



The linear stabilizers could be typical second or higher order filters, depending on the characteristics of the system. Second-order filters are usually adequate, since the signal synthesizer may act as a refiner to fine-tune the control signal.

The fuzzy logic synthesizer accepts one variable indicating the generator loading condition, and generates one output. For that input variable two linguistic terms are used to represent the two extreme cases, and accordingly there are two membership curves. There are two rules in the following form:

Rule (i): IF the loading condition is E_i, THEN the output signal is S_i.

Here E_i denotes one of the extreme cases, and S_i denotes the corresponding stabilizing signal.

We adopt a Takagi-Sugeno fuzzy model [17], so Si is crisp and the defuzzification is simply a weighted summation that is expressed as follows:

$$S = \sum_i w_i \cdot S_i \tag{3.1}$$

where w_i is the truth value (weight) of the i^{th} rule, which is obtained by comparing the input variable against the membership function curve. Based on (3.1), the overall transfer function of the proposed PSS is then

$$H(s) = K \cdot \sum_i w_i \cdot H_i(s) \tag{3.2}$$

where $H_i(s)$ is the transfer function of the i^{th} linear stabilizer (called basis functions hereafter), and K is a real gain factor.

From (3.2) we can see that the performance of the proposed PSS depends on the linear stabilizer $H_i(s)$ and the membership functions. These two issues will be discussed in detail in the following two subsections.

Conventional PSS Design

The conventional frequency domain PSS design is used [2]. Under the operating points of interest, the dynamic equations are linearized to form the standard state space model, with the rotor angle dynamics properly removed. From this model, the transfer function for the excitation-generation part is obtained:

$$G(s) = \frac{\Delta T_e(s)}{\Delta V_s(s)} \tag{3.3}$$

where T_e is the electric torque and V_s is the input to the voltage regulator. The frequency response characteristics obtained from $G(j2\pi f)$ show the phase lag caused by the excitation-generation sub-system. Ideally, The transfer function of a compensator $H(s)$ aimed to completely compensate for the phase lag of $G(s)$, is just the inverse of $G(s)$. However, in most cases it is physically impractical to have $1/G(s)$ as the transfer function of the compensator, and therefore it has to be designed manually. We assume that it takes the form of a second or higher order filter and tune its time constants so that its leading phase characteristic cancels out the phase lag of $G(s)$ over the frequency range of interest (0~3Hz in this study). The magnitude gain of $H(s)$ is of less concern, and therefore, a nominal gain is assumed.

Fuzzy Logic Signal Synthesizer Design and Optimization

As discussed in a previous subsection, membership functions have a significant impact on the behavior of the proposed PSS, and optimal performance can be achieved only with optimized membership functions. In our design, an optimization algorithm is used to determine membership curves point by point with a small step size. Interpolation is used to obtain the membership values for intermediate points.

Given a loading condition, the desired characteristic of the PSS $H_D(s)$ is the inverse of $G(s)$. Suppose the basis functions $H_i(s)$ have already been obtained as explained in the preceding subsection, and the corresponding weights for that particular loading condition are to be determined to form a suitable stabilizer. The goal of our design is to obtain the weights that make $H(s)$ as close as possible to the desired transfer function $H_D(s)$. The performance of the stabilizer is then evaluated in terms of squared errors. To achieve this, we define a series of radian frequencies, at which the error is evaluated:

$$\omega_k = \frac{2k\pi f_{\max}}{n}, \; k=1,\ldots,n \tag{3.4}$$

where f_{max} is the maximum frequency of interest (3Hz in this study), and n is the number of evaluating points. Here we simply assume the gain factor K to be one, since it can be contained in w_1 and w_2 and therefore is trivial. For the transfer function $H(s) = w_1 H_1(s) + w_2 H_2(s)$, we define the error function below and try to minimize it:

$$f(w_1, w_2) = \sum_{k=1}^{n} \left\| H(j\omega_k) - H_D(j\omega_k) \right\|^2 = \sum_{k=1}^{n} \left\| w_1 H_1(j\omega_k) + w_2 H_2(j\omega_k) - H_D(j\omega_k) \right\|^2 \tag{3.5}$$

For notational briefness, we define $R_{i,k}$ and $I_{i,k}$ as the real and imaginary parts of $H_i(j\omega_k)$ respectively:

$$H_i(j\omega_k) = R_{i,k} + jI_{i,k}, \; i=1,2 \tag{3.6}$$

Similarly we define $R_{D,k}$ and $I_{D,k}$ as the real and imaginary parts of $H_D(j\omega_k)$:

$$H_D(j\omega_k) = R_{D,k} + jI_{D,k} \tag{3.7}$$

Next, several aggregation terms are defined:

$$A_i = \sum_{k=1}^{n} (R_{i,k}^2 + I_{i,k}^2), \; i = 1, 2 \tag{3.8}$$

$$A_3 = \sum_{k=1}^{n} (R_{D,k}^2 + I_{D,k}^2) \tag{3.9}$$

$$A_4 = \sum_{k=1}^{n} (R_{1,k} \cdot R_{2,k} + I_{1,k} \cdot I_{2,k}) \tag{3.10}$$

$$A_5 = \sum_{k=1}^{n} (R_{1,k} \cdot R_{D,k} + I_{1,k} \cdot I_{D,k}) \tag{3.11}$$

and

$$A_6 = \sum_{k=1}^{n} (R_{2,k} \cdot R_{D,k} + I_{2,k} \cdot I_{D,k}) \tag{3.12}$$

With these terms, the expression for $f\,(w_1, w2)$ of (3.5) is reduced to

$$f(w_1, w_2) = A_1 w_1^2 + A_2 w_2^2 + A_3 + 2A_4 w_1 w_2 - 2A_5 w_1 - 2A_6 w_2 \tag{3.13}$$

Now, it is clear that we have a problem of quadratic minimization at hand, and the optimal values of w_1 and w_2 are obtained through an algebraic equation:

$$\frac{\partial f}{\partial w_1} = \frac{\partial f}{\partial w_2} = 0 \tag{3.14}$$

which is reduced to

$$\begin{bmatrix} A_1 & A_4 \\ A_4 & A_2 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} A_5 \\ A_6 \end{bmatrix} \tag{3.15}$$

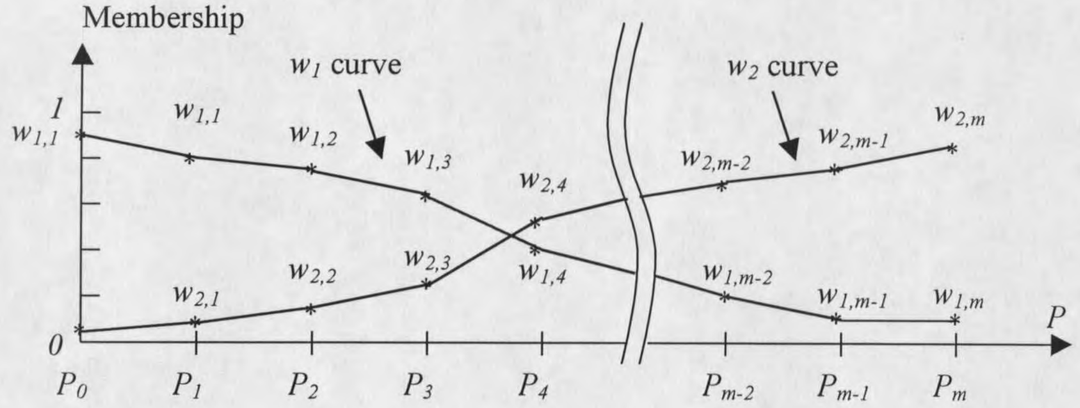
Suppose the generator in consideration operates within its power limits (P_{min} to P_{max}), and we apply the procedure to obtain the weights w_1 and w_2, for different loading conditions between P_{min} and P_{max} as follows:

$$P_l = \tfrac{l}{m}(P_{max} - P_{min}) + P_{min}\,,\; l = 0, 1, \ldots, m \tag{3.16}$$

where there are $(m+1)$ operating points.

As a result, a series of $w_{i,l}$, $i=1,2$ and $l=0\text{-}m$, are obtained. In cases where we want $w_{1,0}$ and $w_{2,m}$ (the first and the last weights) to be unity, a normalization procedure is applied; that is, $H_1(s)$ and $H_2(s)$ are multiplied by $w_{1,0}$ and $w_{2,m}$ respectively. Then, all the $w_{1,l}$ and $w_{2,l}$ are divided by $w_{1,0}$ and $w_{2,m}$ respectively. Now, we have a series of normalized $w_{i,l}$ and $H_i(s)$. With some interpolation involved, the coefficients $w_{i,l}$ form the membership function curves, shown in Fig. 12, which are used to determine the truth value of the i^{th} rule.

Figure 12. Membership function curves.



To achieve best performance, the gain of $H(s)$ (K given in (3.2)) should be adjusted properly. Simulation or eigenvalue analysis can be used for this purpose. The former is used in this study.

When used on-line, the signal synthesizer simply checks the steady-state value of the active power (obtained by measuring the mechanical power or measuring the electric power and removing its transient components using a low pass filter) against the membership curves to decide the appropriate weights, and then blends them as illustrated in Fig.11.

Simulation Results

To test the performance of the proposed stabilizer, simulation studies were performed on three systems: a one-machine-infinite-bus system, a 2-area-4-machine-13-bus system and a 16-machine-68-bus system [26]. Three-phase short-circuits were applied on the systems under different operating conditions. Faults occurred at the ends of transmission lines and then were cleared after 0.05 second.

