Paper

Simultaneous Tuning of Power System Stabilizers Based on a Combined Method of a Micro-GA, HGA and Minimum Phase Control

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This paper presents an incorporated use of an intelligent method using a micro-genetic algorithm (micro-GA), hierarchical genetic algorithm (HGA), and an analytical method so called a minimum phase control for an off-line power system stabilizer (PSS) tuning in multimachine power systems. First, the problem of selecting proper PSS parameters is converted to a simple optimization problem. Then, the problem will be solved by a micro-GA with a small population and reinitialization process. HGA is also adopted in the encoding process of a micro-GA for the purpose of self-identifying the appropriate choice of PSS locations. Experiences have shown that the time consumed by GA can be hastened if a few legal solutions are used in the GA initialized process. In this paper, a reasonable choice of initial solutions is obtained by a minimum phase control method. These added features provide a considerably improvement of time efficiency and flexibility in PSS tuning of large-scale power systems. A 68-bus and 16-generator system which is complex enough and close to realistic power systems has been used as an example to validate the effectiveness of the proposed tuning approach.

Keywords : power system stabilizer, minimum phase control, genetic algorithm, micro-genetic algorithm, hierarchical genetic algorithm, simultaneous tuning

1. Introduction

Applying power system stabilizers (PSSs) can enhance power transfer stability limit by adding modulation signal through excitation control system. This method has been used for several decades in utilities for the purposes of adding damping to electromechanical oscillations. In perspective, PSSs act through the generator excitation system in such the way that electrical torque on the rotor is in phase, or nearly in phase, with speed variation. It will provide damping to the power system thereby aid in the stability of the power systems. Over decades, this measure has been proved to be one of the most cost-effective electromechanical damping control comparing to using such expensive FACTS devices. The reason is that the necessary part of power amplifier is embodied in the generator already.

PSS tuning for stability system modes of oscillations has been the subject of much research since several years ago. The work reported in [1] has shown that the damping performance can be improved by introducing a classical root locus and phase compensation technique. In general, the PSS parameters are chosen to ensure the damping performance for local modes. Tuning PSS by using such conventional techniques to ensure all oscillation modes is very much difficult in multimahcine power systems.

Recently, the advent of microcomputer technology with low cost and high reliability has risen much research interest in the application of intelligent techniques to power systems. Genetic algorithm (GA) is one kind of those that its basic operation is conceptually simple and is proved to be a powerful optimization technique for solving many difficult problems especially when little or no prior knowledge is available in the problem being solved. Literature survey has revealed that some similar works showed great advantages of using GA's to simultaneously tune PSSs which have been fixed both parameters and locations in multimachine power systems [2-4]. However, the major problem when applying GA to large-scale power systems is computational time consumed by GA. The method of defining a GA performance index based on time domain simulations as in many literatures seems to be unsuitable by the following reasons, (1) it consumes very long time to solve all differential and algebraic equations in the power system model to obtain a performance index, (2) few scenarios can be taken into consideration in the optimization due to the limit of calculation time. The above problems become more evident when fixed-time step simulation is used and many scenarios are included in the optimization. An alternative method that can relax the problem of execution time is preferred. Defining a GA performance index based on eigenvalue analysis is an alternative way and is good enough to ensure the global damping performance of large-scale power systems by taking lesser time. In addition, more scenarios can be added into the optimization. However, another problem still exists. Because in many literatures, GA is usually used for optimizing fixed-structure controllers, the PSS locations must be chosen carefully due to the different PSS actions with different locations. Using participation factor to identify the possible locations has been extensively used. However, the drawback of this method is it may not guarantee for the effectiveness of global damping performance. PSS may increase damping of local modes effectively while the damping of inter-area modes may be degrade. Therefore, this information may lead to wrong choices of PSS locations when ones try to optimize the control parameters of PSS in multimachine power systems by fixing the locations.

To overcome all above problems, the authors propose an incorporated use of an analytical method so called a minimum phase control and a GA which is a micro-GA combined with a hierarchical genetic algorithm (HGA). The problem of time can be alleviated by incorporating the use of an initial solution obtained from a minimum phase control method and the use of a micro-GA. The problem of PSS location can be solved by the use of HGA concept [7,8]. The proposed method is applied to a 68-bus and 16-generator power system which is large and close to realistic power system. Many scenarios with different loading conditons have been included into the process of simultaneous tuning so as to guarantee the robustness and their performance of resulting power system stabilizers. The results of close-loop eigenvalues and time domain simulations have been carried out to validate the effective of the proposed method. The results demonstrate that an excellent improvement in the damping for every scenarios has been achieved with one set of PSS parameters.

