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DESIGN OF MULTI-MACHINE POWER SYSTEM STABILIZER USING EVOLUTIONARY ALGORITHM

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ABSTRACT

This paper presents the design of power system stabilizers using evolutionary algorithms. Three techniques were considered, namely: Population Based Incremental Learning (PBIL), Genetic Algorithm (GA) and the Breeder Genetic Algorithm (BGA) with adaptive mutation. Eigen value analysis was used in the objective for the respective PSS designs, whereby the lowest damped ratio was to be maximized. Simulation was used to compare the performance of the PSSs designed using the different techniques. Theoretically BGA optimizes slightly better than PBIL, while PBIL gives better results than GA. Overall evolution algorithm techniques work better than conventional methods, which is the CPSS. As a verification of the above, simulation results are presented for multiple operating conditions with PSS designed with all the above mentioned methods. Time domain for both smaller and larger disturbances showed that PBIL and BGA performed slightly similar, but performed better than GA. All evolution algorithms perform better than CPSS.

KEY WORDS

Stability, breeder genetic algorithm, cross over, premature convergence, low frequency oscillations, eigenvalues

1. Introduction

Interconnected power systems tend to experience electromechanical oscillations, especially during and after disturbances. Stability of electromechanical oscillations is of greater importance to power system operation and forms a major requirement for power system secure operation [1-2]. In the past decades, single generator/single machines to infinite bus system have been major recipients for these types of low frequency oscillations. The low frequency modes called inter area in interconnected systems occur as a result of a group of generators in one area oscillating against a group of generators in another area [1-2]. They are usually in the range of 0.1Hz to 0.8Hz. There are also local oscillations in the range of 1Hz to 3Hz, which are associated with a single generator oscillating against a group of generators. But of importance are the inter area modes which are prominent in multi machine systems [3]. It is therefore important that special attention be given to these modes, so that they can be adequately damped. Power System Stabilizers (PSS) have been developed and used over the years as a tool to provide extra and adequate damping to the low frequency oscillations in power systems. Conventional Power System Stabilizer (CPSS) designed over a certain nominal operating condition has been widely used by power system utilities. CPSS does a decent job, but its performance tends to degrade as the system dynamics change [3-8]. To take care of this setback, modern control techniques have been proposed and applied to the design of PSS in recent years [4-6]. Evolution Algorithms (EA) are some of the recent techniques that have received increased attention recently [4-8]. As part of EAs, GAs are biologically motivated adaptive systems based on natural selection and genetics. They represent a heuristic search technique based on the evolutionary ideas of natural selection and genetics, and they operate by virtue of survival of the fittest logic [6,8]. GA has been popular in academia and most recently is accepted by some industry mainly because of its ease of implementation, and the ability to solve highly non-linear, mixed integer optimization problems that are typically define engineering problems [6,9]. Other families of Evolutionary Algorithm that are considered in this work are the Breeder Genetic Algorithm (BGA) and the Population Based Incremental Learning (PBIL). BGA employs the same concept of survival of the fittest as employed in GA; however BGA use the artificial breeding similar to the one practiced in animal breeding. This work uses a slightly different version of BGA, called the Adaptive Breeder Genetic Algorithm (AMBA) [10]. PBIL is based on combining the GA and the competitive learning for function optimization. PBIL is an extension to the Evolution Genetic Algorithm achieved through the re-examination in terms of competitive learning [11].

2. Description of the study system

Power system considered in this work is a hypothetical two area network system [1]. The system consists of two identical areas separated by a relatively weak tie-line. Each area includes two identical generating units with equal power outputs. The system model is shown in Figure 1. G1 to G4 represents identical generators, with G1 being the reference generator.