A One-Machine-Infinite-Bus System

A generator was connected to an infinite bus through a transformer and two parallel lines. Machine data is given in the Appendix. For this system, P_{max} is *9.9* p.u., and we select $P_l \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 9.9\}$.

The basis functions are obtained as follows:

$$H_1(s) = 2.30 \cdot \frac{(0.316s+1)(0.254s+1)(0.8766s+1)}{(s+1)(0.001s^2+0.01s+1)} \tag{3.17}$$

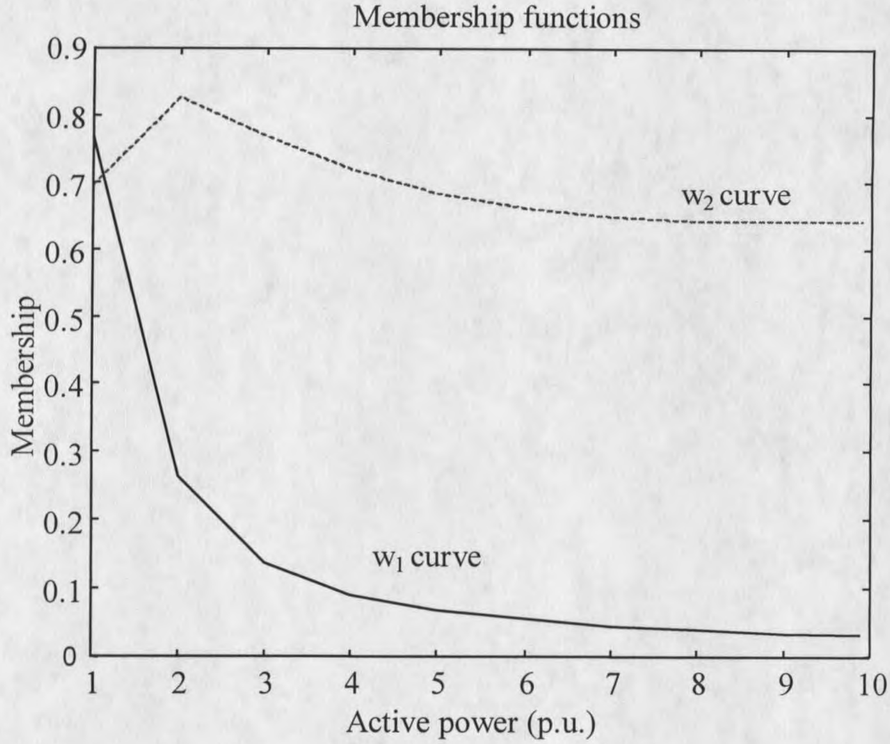
$$H_2(s) = 0.36 \cdot \frac{(0.0292s+1)(0.4965s+1)}{(0.0163s+1)(0.001s^2+0.01s+1)} \tag{3.18}$$

The respective membership functions for the above basis functions are obtained as shown in Fig. 13. In Fig. 13, the membership curve w_2 does not increase monotonically. This is because at light loading conditions a large magnitude gain of *H(s)* is desired to minimize the error defined in (3.5) and the membership functions are tuned to meet this gain requirement since the magnitude gains of basis functions are fixed during membership functions calculation.

The time constant of the washout filter was set at 10 seconds, and the gain factor K was selected so that the DC gain of the stabilizer (excluding the washout filter) at the heaviest loading condition is 30. The overall transfer function of the stabilizer is:

$$H(s) = K \cdot \frac{10s}{10s+1} \cdot [w_1 \cdot H_1(s) + w_2 \cdot H_2(s)] \tag{3.19}$$

Figure 13. Membership function curves.



A conventional stabilizer $H_c(s)$ was also designed for comparison using the frequency domain method [2].

$$H_c(s) = 30 \cdot \frac{10s}{10s+1} \cdot \frac{(0.1s+1)^2}{(0.01s+1)^2} \tag{3.20}$$

With the proposed PSS applied, Figs. 14 and 15 show the generator speed deviation as a function of time, for a light loading condition (P=2.5 pu) and a heavy loading condition (P=7.8pu), respectively. For comparison purpose, the generator responses are also shown when no PSS is applied and when a conventional PSS is applied. It is clear that the effectiveness of the proposed PSS is superior to a conventional PSS under both loading conditions.

Figure 14. Generator response under light loading (P=2.5 pu).

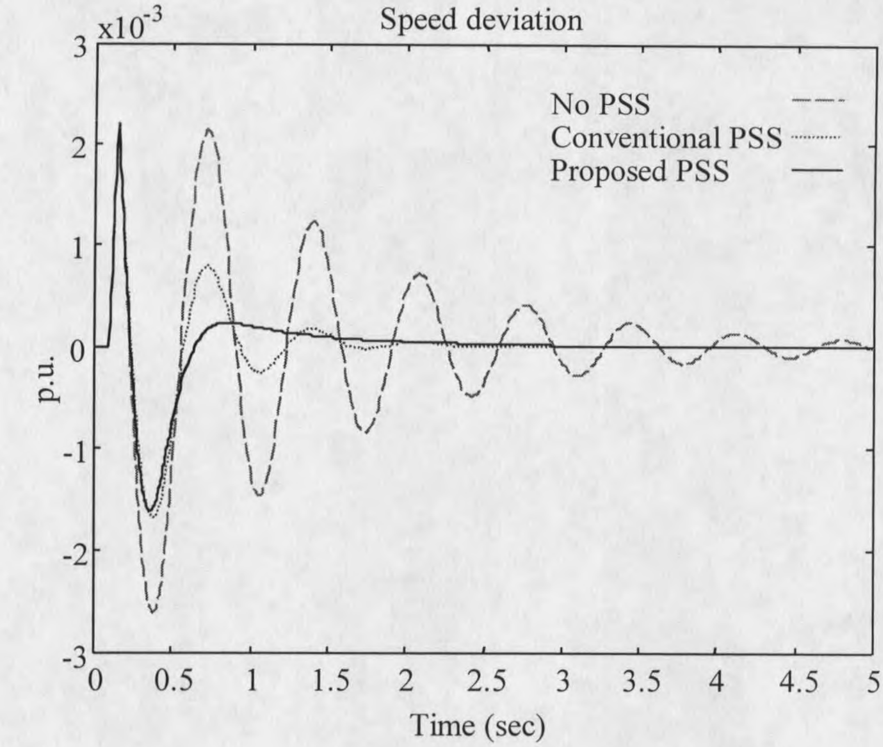
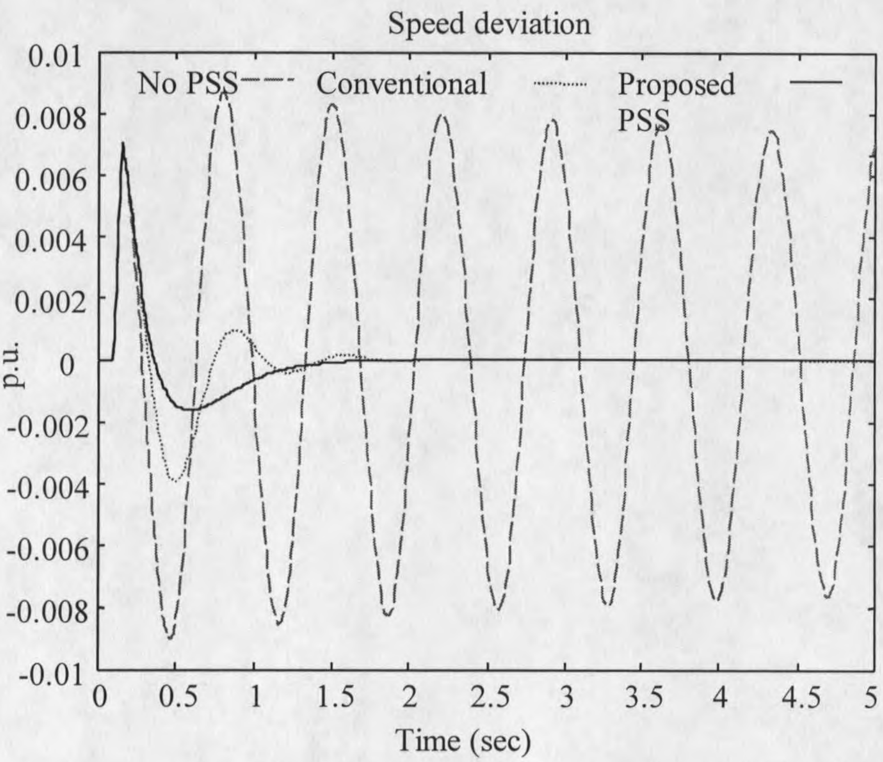


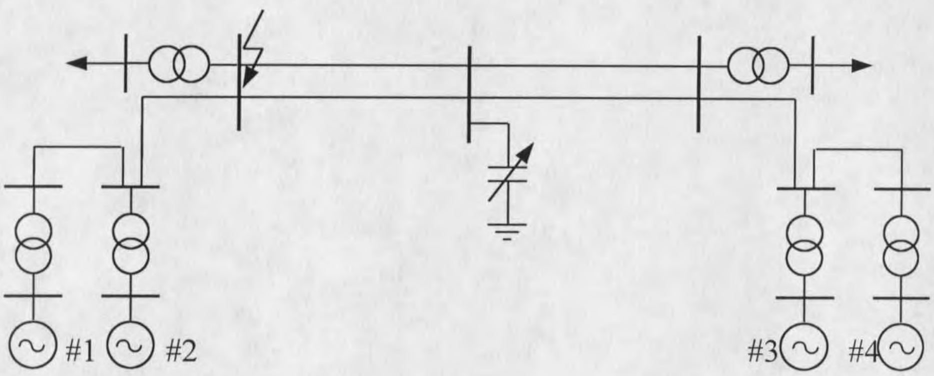
Figure 15. Generator response under heavy loading (P=7.8 pu).