2. Power System Description

The power system considered in this paper is shown in Fig.1.The system contains 5 coherent groups representing a reduced order of the New England and New York interconnected system. The thick lines indicate the major weak tie lines that cause the low frequency inter-area oscillations. Without PSS, this system is very unstable as confirmed by the eigenvalue calculation in Table 1 where G_p is the generator having the maximum speed participation factor that will be discussed later. There are a number of aspects of power system stabilizer interaction which becomes apparent in this model. Details of network parameters, machines, excitation systems, load flow are given in [5].

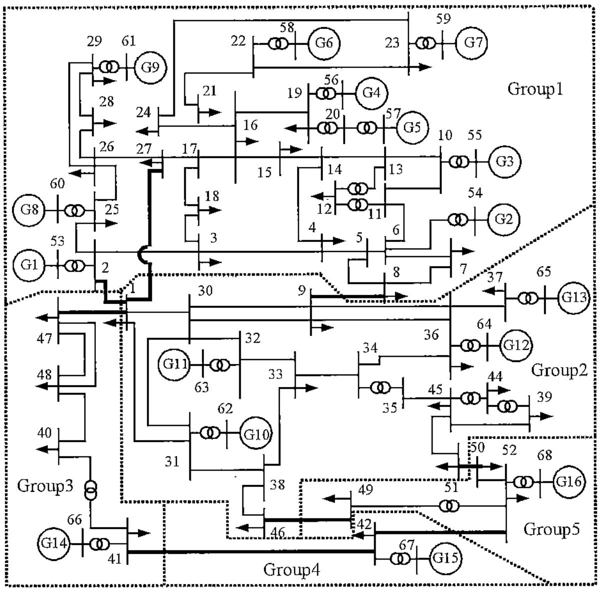

Fig. 1. A 68-bus and 16-generator power system model

Table 1. Under damped and unstable modes (no PSS)

Mode	eigenvalue	G_p	Mode	eigenvalue	G_p
1	-0.064±2.756i	13	9	0.290±8.462i	9
2	-0.032±3.590i	16	10	0.477±8.615i	3
3	-0.003±4.401i	13	11	0.167±8.690i	10
4	-0.131±5.170i	15	12	-0.116±10.095i	4
5	0.408±7.672i	12	13	0.092±10.188i	4
6	0.240±7.722i	6	14	-0.383±10.207i	8
7	0.647±7.790i	9	15	0.519±12.543i	11
8	-0.157±8.357i	5			

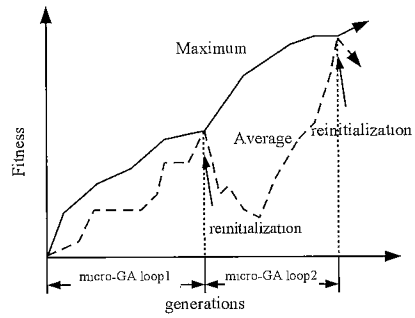

Fig. 2. Micro-GA concept

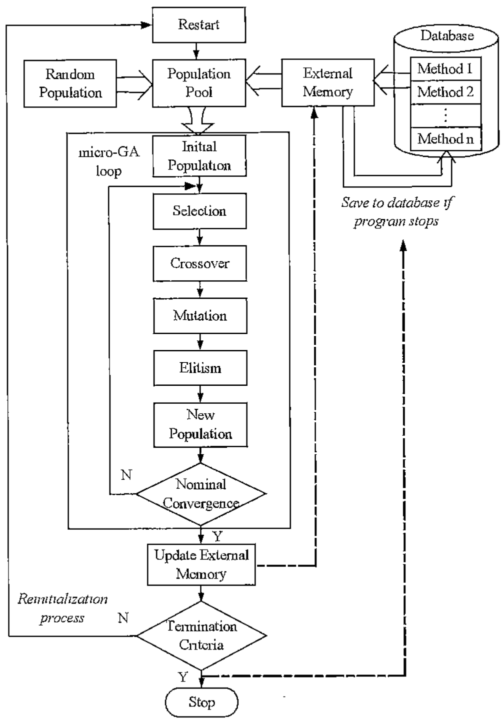

Fig. 3. Algorithm flowchart of a micro-GA

3. Genetic Algorithms

A genetic algorithm, in comparison with other optimization techniques, is desirable due to several reasons. Importantly, first all sort of criteria may be applied for maximization or minimization problem without constraints on the form of fitness function whether or not it is differentiable or continuous. This is a great deal of freedom of users rather than having to interpret those goals into some complicated mathematical formulas. Secondly, in solving the problems that analytical solution has been unknown yet, GA is computationally simple and easy to implement. The result will be better within the time limit since GA always produce high quality solutions. However, its important drawback is the execute time which is time-consuming.