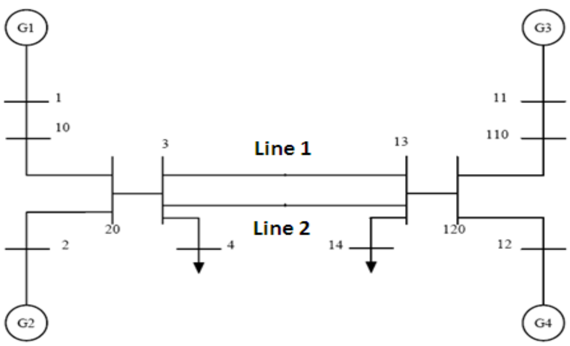

Figure 1: Two area system model

3. Genetic Algorithm overview

This section gives an overview of the traditional Genetic Algorithm (GA). GA has been used to solve complex and difficult problems in engineering that are difficult or impossible to solve by conventional optimization methods. GA manipulates a set of potential solutions in a view to generate solutions which are better and fitter thereby using the principle of survival of the fittest. The fittest individuals in a population reproduce and survive to the next generation [9].

4. Overview of BGA

As mentioned in previous sections, BGA is a relatively new evolution algorithm. It is also based on survival of the fittest as in GAs with the difference that BGA is based on artificial selection. This work uses a modified version of BGA called the Adaptive Mutation BGA or AMBA [10]. The BGA usually uses real-valued representation as opposed to GA which mainly uses binary and sometimes floating or integer representation. The BGA uses truncation selection method, whereby a selected top T% of the fittest individuals are chosen from the current generation goes through recombination and cross over to form the next generation. The rest are discarded. In truncation method, the fittest individual called an *ellist* is guaranteed a place in the next generation. The other top (T-1) % goes through recombination and mutation to form up the rest of the individuals in the next generation. The process is repeated until an optimal solution is obtained or the maximum numbers of iterations have been reached.

5. Overview of PBIL

Population Based Incremental Learning (PBIL) has been preferred by many researchers over GA due to its simplicity, less computation time and capacity that is needed and which on numerous occasions outperforms the GA. PBIL was originally proposed by and developed in [11, 13]. PBIL combines some aspects of GAs and competitive learning [11- 13]. It is an extension to the Evolution Genetic Algorithm (EGA) achieved through the re-examination of the performance of the EGA in terms of competitive learning [11, 13]. The crossover operator is taken away in PBIL, redefining the role of the population. PBIL works with probabilistic vectors. The probability vectors control the random bit strings generated by PBIL and are used to create other individuals through learning [12]. Learning in PBIL consists of using the current probability distribution to create N individuals. Using the objective function, the performance of these individuals is vindicated. Using the best individual, the probability vector is updated, increasing the probability of producing solutions similar to the current best individuals. Mutation is used to maintain diversity in PBIL. PBIL has the following properties [12, 13]:

- There is no crossover or fitness operator.
- It works with probability vectors which control the random bit strings generated by the PBIL and is used to create other individuals through learning.
- There is no need to store all solutions. It only stores the current best solution and the current solution being evaluated

6. Objective function

The objective function used in all the evolutionary algorithms was to maximize the lowest damped eigenvalues over multiple operating conditions [8]. PSS parameters to be optimized were the gain K and the lead-lag time constants T1 to T4. Only generators G1 and G3 were equipped with a PSS and optimized.. This was done due to their effects on the stability of the entire system. Generators G1 and G3 have the highest participation factors in the inter area modes of the system. This objective function was used both in GA, BGA and PBIL. This objective function is given as:

$$val = \max\left(\min\left(\zeta_i\right)\right) \qquad (1)$$

$$i = 1,2,3 \ldots\ldots\ldots.. n$$

i represents the number of the eigenvalue, while $\zeta_i = \frac{-\sigma_i}{\sqrt{\sigma_i^2+\omega_i^2}}$ is the damping ratio of the i^{th} eigenvalue.

σ_i, ω_i Are the real part and the imaginary part (frequency) of the i^{th} eigenvalues respectively.