A 4-Machine-13-Bus System

Fig. 16 shows a 4-machine, 13-bus system, where the generators are located in two distant areas [26]. A stabilizer for generator #2 is designed using the proposed method. For this generator, P_{max} is *8.0* p.u., and we select $P_l \in \{1, 2, 3, 4, 5, 6, 7, 8\}$.

Figure 16. A two-area four-bus system.



The basis functions are as follows:

$$H_1(s) = 1.05 \cdot \frac{(0.06s+1)(0.09s+1)(0.32s+1)}{(0.02s+1)^3} \tag{3.21}$$

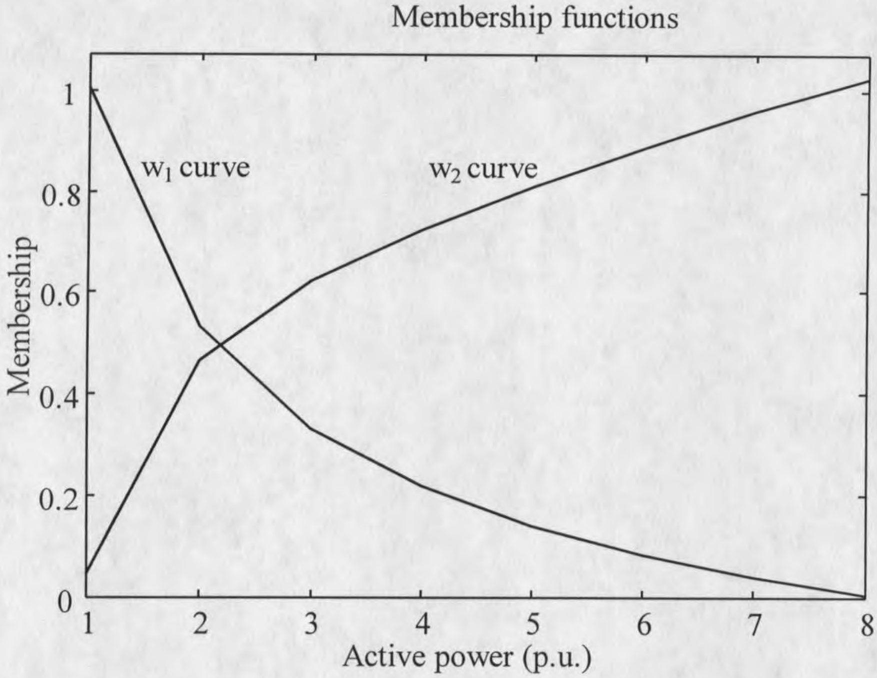
$$H_2(s) = 0.34 \cdot \frac{(0.13s+1)(0.28s+1)}{(0.015s+1)^2} \tag{3.22}$$

The respective membership functions for the above basis functions are obtained as shown in Fig. 17.

The time constant of the washout filter was set at 20 seconds, and the gain factor K was selected so that the DC gain of the stabilizer (excluding the washout filter) at the heaviest loading condition is 50. The transfer function of the stabilizer is:

$$H(s) = K \cdot \frac{20s}{20s+1} \cdot [w_1 \cdot H_1(s) + w_2 \cdot H_2(s)] \tag{3.23}$$

Figure 17. Membership function curves.



A conventional stabilizer $H_c(s)$ was also designed for comparison:

$$H_c(s) = 50 \cdot \frac{20s}{20s+1} \cdot \frac{(0.23s+1)^2}{(0.02s+1)^2} \tag{3.24}$$

Figs. 18 and 19 show the speed deviation of generator #2 as a function of time, for a light loading condition (P=2.5 pu) and a heavy loading condition (P=6.5pu), respectively. For comparison, generator responses are shown with the proposed fuzzy PSS, with a conventional PSS, and with no PSS applied (in Fig. 19 only, since under heavy loading conditions, the system is unstable without an acting stabilizer). It is clear from Fig. 18 that under light loading the proposed PSS is more effective than the conventional one in damping the generator oscillations; it also performs at least as effectively as the conventional controller under heavy loading.

Figure 18. Generator response under light loading (P=2.5 pu).

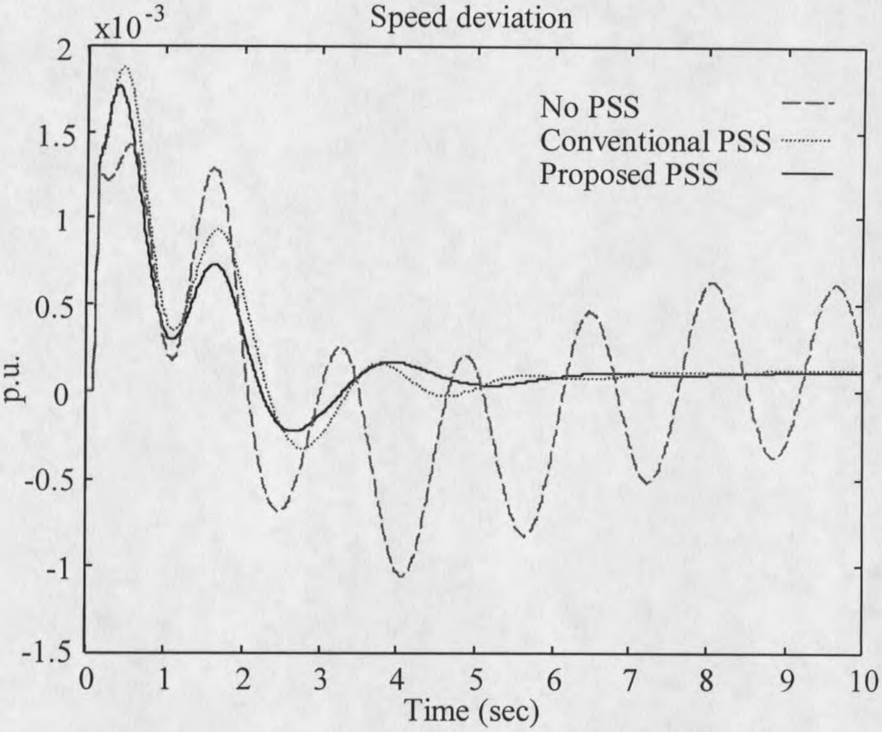
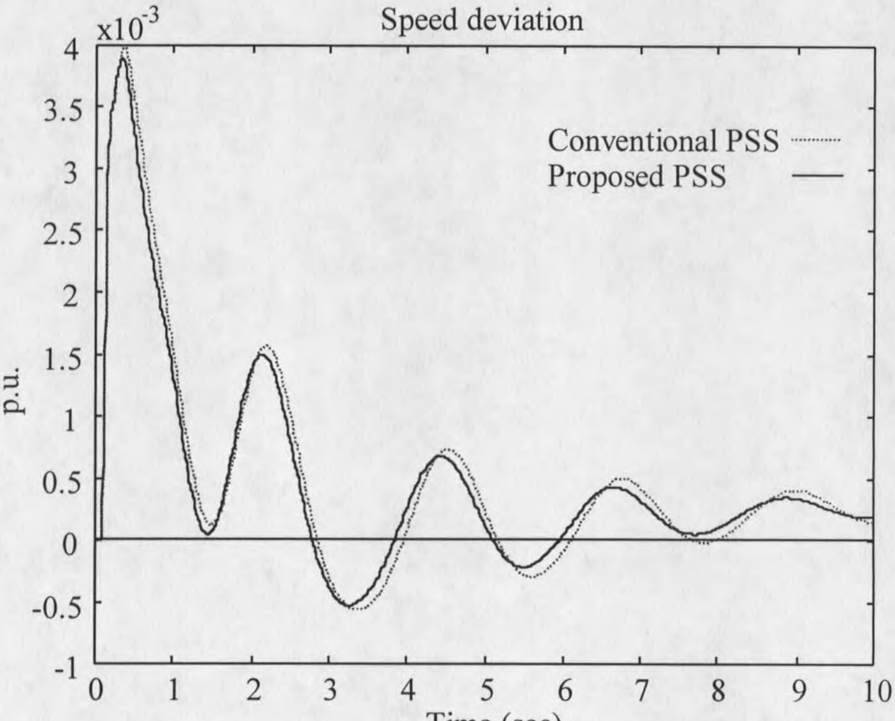


Figure 19. Generator response under heavy loading (P=6.5 pu).



A 16-Machine-68-Bus System

This system has sixteen generators, seven of which actually represent external systems [26]. A stabilizer is designed for generator #9 using the proposed method. For this generator, P_{max} is *10.0* p.u., and we select $P_l \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$.