In this paper, the authors propose a combined method of a micro-genetic algorithm (micro-GA) and a hierarchical genetic algorithm (HGA).

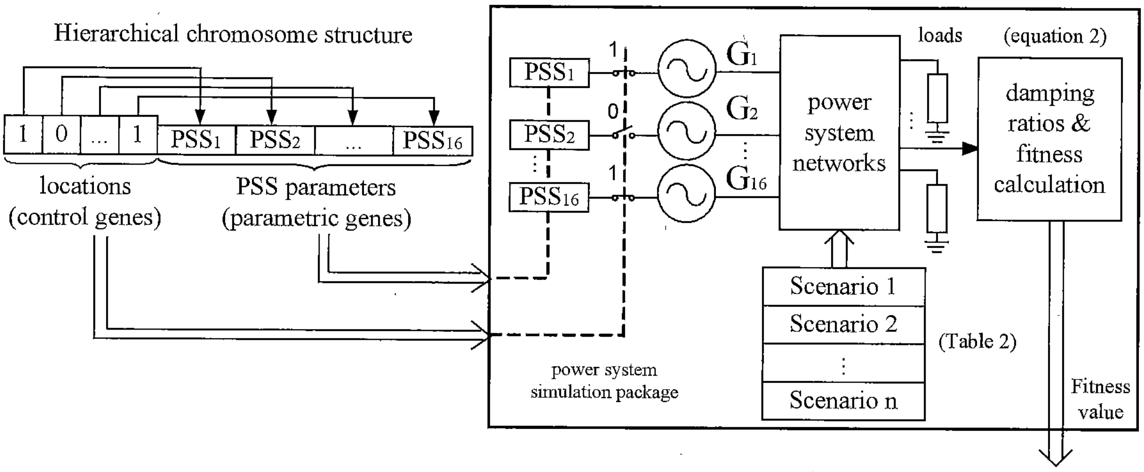

Fig. 4. Hierarchical chromosome structure and interfacing to simulation package for calculating the fitness value

3.1 Micro-genetic algorithm (micro-GA) Typically, for a basic GA, if the population size is too large, the GA tends to take longer time to converge upon a solution. Conversely, if the population size is too small, it is in danger that GA will converge to a suboptimal solution. The reason why the basic GA cannot apply a small population size is there is not enough diversity in the population pool to allow the GA to escape from the local optima. If the population size problem can be solved, the speed of GA will be improved significantly allowing the motivation to apply GA to large-scale power system applications.

In this paper, a micro-GA which is based on the concept that it is a genetic algorithm with a very small population size and reinitialization process is used [9]. The concept can be explained with Fig.2. In Fig.2 the total generations have been divided into small sub-generations dependent on the numbers of reinitialization process.For each sub-generation, the population size is rather small (usually not more than 10). The average and best are gradually improved as in normal GA. Until the average and maximum fitness are different 5%, the reinitialization process is performed. It should be noted that the aim of a micro-GA is to find the optimum as quickly as possible without improving any average performance. Reinitialization process is used as a source of diversity where the diversity is increased, the possibility in escaping the local minima is increased.

Fig.3 shows the algorithm flowchart of a micro-GA used in this study. The algorithm itself has been designed to support parallel processing since other computers can access to the database through the network computer. However it is somewhat beyond the scope of this paper to explain about the parallel processing. Therefore, we assume that only one computer is used throughout the study. In Fig.3, the population pool works as the source of diversity of the approach and the external memory is used to keep the competitive solutions from the database. The database keeps solutions obtained by several methods and from user's experience. In this study a solution obtained from a minimum phase control method is always kept in "method 1" and the last field for the previous result of a micro-GA. Population pool is derived from two portions; from random population and external memory where the percentage of each can be regulated by the user. The initial population of a micro-GA at the beginning of each its cycle is taken from both portions. During each cycle, a micro-GA undergoes conventional genetic operators; selection, crossover, mutation and elitism. Until the normal convergence is detected which is done by checking the percentage difference of the average and best fitness whether it is 5% or not. The dominated string (best string) from current population will be chosen and be copied into external memory such that the best string so far from the previous micro-GA loop will always appear in the future run.