7. PSS design

For comparison purpose a CPSS was also designed. In all, three PSSs were designed and their performances compared. For the BGA, PBIL and GA, five parameters for each optimization type were optimized: K, T1, T2, T3 and T4. The washout time constant (Tw) was set at 10 seconds. Ten parameters were optimized for Generators G1 and G3.

7.1 CPSS Design

The parameters for the CPSS were tuned using a chosen nominal operating condition by using the technique of trial and error approach as well as phase compensation method. The continuous transfer function was:

$$Upss(s) = K\frac{sT_5}{1+sT_5}\frac{1+sT_1}{1+sT_2}\frac{1+sT_3}{1+sT_4}\Delta\omega(s) \qquad (2)$$

7.2 Operating conditions considered

The following operating conditions were considered in tuning the PSS parameters.

Table 1: Operating conditions considered PSS design

Operating condition	Generator	Active power (pu)	Line Reactance (pu)
1	G1 G2 G3 G4	5 7 8 8	0.11
2	G1 G2 G3 G4	5 7 8 8	0.22
3	G1 G2 G3 G4	7.2615 7 7 7	0.11
4	G1 G2 G3 G4	7.2615 7 7 7	0.22
5	G1 G2 G3 G4	5.2615 9 5 9	0.11
6	G1 G2 G3 G4	5.2615 9 5 9	0.22

8. Simulation Results

This section presents the simulation results. Only time domain simulations are presented in this paper. This is a 10% step change in the reference voltage of generator 2 and a 6 cycle three phase fault in the middle of Line 1, cleared by removing the Line 1 entirely.

8.1 Step Response

The step responses for generator G2 to a step response in voltage reference of generator G2 are shown in this section for different operating conditions.