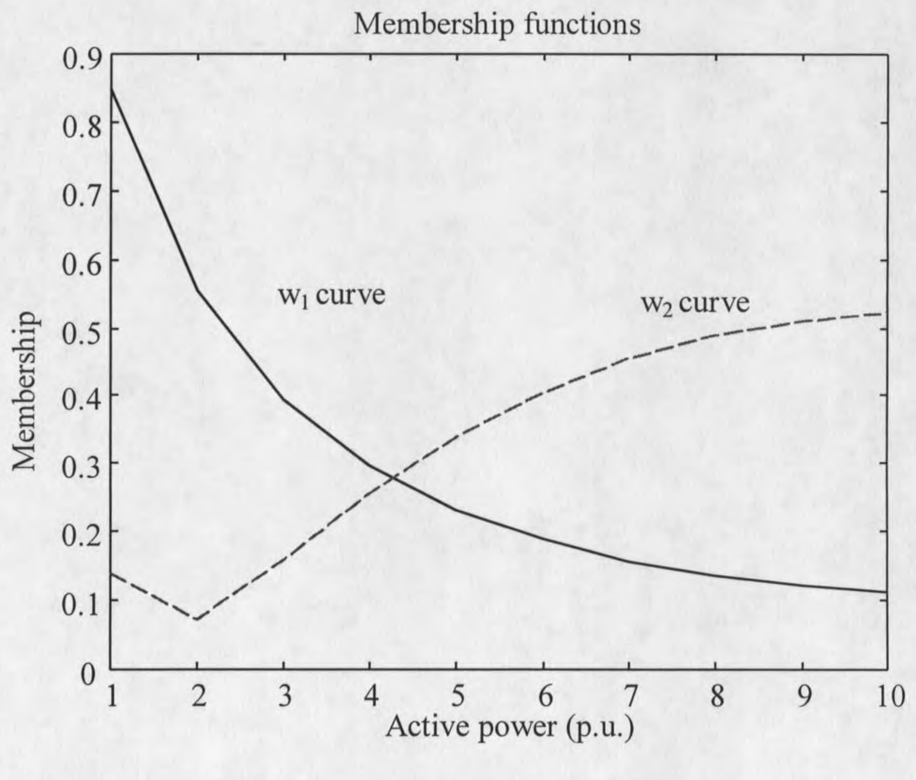
The basis functions are as follows:

$$H_1(s) = 0.186 \cdot \frac{0.0169s^2 + 0.26s + 1}{0.0004s^2 + 0.04s + 1} \tag{3.25}$$

$$H_2(s) = 0.035 \cdot \frac{0.04s^2 + 0.4s + 1}{0.000784s^2 + 0.056s + 1} \tag{3.26}$$

The respective membership functions for the above basis functions are given in Fig. 20.

Figure 20. Membership function curves.



The time constant of the washout filter was 10 seconds, and the gain factor K was set so that the DC gain of the stabilizer (excluding the washout filter) at the heaviest loading condition is 1.00. The transfer function of the stabilizer has the same form as in (3.19).

The conventional stabilizer $H_c(s)$ designed for the above generator is

$$H_c(s) = 100 \cdot \frac{10s}{10s+1} \cdot \frac{(0.18s+1)^2}{(0.024s+1)^2} \tag{3.27}$$

With the proposed PSS applied, Figs. 21 and 22 show the speed deviation of generator #9 as a function of time, for a light loading condition (P=3.5 pu) and a heavy loading condition (P=7.5 pu), respectively. The generator responses are also shown when a conventional PSS is applied and when no PSS is applied (in Fig. 21 only, since at the heavy loading condition, the system is unstable without an acting stabilizer). In this case superiority may not be so much as in the previous cases, but we are still able to observe some improvement.

Figure 21. Generator response under light loading (P=3.5 pu).

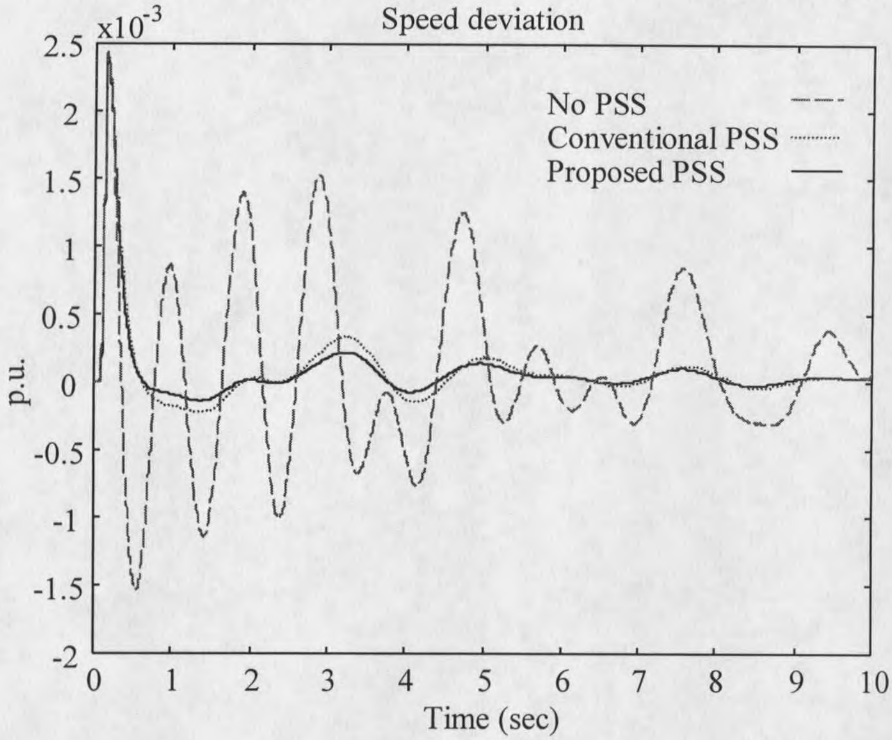
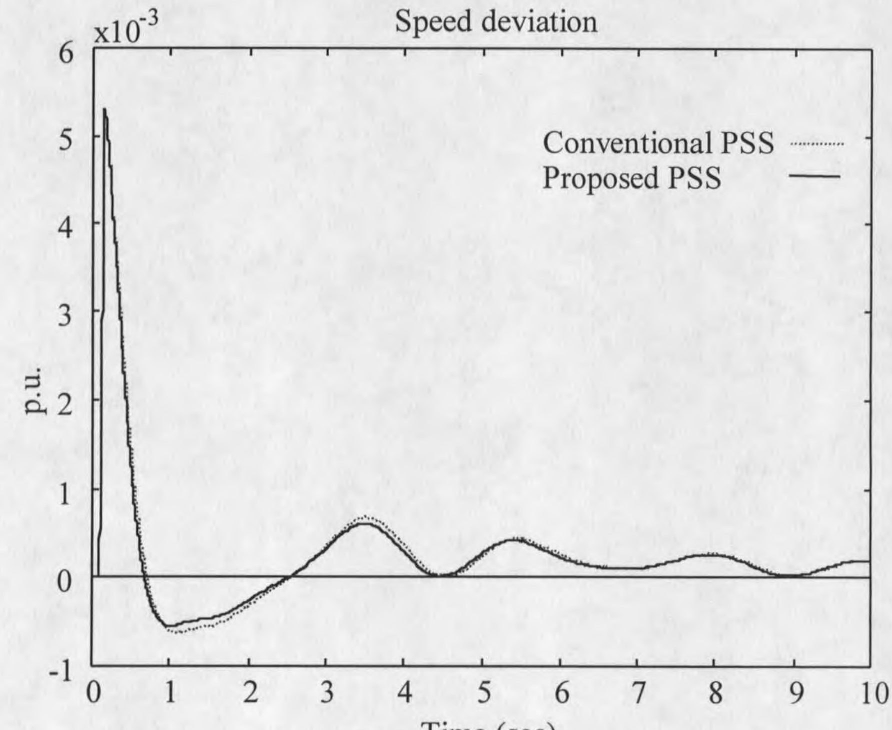


Figure 22. Generator response under heavy loading (P=7.5 pu).



CHAPTER 4

A FUZZY SVC DAMPING CONTROLLER

Introduction

The purpose of this chapter is to describe a fuzzy adaptive controller for SVC in power systems to damp low frequency oscillations. SVC is a FACTS device that electronically switches capacitors or reactors so that their shunt susceptance can be controlled. Two main advantages of SVC over traditional capacitor banks are: (1) faster response time, as the latter has to be switched on and off mechanically, and (2) finer control on susceptance, as SVC can produce an exact amount of susceptance up to its physical limit whereas mechanically switched capacitor banks can not adjust capacitance continuously. Due to these advantages, SVCs have been applied in power systems for a long time, primarily for the purpose of reactive power support and voltage control. However, if equipped with a supplementary controller, an SVC can also provide damping against electro-mechanical oscillations.

As mentioned in Chapter 1, damping controller designs can be grouped into two categories; one is based on the concepts of damping torque [27-32], while the other treats the damping controller design as a generic control problem and applies various control theories to tackle it; though some degree of physical analysis may be involved [33-36]. The method used in this chapter is categorized into the latter type, using an optimal controller design based on the complex frequency domain and a fuzzy logic tuning mechanism similar to the one presented in Chapter 3 to provide adaptiveness against changes in the loading condition.

In this method, a fuzzy model is used to represent the fuzzy logic tuning mechanism. The underlying idea is that any operating condition partially belongs to two fuzzy sets: a "heavy" condition set and a "light" condition set. We have damping controllers for the two extreme conditions, and the control action for intermediate conditions is given by the fuzzy logic operation; the more the operating condition belongs to one of the fuzzy sets, the stronger is the contribution of the control signal for that set in the output signal.