The implementation of a micro-GA in this study used real-valued encoding chromosome, a population size 5, maximum generation 60, a uniform crossover rate of 1 and a uniform mutation rate of 0.01. The approach also adopt an elitist strategy that copy the best string found in the current generation to the future generation. Selecting was performed by using the tournament selection with tournament size of 2.

3.2 Hierarchical genetic algorithm (HGA) The operation cycle of the HGA is similar to those in the basic GA. The major difference between them is its hierarchical structure. Each hierarchical chromosome consists of a multilevel of genes, as demonstrated in Fig. 4 showing the HGA chromosome representation with one-level control genes and parametric genes. In this configuration, the control genes are analogous to the PSS locations. The control gene signified as "0" in the corresponding site, is not being activated meaning that the PSS at the corresponding location will not be installed into the power system during the simulation. Parametric genes are analogous to the PSS parameters to be optimized. Using the HGA concept, locations and PSS parameters can be simultaneously tuned. Fig. 4 illustrates the interfacing of HGA chromosome and simulation package for calculating the fitness value. In many cases, other scenarios may be added arbitrarily by the users depending on the critical events in power system operation.

It is important to point out how HGA chromosome structure works in a different way compared to chromosome structures in basic GA's. In basic GA's, if ones want to reduce the number of parameters to be optimized, knowing the appropriate locations to install PSSs becomes important. Clearly, optimal solution may be lost due to wrong decision to choose PSS locations. Alternatively, ones may install PSSs at every generators and if the final results show us that PSS gain at some generators is very small, it means that PSS at the corresponding generator can be neglected. By doing this way, time spent during the optimization will be increased when the number of PSS locations is increased. In contrast, with HGA chromosome structure, we do not need to take care about PSS locations and do not need to wait until the end in order to know the suitable location. This would be more flexible and we will not lose the optimal solution by wrong decision to install PSSs.

3.3 GA operators

3.3.1 Crossover (recombination) When uniform crossover is used with real-valued encoding chromosome, it is usually referred to as discrete recombination. Discrete recombination can be utilized with any kind of variables such as binary, integer, real or symbols. It performs an exchange of variable values between the individuals.

Let $x=[x_1,...,x_n]$ and $y=[y_1,...,y_n]$ be the parent chromosomes. Then the offspring can be generated according to:

$$z_i = x_i \cdot a_i + y_i \cdot (1-a_i) \quad \cdots\cdots (1)$$

where $i = 1, 2, \ldots,$ no. of variables
z_i is a variable after recombination
$a_i \in \{0,1\}$ uniform at random

To illustrate how discrete recombination works, consider the following two chromosomes with 8 variables. In this example, the first four variables correspond to the control genes and the others correspond to the parametric genes.

Individual 1 :	1	0	1	0	0.01	0.24	0.56	0.37
Individual 2 :	0	1	1	1	0.52	0.89	0.02	0.15

For each variable the parent who contributes its variable to the offspring is chosen randomly with probability 0.5. The internal mask determining which parent produces the offspring are assumed to be:

Mask 1 :	2	2	1	2	1	2	2	1
Mask 2 :	1	2	2	2	1	2	1	2

1 means this part is produced by parent 1
2 means this part is produced by parent 2

After recombination the offspring are created as:

Offspring 1 :	0	1	1	1	0.01	0.89	0.02	0.37
Offspring 2 :	1	1	1	1	0.01	0.89	0.56	0.15

3.3.2 Mutation The concept of using mutation is to recover good genetic material that may be lost through the acting of selection and crossover. Mutation of real variable means that randomly created values are added to the variables with a low probability. The new value is computed according to

$$z_i = x_i + s_i \cdot r_i \cdot a_i \quad \cdots\cdots (2)$$

where $i = 1, 2, \ldots,$ no. of variables
x_i is a variable before mutation
z_i is a variable after mutation
$s_i \in \{-1,+1\}$ uniform at random
$r_i = r \cdot$ search interval, r: mutation range (0.1 for standard)
$a_i = 2^{-u \cdot k}$, $u \in [0,1]$ uniform at random, k: mutation precision

The above algorithm means, probability of small step-sizes is greater than that of bigger steps. Thus most of mutated individuals will be generated near the individual before mutation. Parameter k defines the minimal step-size. The mutation steps are created inside the area $[r, r \cdot 2^{-k}]$. To illustrate how mutation works, consider two chromosomes with 8 variables. In this example, the first four variables correspond to the control genes and the others correspond to the parametric genes.