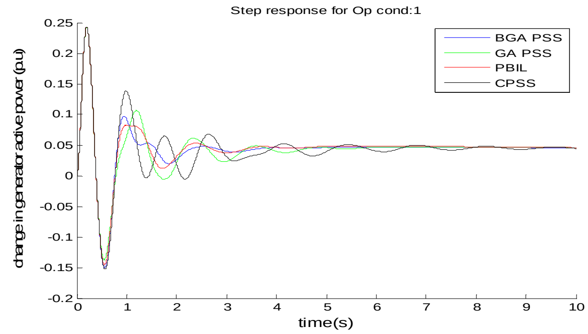

Figure 2: G2 step response to 10% change in Vref at Op cond: 1

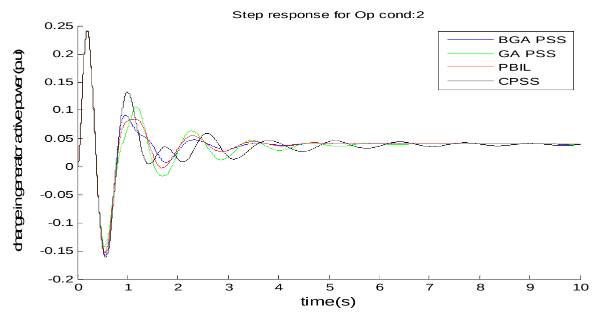

Figure 3: G2 step response to a 10% change in Vref at Op cond: 2

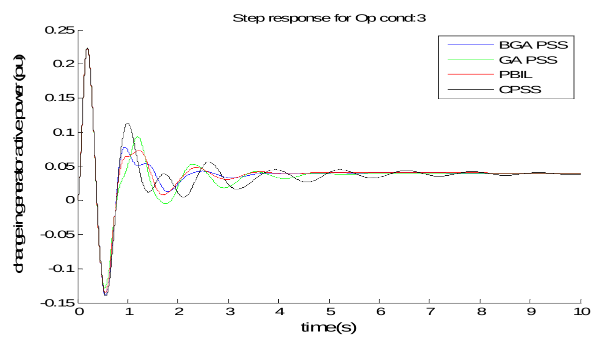

Figure 4: G2 step response to a 10% change in Vref at Op cond: 3

Figures 2, 3 and 4, show the time responses for the power deviation of generator G2 to a step response of a 10% change in the voltage reference of generator G2. The results show that the system is well stable and damped with all four PSS considered. But comparing the evolutionary algorithm based PSSs with the CPSS, the BGA, PBIL and GA perform much better than the CPSS across all the operating conditions considered. Having said that, the BGA and PBIL have a better damping as compared to the GA designed PSS. Considering case 1, the second swing of the system with CPSS is approximately 0.15 maximum, GA-PSS is around 0.11, BGA and PBIL are close to 0.1 respectively. The system with CPSS settles in around 8 to 9 seconds, around 5 to 6 for the GA and 3 to 4 seconds for the BGA and PBIL, respectively. This same trend is evident for cases 2 and 3. In case 3 shown in Figure 4, the system with CPSS settles after 10 seconds, GA-PSS settles in around 4.5 seconds while the BGA and PBIL settles in around 3.5 seconds. The second swing amplitude is still high for the CPSS, which is close 0.1pu, while the same is 0.08 pu for GA-PSS and 0.06 pu for PBIL and BGA-PSS respectively.

8.2 Transient Response

The system responses to a 6 cycles three phase fault in Line 2 are shown in Figure 5 and Figure 6. Figure 5 shows that the system equipped with CPSS settles after 7 seconds, but has a smaller overshoot than all the other PSSs. On the other hand, GA settles after 4 seconds while with the BGA and PBIL, the system settles around 3 seconds for the same condition.

Figure 6 shows the AVR field voltage. For all the cases, the field voltage value reaches the ceiling for the first and second swing due to the limitations of the PSS output.

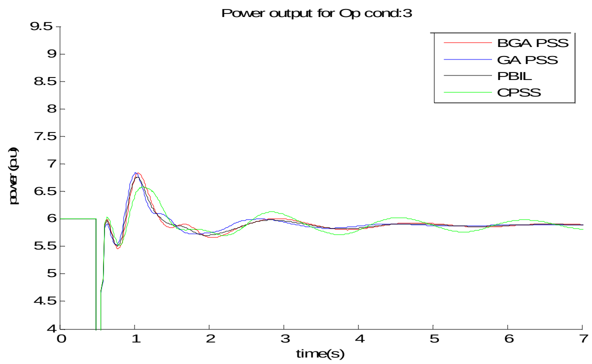

Figure 5: G2 Power response to a 3 phase fault on Line 1

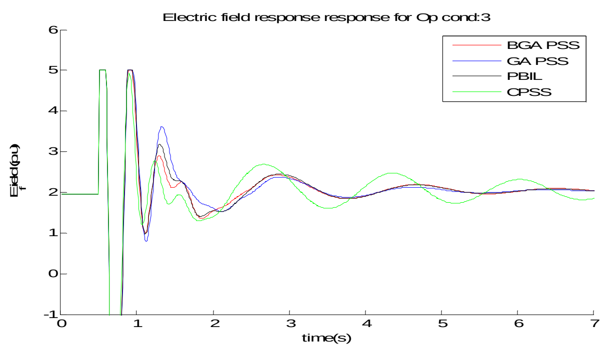

Figure 6: G2 Electric field response to a 3 phase fault on Line 1

9. Conclusion

Power system stabilizers were designed using the three different evolutionary algorithms for a multi-machine power system having local and inter-area oscillations. These PSSs were tested using both small and large disturbances and the time domain simulation results were presented. The results showed that the BGA-PSS and PBIL-PSS perform slightly similar to one another, but they all perform better than the GA-PSS. All the three PSS designs based on evolutionary algorithm perform better than the CPSS for all the operating conditions as expected. The results showed that the system is well damped with EA PSSs as compared to CPSS, across all operating conditions. A standard system (WSCC or IEEE 14) will be used in future research, in order to allow better comparison for the PSS design. PSS parameters have not been included in the paper due to space limitations

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