As the first step in the design procedure, a series of evenly spaced operating conditions are selected. The two extremes are considered fully belonging to heavy and light condition sets respectively, and for them linear optimal controllers are designed. At any intermediate operating point, the output of the controller is a weighted summation of the outputs of these two controllers, the membership grades being the respective weighting coefficients. For the controller to approach desired characteristics as close as possible, an algorithm based on a least squares error criterion is used to determine the best membership grades at all the pre-chosen intermediate points. Using linear interpolation, two membership curves are obtained. When used in real time, the two controllers work simultaneously and independently providing two damping signals. Fuzzy reasoning is then applied to determine how the two signals are to be mixed to generate one output signal for the operating condition at that time. As a result, an adaptive damping controller is constructed.

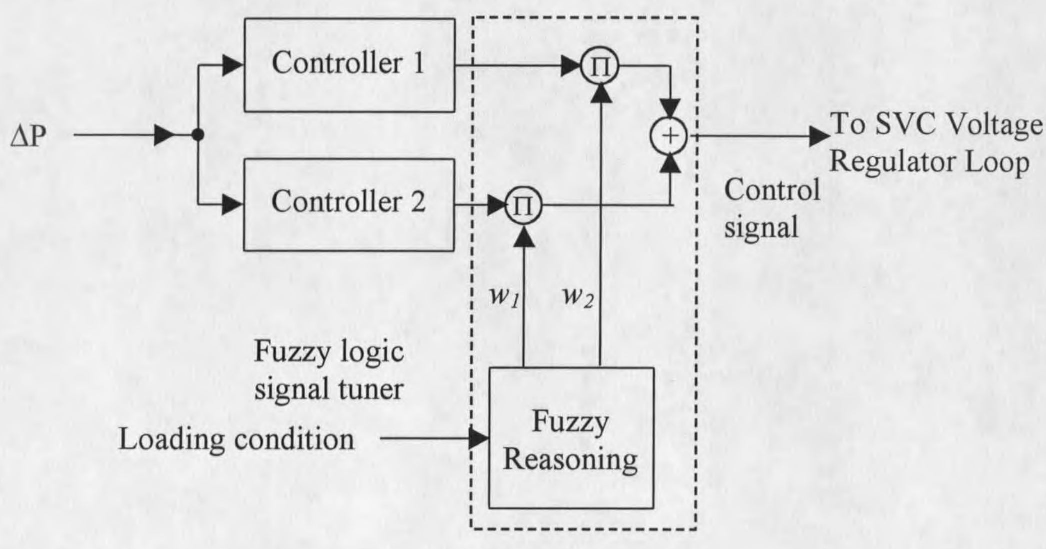
A detailed description of the proposed design procedure is given in the following section. Simulation results are given for a single-machine-infinite-bus system and a 4-machine 13-bus system to demonstrate the effectiveness of the proposed method.

Proposed Controller

The Structure of the Controller

The proposed fuzzy logic damping controller consists of two linear controllers and a fuzzy logic-based signal tuner. These two controllers are designed for extreme (heavy and light) loading conditions; therefore, they generate damping signals working best under those extreme conditions. It is generally reasonable to assume that a proper combination of them would work best for the conditions between these extreme ones. How far away the current condition is from each extreme case, or in fuzzy language how much it belongs to one of the two fuzzy condition sets, determines how much the respective damping signal is weighted in the output. The fuzzy tuner combines the two individual signals in such a way that the signal fits the loading condition optimally. Fig. 23 illustrates the structure of the stabilizer, where the input ΔP is the transient component

Figure 23. The overall structure of the proposed damping controller.



of the transmitted power through the bus where the SVC is located and the loading condition is the steady-state component of that power. The steady-state and transient components are obtained by applying low-pass and high-pass filters, respectively, to the measured power signal in real time.

Generally the two linear controllers can be designed with any one of available control theories. However, it would be somewhat off the topic elaborating on this, since the focus of this chapter is the application of the fuzzy logic control. For simplicity and best damping result, a complex frequency domain based optimal controller is adopted as discussed in a later subsection in this chapter.

The fuzzy logic tuner accepts one variable indicating the loading condition, and generates one output. In this study, the steady state value of the transmitted power through the bus where the SVC is located is selected as the input variable. For this variable two fuzzy sets and accordingly two membership functions are defined. There are two rules in the following form:

Rule (i): IF the loading condition is E_i, *THEN the output signal is* S_i.

Here E_i denotes one of already defined fuzzy sets, and S_i denotes the corresponding damping signal.

Similar to the preceding chapter, a Takagi-Sugeno fuzzy model is adopted here, so S_i is crisp and the defuzzification is simply a weighted summation expressed as follows:

$$S = \sum_i w_i \cdot S_i \tag{4.1}$$

where, w_i is the truth value (weight) of the i^{th} rule, which is obtained by comparing the input variable against the membership function curve. Based on (4.1), the overall transfer function of the proposed controller is

$$H(s) = \sum_i w_i \cdot H_i(s) \tag{4.2}$$

where, $H_i(s)$ is the transfer function of the i^{th} linear controller (called basis functions hereafter).

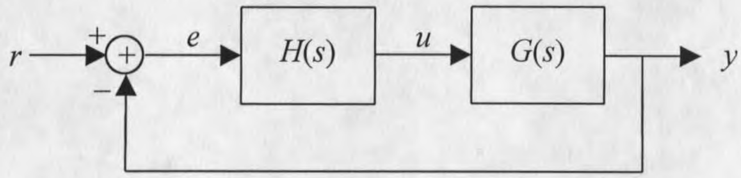
From (4.2) we can see that the performance of the controller depends on the linear controllers $H_i(s)$ and the membership functions. These two issues will be discussed in the following subsections.

Linear Controller Design

As stated before, the linear controller design here can be viewed as a typical control problem. In the first place the framework of the controller design used in this chapter is described as follows [37].

A regulator problem is presented in Fig. 24. The output y of the plant $G(s)$ is expected to stay at the reference value r, and the design goal of the controller $H(s)$ is to minimize the integral square error:

Figure 24. A regulator system.



$$J = \int_{-\infty}^{+\infty} [e(t)]^2 \, dt \tag{4.3}$$

Applying two-sided Laplace transformation and Parseval's theorem, (4.3) is equivalent to

$$J = \frac{1}{2\pi j} \int_{-j\infty}^{+j\infty} E(s)E(-s) ds \tag{4.4}$$

Using Wiener-Hopf factorization [37], the optimal controller $H(s)$ is found to be in the following form, assuming no right-hand side zeros contained in the plant transfer function $G(s)$:

$$H(s) = \frac{1}{G(s)} \cdot \frac{1}{h \cdot s} \tag{4.5}$$

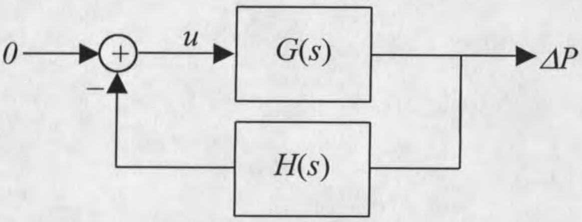
or

$$H(s) = \frac{1}{G'(s)} \cdot \frac{1}{h \cdot s} \tag{4.6}$$

if $G(s)$ contains a right-hand side zero.

In the above equations $G'(s)$ is identical to $G(s)$ except that the right-hand zero is removed, and h is a constant. In classical theory, the value of h depends on an energy constraint on the control signal; a zero value of h indicates that no energy constraint is imposed at all. In practice the value of h is not only concerned in terms of required energy, but also (and often more importantly) in terms of side effects incurred by very high gain. For example, usually $G(s)$ is a reduced-order representation of the nonlinear plant, and if the gain of the controller is too high, some modes which are not manifest normally can be excited; therefore $G(s)$ is rendered so imprecise that the controller will fail to work as designed. Also, in some conditions energy constraints are hard to find and

Figure 25. Modified system.



the gain is subject to saturation in the signal path. With these factors considered, the magnitude gain is often determined by other means.

In our application, the reference signal is always zero, and the output of the plant y is ΔP (as shown in Fig. 25), which is then expected to stay around zero. The way to determine the magnitude gains of the controller is by simulation. It is also found that the integrator factor $1/s$ yields too high DC gain which can cause unacceptable performance. Therefore, the expression of the controller is slightly modified to

$$H(s) = \frac{1}{G(s)} \cdot \frac{K}{Ts+1} \tag{4.7}$$

where T is a large time constant.

Another issue here is the method used to identify the plant. To obtain a low-order model without losing the essential modes, the Prony method which is introduced and used in Chapter 2, is also used here due to its simplicity and proven effectiveness.

Fuzzy Logic Signal Synthesizer Design and Optimization

As discussed previously in this chapter, membership functions affect the behavior of the proposed controller significantly, and optimal controller performance can be achieved only with optimized membership functions. In this chapter, the same optimization algorithm as in Chapter 3 is used to determine the membership functions. However, since the linear controller design approach is different from that in Chapter 3, the optimization procedure is slightly different, as described below.

Suppose two basis functions $H_i(s)$ have already been obtained in the procedure explained in the preceding subsection, and the corresponding weights for a particular loading condition are to be determined to form a suitable controller. The goal of our design is to obtain the weights that make $H(s)$ as close as possible to the desired transfer function $H_D(s)$. Different from Chapter 3, where the whole desired characteristics, which were represented by a physically unrealizable transfer function $H_D(s)$, are solely determined by the identified transfer function of the plant $G(s)$, here the magnitude part has to be determined by simulations, as mentioned in the preceding subsection. This requires that an actual implementation of the controller be obtained before the membership curves can be solved for, whereas in Chapter 3 a physical implementation of the stabilizer, which is expected to have characteristics $H_D(j\omega)$, is not required.