Individual 1 :	0	1	1	1	0.01	0.89	0.02	0.37
Individual 2 :	1	1	1	1	0.01	0.89	0.56	0.15

The internal masks determining which variable to be mutated and its sign for adding are assumed to be:

Mask 1 :	0	0	0	0	1	−1	0	0
Mask 2 :	0	0	−1	0	0	0	1	0

If the mutation steps can be calculated as:

Mutation step 1 :	0	0	0	0	0.001	-0.12	0	0
Mutation step 2 :	0	0	-0.001	0	0	0	0.22	0

Thus after mutation, the new chromosome becomes:

Individual 1 :	0	1	1	1	0.011	0.77	0.02	0.37
Individual 2 :	1	1	0.999	1	0.01	0.89	0.78	0.15

It can be seen that one part of the above control gene in individual 2 is not "1" or "0" as assumed to be in our criterion. The chromosome must be fixed by gene correcting method. If the value of control gene is equal or greater than the value 0.5, the correcting value will be 1, otherwise it will be 0. After correcting, the chromosome becomes:

Individual 1 :	0	1	1	1	0.011	0.77	0.02	0.37
Individual 2 :	1	1	1	1	0.01	0.89	0.78	0.15

4. Formulation of the Problem

4.1 Formulation of the cost function The input to the stabilizer used in this paper is generator shaft speed. It consists of a two-stage lead lag compensation with time constants T_{1i} - T_{4i}, and a gain K_i. The value of washout time constant T_{wi} is large enough and can be considered as a constant (in this study T_{wi} = 10s). Equation 3 shows the transfer function of each PSS where i signifies for i^{th} generator.

$$PSS(s) = K_i \frac{sT_{wi}}{1+sT_{wi}} \left(\frac{1+sT_{1i}}{1+sT_{2i}} \frac{1+sT_{3i}}{1+sT_{4i}} \right) \quad \cdots\cdots (3)$$

The problem of selecting the PSS parameters is converted to a simple optimization problem. We propose a simple eigenvalue-based objective function shown in (4) for selecting the PSS parameters. The closed-loop eigenvalues are constrained to lie on the left hand side of s-plane (stable region) and to have global minimum damping ratio as maximum as possible. This guarantees the minimum damping ratio of all modes within the predefined scenarios analogous to the robustness of PSS controllers.

$$min\,F = -\left(W_{stable} + W_{unstable}\right) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (4)$$

subject to

$$\delta_i = \frac{-Re(\lambda_i)}{\sqrt{Re(\lambda_i)^2 + Im(\lambda_i)^2}} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (5)$$

$$\text{if } \forall(\delta_i)_j \geq 0 \quad W_{stable} = 2^{10} \min_{1\leq j\leq m} \left(\min_{1\leq i\leq n} \delta_i\right)_j$$

$$\text{else} \quad W_{stable} = 0$$

$$\text{if } \exists(\delta_i)_j \langle 0 \quad W_{unstable} = 2^{15} \min_{1\leq j\leq m} \left(\min_{1\leq i\leq n} \delta_i\right)_j$$

$$\text{else} \quad W_{unstable} = 0$$

where $i = 1, 2, 3, \ldots, n$ (numbers of eigenvalues), λ_i is the i^{th} closed-loop eigenvalues, $j = 1, 2, 3, \ldots, m$ (numbers of scenarios).

Factor 2^{10} and 2^{15} in the constraints of (5) are penalty vales that are arbitrarily defined, however, they should be large enough to explicitly distinguish the weight summation between stable and unstable cases.

4.2 Preparing the initial solution by phase minimum control method According to the method using participation factor, the generator having maximum speed participation factor G_p would be a suitable place for installing PSS to damp out under damped and unstable modes. In Table 1, it shows that 12 generators will participate in these modes. In this way, we have calculated PSS parameters for 12 generators by following the procedure as explained in [5,6] and kept it as an initial solution in the database.

5. Simulation Results

The system is simultaneously tuned by considering three different loading conditions as the following: (1) nominal loading where total load is 14.727 GW, (2) light loading where total load is 7.363 GW, and (3) heavy loading where total load is 31.825 GW. For each case, 9 scenarios as shown in Table 2 are used in the tuning process. Therefore simulations are performed with 27 systems for evaluating the eigenvalues used in the proposed tuning approach.

Table 2. Scenarios considered in the tuning process

Scenario number	description
1	All lines are in service
2	Line 1-27 is out of service
3	Line 1-2 is out of service
4	Line 8-9 is out of service
5	Line 50-51 is out of service
6	Line 3-4 is increased 50%
7	Line 41-42 is increased 50%
8	Line 46-49 is increased 50%
9	Line 42-52 is increased 50%

In a micro-GA, gains of each PSS have been setup with bounds ranging from 0 to 20 and for PSS time constants with bounds ranging from 0-1 second. The population size P is set at 5, total generation N is 60. The execution time of a micro-GA for $PN=300$ is approximately 2 hours for running 9 scenarios of one loading condition. Experiences from several computational experiments using a micro-GA with random initialized population have shown that it would take a few hours to find the first solution having the minimum damping ratio higher than 0. By using the proposed approach with the same length of time, the final solutions are always acceptable. The final results are shown in Table 3. Time consumed by calculating a reasonable initial solution will be compensated by the considerably improvement of time for finding the final best. The proposed tuning approach was performed on PENTIUM III 990 MHz using MATLAB version 6.0 and Power System Toolbox [10] for small signal stability and nonlinear simulations.

In order to demonstrate the outputs effectively, the dominant eigenvalues of 27 systems for five-case studies were each plot on the same figure. The way of understanding these results can be explained by using the information that can be extracted from the plots based on these points:

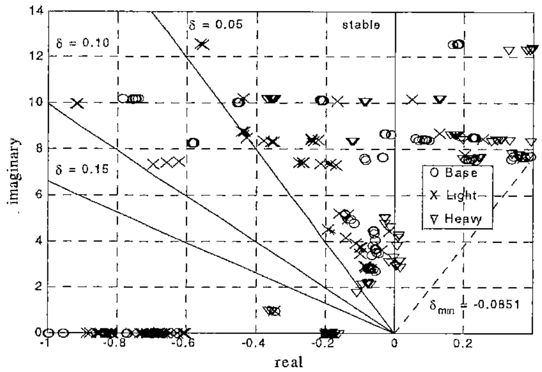

Fig. 5. Open -loop eigenvalues (no PSS)

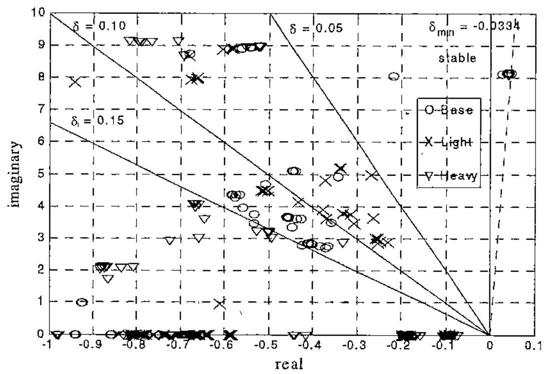

Fig. 6. Fixed 12 PSS locations (a minimum phase control)

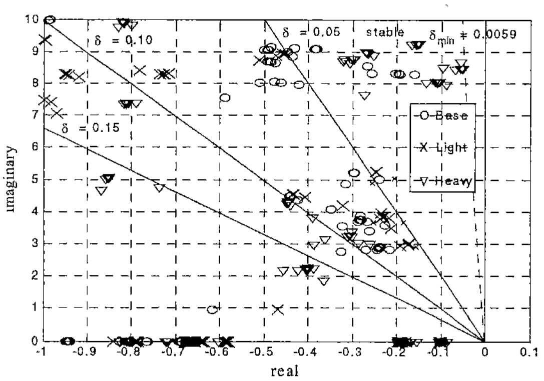

Fig. 7. Fixed 12 PSS locations (a micro-GA)

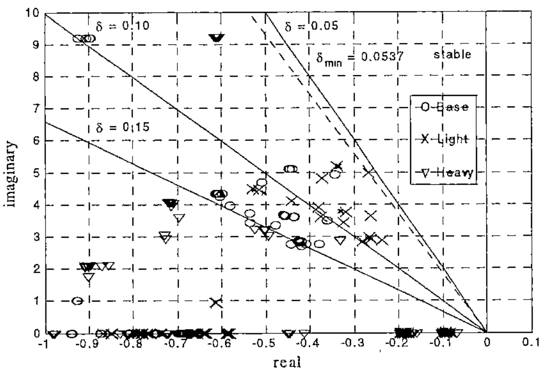

Fig. 8. Fixed 14 PSS locations (a minimum phase control)