After the whole transfer function $H_D(s)$ has been determined, the same algorithm can be applied to solve for weighting coefficients. All the equations (3.4) through (3.16) are applicable for the design procedure explained in this chapter, and membership curves as depicted in Fig. 12 are obtained through the optimization procedure.

When used on-line, the signal tuner simply checks the steady-state value of the active power (used as the input to the controller) against the membership curves to decide the appropriate weights, and then blends them as illustrated in Fig. 23.

Simulation Results

To test the performance of the proposed controller, simulation studies were performed on two systems: a one-machine-infinite-bus system and a 2-area-4-machine-13-bus system. Three-phase short-circuits were applied on the systems under different operating conditions. Faults occurred at the ends of transmission lines and then were cleared after 0.05 second.

A One-Machine-Infinite-Bus System

This system is the same as used in Chapter 3 except that in the middle of the parallel transmission lines there is a bus to which an SVC is connected. For this system, the maximum transmittable power P_{max} is *4* p.u. (limited by stability), and we select $P_l \in \{1, 2, 3, 4\}$.

Linear transfer functions for the plant G(s) are obtained using the Prony method, and the basis functions are obtained using (4.7) as follows:

$$H_1(s) = 3.75 \cdot \frac{0.427s + 1}{1.25s + 1} \tag{4.8}$$

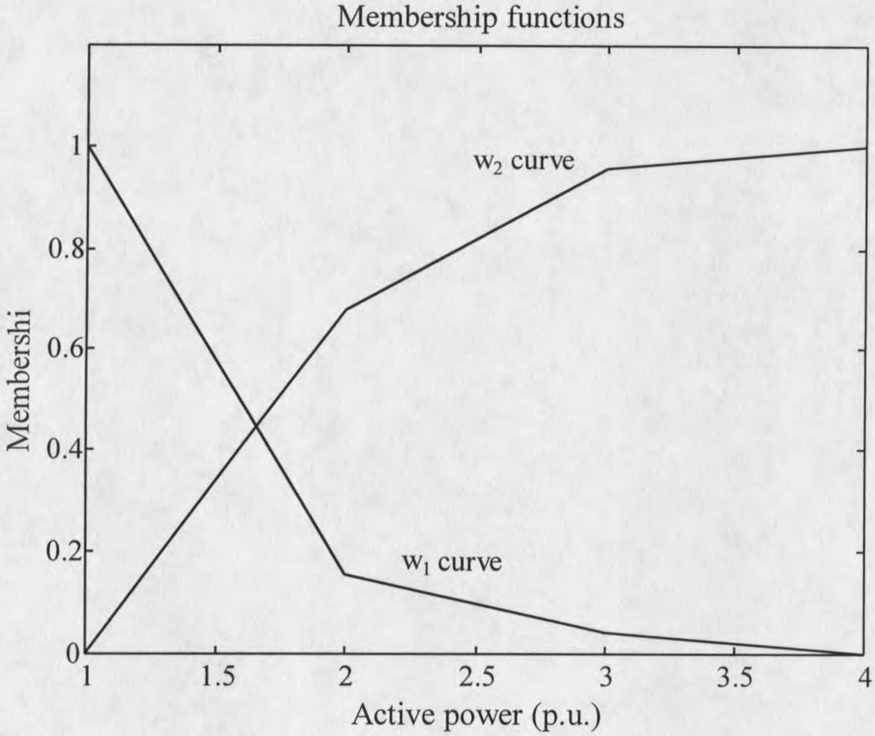
$$H_2(s) = 0.625 \cdot \frac{0.522s + 1}{1.25s + 1} \tag{4.9}$$

The respective membership functions for the above basis functions are obtained as shown in Fig. 26.

The time constant of the washout filter was set at 10 seconds and the overall transfer function of the controller is:

$$H(s) = \frac{10s}{10s + 1} \cdot [w_1 \cdot H_1(s) + w_2 \cdot H_2(s)] \tag{4.10}$$

Figure 26. Membership function curves.



With the proposed controller applied, Figs. 27 and 28 show the generator speed deviation as a function of time, for a light loading condition (P=1.5 pu) and a heavier loading condition (P=2.5 pu), respectively. For comparison purpose, the generator responses are also shown when no controller is applied. It is clear that the proposed controller is effective under both operating conditions and contributes more damping under the light condition. This is because when the transmitted power approaches the limit, it's harder to damp swings. From a viewpoint of optimal control theory, $G(s)$ here exhibits a zero on the right-hand side of the s-plane which approaches the origin when the transmitted power grows. The closer the zero is to the origin, the large the corresponding time constant is, and the larger (worse) the achievable performance index is [37].

Figure 27. Generator response under light loading (P=1.5 pu).

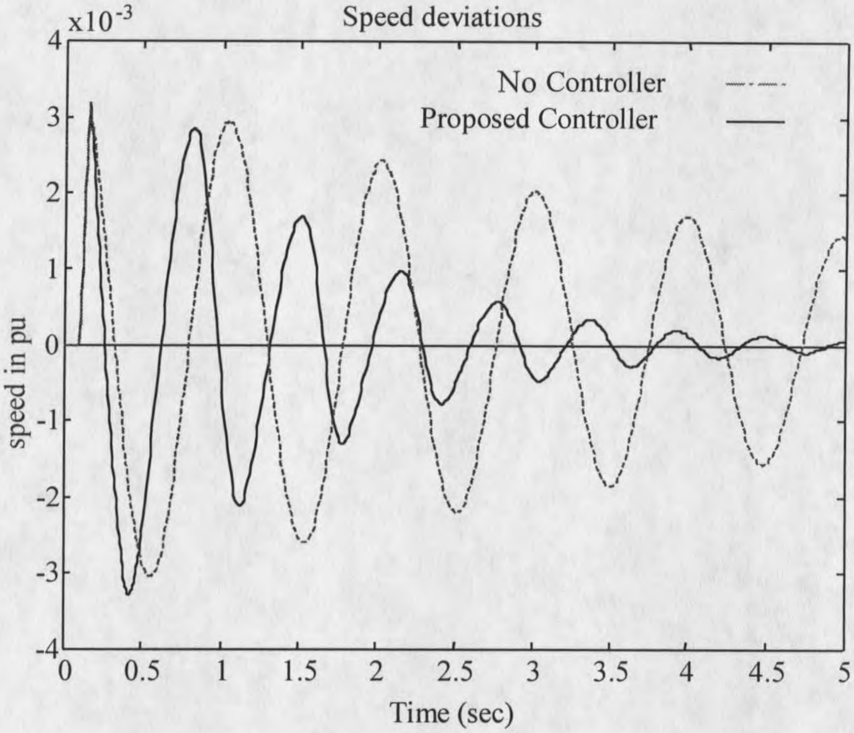
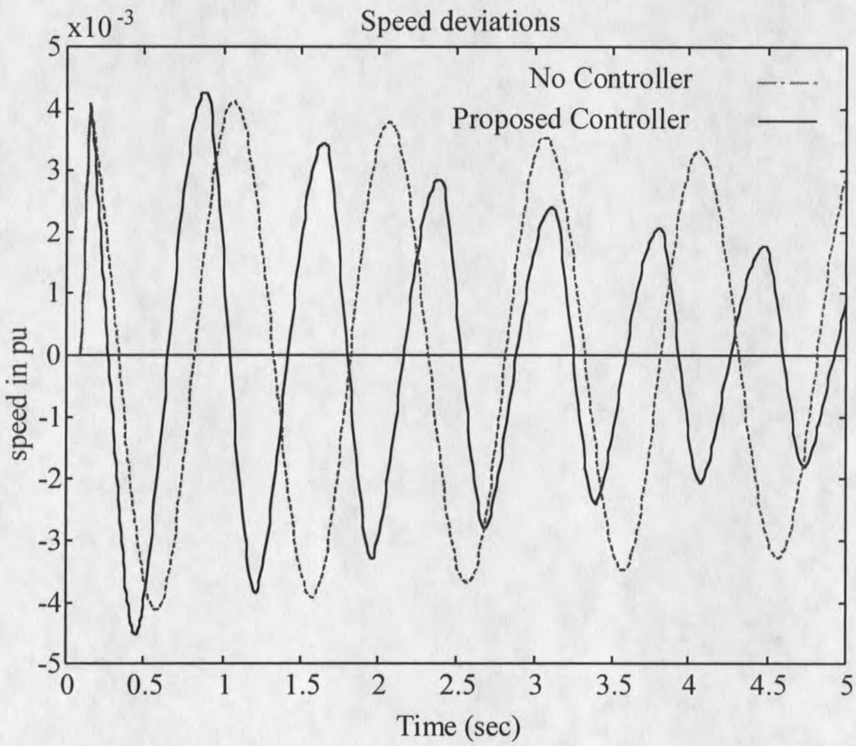


Figure 28. Generator response under heavy loading (P=2.5 pu).



A 4-Machine-13-Bus System

The same 4-machine, 13-bus system used in the last chapter is used to verify the effectiveness of the proposed SVC controller. For this case, P_{max} is *5.0* p.u., and we select $P_l \in \{1, 2, 3, 4, 5\}$.

In a similar way as used above, the basis functions are obtained as follows:

$$H_1(s) = \frac{2\,\mathrm{s}^3 + 269.52\mathrm{s}^2 + 2019.64\mathrm{s} + 4952.04}{126.16\mathrm{s}^3 + 1561.46\mathrm{s}^2 + 2638.19\mathrm{s} + 1175.82} \tag{4.11}$$

$$H_2(s) = \frac{2.5\mathrm{s}^3 + 342.87\mathrm{s}^2 + 3905.55\mathrm{s} + 4065.98}{564.34\mathrm{s}^3 + 8019.12\mathrm{s}^2 + 11441.97\mathrm{s} + 4310.28} \tag{4.12}$$

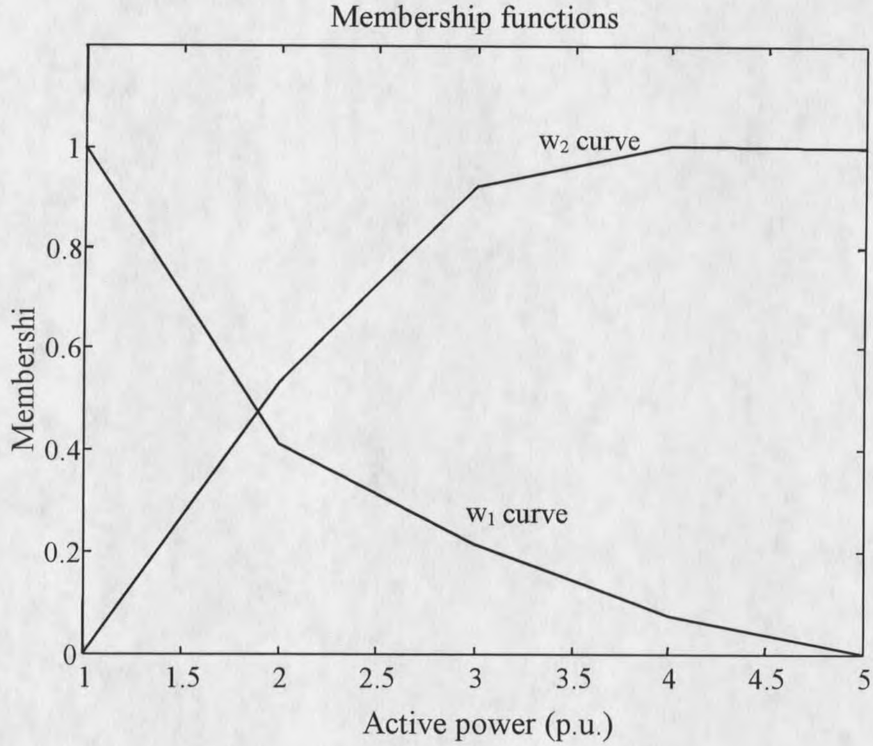
The respective membership functions for the above basis functions are obtained as shown in Fig. 29.

The time constant of the washout filter was set at 20 seconds. The transfer function of the controller is:

$$H(s) = \frac{20s}{20s+1} \cdot [w_1 \cdot H_1(s) + w_2 \cdot H_2(s)] \tag{4.13}$$

Figs. 30 and 32 show the speed deviations of all the generators as functions of time, for a light loading condition (P=2.2 pu) and a heavy loading condition (P=4.5 pu) respectively, both with the proposed SVC controller acting. Notice that there is no infinite bus in the system, and the speed deviations shown in the figures are relative to the center of inertia of these machines. For comparison, generator responses with no controller applied are also shown in Figs. 31 and 33 for light and heavy conditions respectively.

Figure 29. Membership function curves.



It is clear from these figures, that the proposed controller shows effective damping against power oscillations; it prevents the machines from going unstable, which would otherwise occur if no supplementary damping controllers are present.

Figure 30. Generator responses under light loading (P=2.2 pu) with controller.

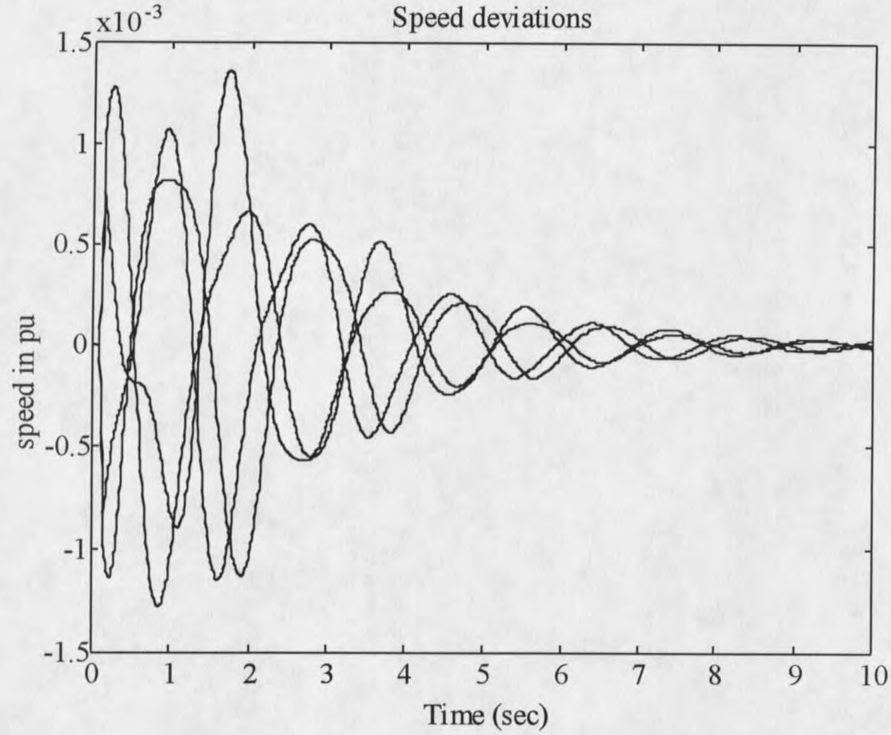


Figure 31. Generator responses under light loading without controller.

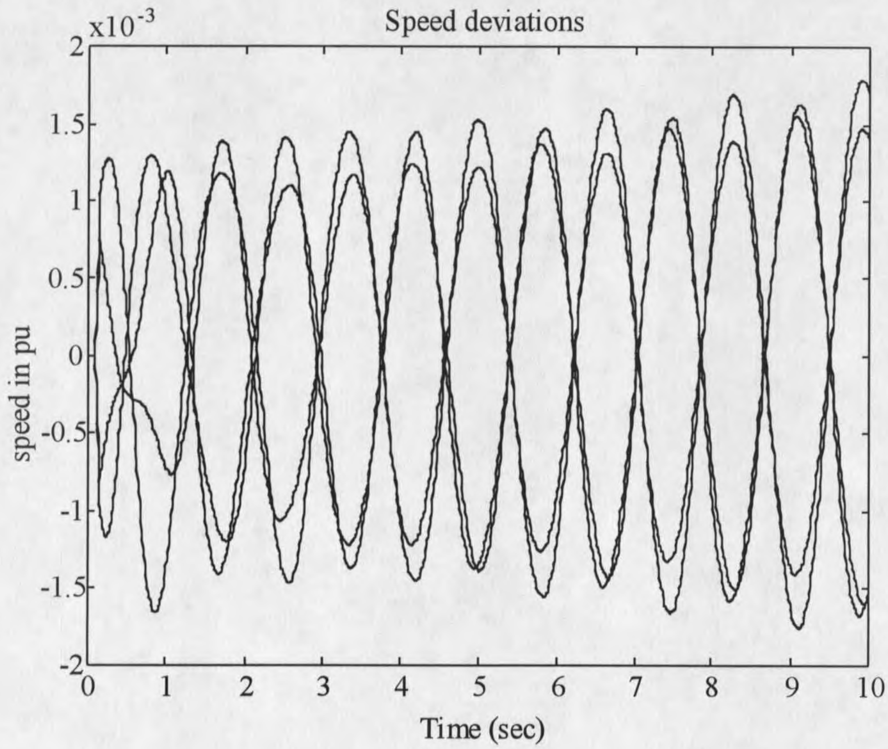


Figure 32. Generator responses under heavy loading (P=4.5 pu) with controller.