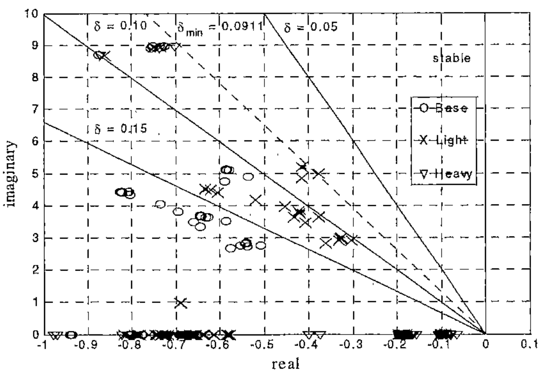

Fig. 9. 15 PSS locations (proposed tuning method)

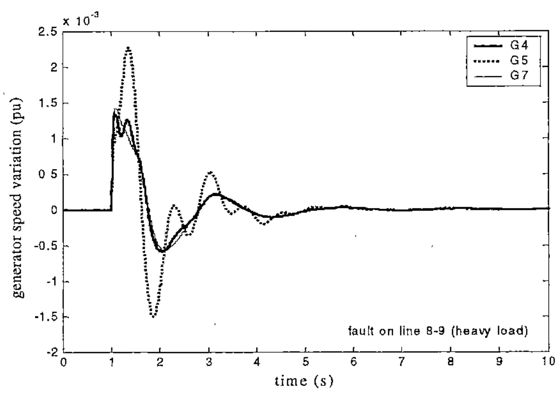

Fig. 10. Fault on line 8-9 (heavy load)

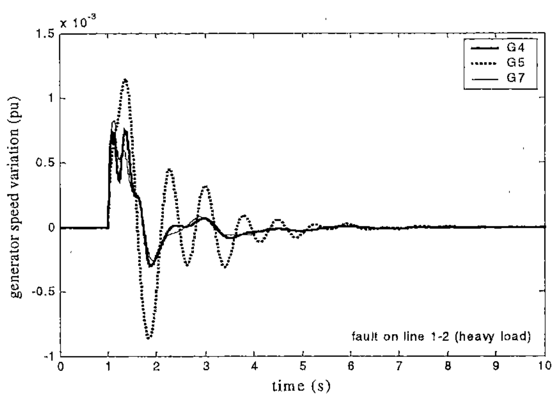

Fig. 11. Fault on line 1-2 (heavy load)

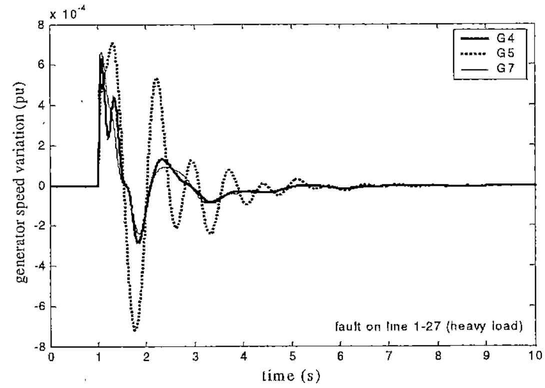

Fig. 12. Fault on line 1-27(heavy load)

If some eigenvalues are located on the right hand side of s-plane (unstable area), the system becomes unstable resulting to growing oscillations and system collapses. If some eigenvalues are located within the stable area but with damping ratio less than the required minimum damping 5%, these modes may not cause to transient instability, however, due to a very poor damping, the system will oscillate last long period and it may be initiated by the normal small changes in system load or a sequence of small disturbances resulting to system collapse. As power system reliability becomes increasingly important, it is necessary to secure the system by keeping all oscillatory modes within the safe operating area for a wide range of operating conditions and for all possible critical events. Oscillations are acceptable as long as they decay. The comparisons of eigenvalue plot for five-case studies are shown in Fig. 5 to Fig.9.

Case 1: with no PSS

It is evident from Fig.5 that it is very risk to operate the system under heavy and base loading condition as most of eigenvalues are located in unstable area. Even for a light loading condtion, some scenarios cause unstable modes while others still have damping ratios below the requirement 5%. Thus we can say that the original system is very unstable under all predefined scenarios

Case 2: Fixed 12 PSS locations and tuning by a minimum phase control method

From the original system, we applied a minimum phase control method. First, all possible PSS locations are evaluated by participation factors. Then, after we know that 12 PSSs are to be installed into the power system, PSS will be designed one by one with hand. The result in Fig.6 shows that there are one unstable mode and one under damped mode which can not be moved to have damping ratio grater than the requirement 5%.

Case 3: Fixed 12 PSS locations and tuning by a micro-GA

With the same PSS locations as in case 2, a micro-GA were used for simultaneous tuning by fixed all 12 PSS location. The result in Fig.7 shows that a micro-GA can provide a better minimum damping ratio compared to Fig.6. However, there is not much effective use since many eigenvalues are located within under damped area. This is the message that though a minimum phase control loop method is simple and practical, it must be done with care since the interaction between PSSs exist and determining the possible PSS locations by participation factors also must be done with care since the system may be lost optimal perform-

Table 3. PSS parameter set obtained by a micro-GA

parameters	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16
K	3.26	14.53	11.06	13.38	-	16.17	20.00	8.07	11.91	17.65	10.64	14.47	20.00	19.57	15.08	20.00
T1	0.074	0.053	0.045	0 100	-	0.097	0.059	0 100	0.060	0.089	0.092	0.019	0.024	0.060	0.095	0.100
T2	0.085	0.011	0.037	0.042	-	0.035	0.013	0 014	0.055	0.009	0.039	0.008	0.065	0 044	0.045	0.057
T3	0 092	0.072	0.097	0.090	-	0.100	0.078	0.055	0.092	0.053	0 074	0.089	0.038	0.094	0.097	0.039
T4	0.031	0.011	0.018	0.026	-	0 089	0.011	0.084	0.011	0.020	0.017	0.004	0.036	0.049	0.052	0.058

ance by choosing wrong choices of locations.

Case 4: Fixed 14 PSS locations and tuning by a minimum phase control method

Again, the root causes of unstable and under damped modes in case 2 were evaluated by participation factors. It was found that generator 2 is significant for unstable mode and generator 1 for under damped mode. Because these two generators are not associated in case 2, it is necessary to install PSSs to these two generators. Fig. 8 shows that now all modes have damping ratios greater than 0.05.

Case 5: 15 PSS locations and tuning by the proposed tuning method

With the proposed tuning method, locations become variables. We found that in order to obtain a minimum damping ratio better than in Fig.8, 15 PSSs are necessary. In Fig.9, we can observe that a minimum damping ratio is 9.11% which is a factor that guarantees for all predefined scenarios for 3 loading conditions. The operation under heavy loading condition has no problem. Some of them have been shifted beyond the scale of Fig.9. Thus we can concluded from Fig.9 that with three loading conditions and predefined scenarios, the system will be secured by a minimum damping ratio 9.11%.

To see how damping ratio 9.11% effects to the power system, it is important to show non-linear time domain simulations. The generators that associated with the mode with damping ratio 9.11% have been calculated by participation factors again. It has been found that generator 4, 5 and 7 are significant for this mode. Fig. 10 to Fig.12 show dynamic simulations for three-phase to ground faults on line 8-9, 1-2 and 1-27 by the faulted line is cleared after 6 cycles respectively. The system is stable and sufficiently damped. In addition, these results confirm that with one set of the proposed PSSs, the system will be good both transient and dynamic stability with less than 10 seconds that system can become stable after oscillations.

6. Conclusions

This paper describes an off-line PSS tuning method by the incorporated use of GA and an analytical method so called minimum phase control. We propose using HGA concept for automatically identifying the PSS locations. We have shown that our proposed tuning approach gives better result for the minimum damping requirement since the interaction among stabilizers is taken into consideration.

We also propose the application of a micro-GA with the selected initial solution from the database which may be obtained from other calculation methods or user's experiences. The minimum phase control method which is easy to implement was selected as a reasonable choice of initial solution. The results show that the combination of these features can speed up the GA calculation time significantly. An excellent improvement in the damping for every scenarios has been achieved with one set of PSS parameters.

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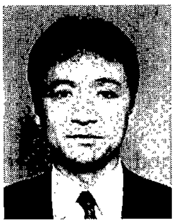

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