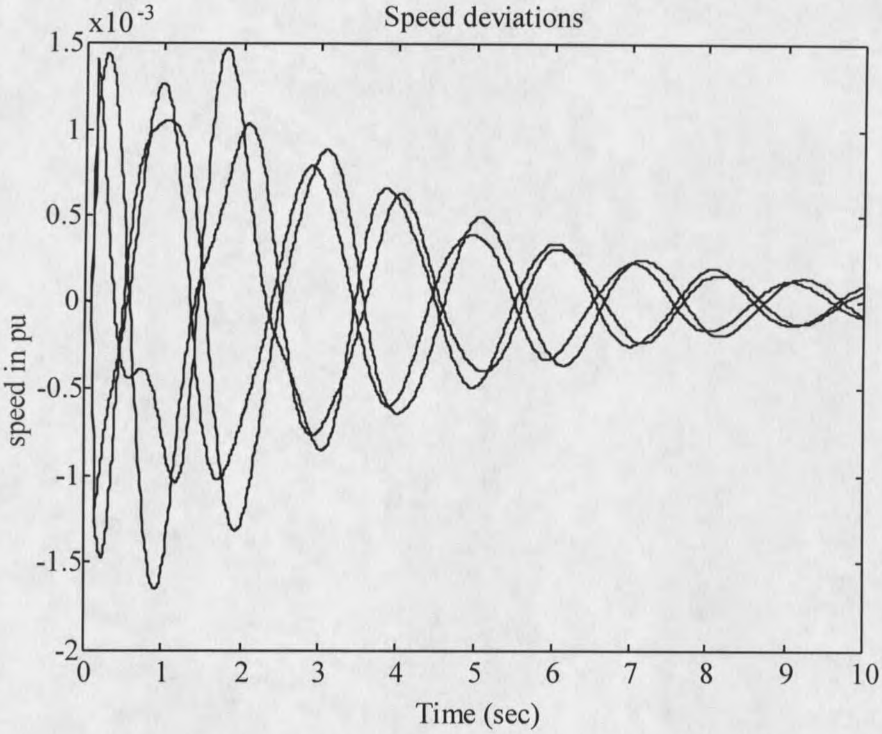
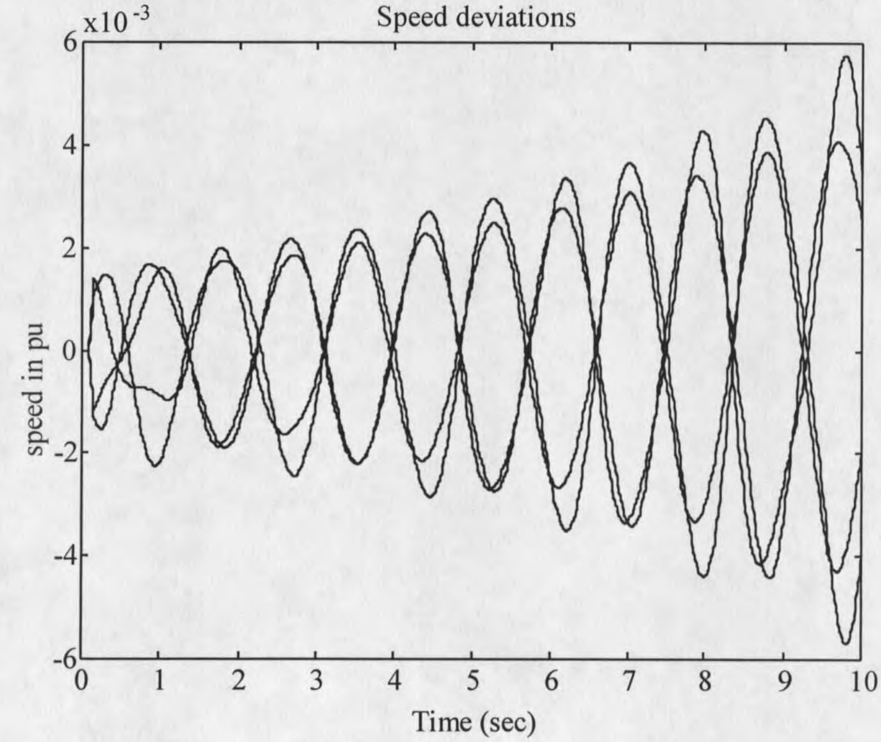


Figure 33. Generator responses under heavy loading without controller.



CHAPTER 5

CONCLUSIONS AND FUTURE WORK

General Comments

This thesis presents design methods for power system stabilizers and SVC controllers for damping low frequency electro-mechanical oscillations in power systems. These design methods combine fuzzy logic control and traditional control theories together to take advantages of both but avoid their drawbacks. The main advantage of traditional techniques of designing linear controllers for damping purposes is that, generally, they will yield better performance at the operating points for which they are designed. However, they may suffer the drawback that once the operating point drifts from those expected, their performance deteriorates. On the other hand, design of fuzzy logic controllers can be very intuitive, straightforward (especially for Mamdani type) and somewhat robust, but as exhibited in many researches, setting parameters for them such as input-output scaling factors to achieve optimal performance is always a difficult, if not impossible, task. Therefore, the idea to use fuzzy logic mechanisms to tune controllers so that they will retain their optimality becomes a reasonable option. The applications in the previous chapters prove the effectiveness of this approach.

Power System Stabilizer

Power system stabilizer is actually the conventional name for excitation system-based damping controllers. Apart from being based on excitation systems, it is not much different from any other damping controllers. However, this difference is more important than it appears. An excitation system is an integral part of a generator system, which implies that it has two advantages: the first, an important indicative measurement of oscillations, the machine speed is a local signal to it; the second, the signal path from the machine speed to the electrical torque of the generator is rarely affected by external conditions, especially in terms of phase characteristics. These two almost ensure a robust stabilizer design using damping torque analysis and frequency domain design methods.

We have shown that fuzzy logic can be used to bring adaptiveness to stabilizers so that optimality is not sacrificed as a cost for robustness. For PSS cases, there may not be much room left for further improvement with this type of fuzzy logic tuning over a well designed stabilizer; it almost reaches the physical limits of what excitation systems can do.

FACTS Devices-based Controllers

The situation for FACTS devices-based controllers is fairly different from the PSS case. While FACTS devices enjoy their faster response time, they often lack direct access to generator speed signals. This is why FACTS devices-based controllers generally do not outperform PSS on damping local mode oscillations. On the other hand, for inter-area modes, the advantage of having speed as a local signal is not so significant as for local modes, and FACTS devices can be used when inter-area modes are hard to damp out using PSS's only.

An inherent limitation of applying FACTS devices for damping is that the interactions between generators and FACTS devices are dependent of the network structure and the operating point because, unlike the excitation system, FACTS devices are external to generators. This makes a robust design of a damping controller for these devices much harder than that of a PSS, and renders damping torque analysis-based design less attractive than it is with PSS design. In Chapter 4 of this thesis, fuzzy logic is applied so an SVC controller can adapt according to changes in the operating conditions. But if the network structure changes significantly, the robustness of the fuzzy adaptive controller can not be guaranteed. This point is left for the future research.

Another aspect which may necessitate some future work is using damping torque analysis in lieu of optimal control theory for SVC controller design as done in Chapter 4. This is attractive because the root cause of oscillations is the lack of damping to oscillation modes. Once the explicit expression of damping can be obtained, using some optimization techniques, an optimal linear controller can be designed to maximize damping of one or more oscillatory modes. Then, fuzzy logic can be used to make the controller resistant to changes in the operating condition.

Some final words are on coordination of multiple controllers for damping. This is of particular importance for FACTS devices-based controllers due to their sensitivity to external conditions. For example, if a PSS and an SVC controller are to be designed, the SVC controller should be designed after the PSS is designed; normally PSS does not vary significantly due to the presence of an SVC controller if designed with damping torque analysis and frequency domain methods. If two SVC controllers are to be designed, sequential optimization or some other coordination technique has to be adopted since the presence of one controller may affect the optimality of the other. When a fuzzy logic adaptive tuner is involved, coordination becomes more difficult. This is because fuzzy logic introduces nonlinearity and more importantly it tunes controller and other controllers might not be aware of this adaptive behavior, do not change themselves accordingly and therefore lose optimality. In this case, the loss of some optimality may be inevitable, but it is still possible to develop some coordinating mechanism to keep as much optimality as possible.

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APPENDIX

THE DATA OF THE SINGLE MACHINE SYSTEM USED IN CHAPTER 3

Generator parameters:
armature resistance: $R_a = 0$ p.u.
leakage reactance: $X_l = 0.015$ p.u.
d-axis open-circuit time constant $T'_{do} = 5.0$ sec
d-axis open-circuit subtransient time constant $T''_{do} = 0.031$ sec
d-axis synchronous reactance $X_d = 0.2$ p.u.
d-axis transient reactance $X'_d = 0.025$ p.u.
d-axis subtransient reactance $X''_d = 0.02$ p.u.
q-axis open-circuit time constant $T'_{qo} = 0.66$ sec
q-axis open-circuit subtransient time constant $T''_{qo} = 0.061$ sec
q-axis synchronous reactance $X_q = 0.19$ p.u.
q-axis transient reactance $X'_q = 0.042$ p.u.
q-axis subtransient reactance $X''_q = 0.02$ p.u.
inertia constant $H = 2.8756$ sec
damping coefficient $D = 0$ p.u.s.

Exciter parameters: (IEEE Type ST-3 Model)
input filter time constant $T_R = 0.0$ sec
voltage regulator gain $K_A = 7.04$
voltage regulator time constant $T_A = 0.4$ sec
voltage regulator time constant $T_B = 6.67$ sec
voltage regulator time constant $T_C = 1.0$ sec
maximum voltage regulator output $V_{Rmax} = 7.57$ p.u.
minimum voltage regulator output $V_{Rmin} = 0$ p.u.
maximum internal signal $V_{Imax} = 0.2$ p.u.
minimum internal signal $V_{Imin} = -0.2$ p.u.
first stage regulator gain $K_J = 200$
potential circuit gain coefficient $K_p = 4.365$
potential circuit phase angle $\theta_p = 20$ degree
current circuit gain coefficient $K_I = 24.2$
potential source reactance $X_L = 0.091$ p.u.
rectifier loading factor $K_C = 1.096$
maximum field voltage $E_{fdmax} = 6.53$ p.u.
inner loop feedback constant $K_G = 1$
maximum inner loop voltage feedback $V_{Gmax} = 6.53$ p.u.

Transformer reactance 0.02 p.u.
Transmission line reactance 0.04 p.u.
The AVR is set to maintain the terminal voltage at 1.05 p.u.
Voltage of infinite bus: 1.08 p.u.