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COMPARATIVE STUDY ON HEURISTIC OPTIMIZATION TECHNIQUES IN THE DESIGN OF ROBUST POWER SYSTEMS STABILIZERS USING H_∞ CRITERION

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Abstract. *This work employs a combination of Relative Gains Array (RGA) and singular values, adapted for a multi-machine system, in order to simplify the application of their controllers and reducing their order, without reducing the power system model. After that, three optimization techniques, genetic algorithms, particle swarm and simulated annealing, which are based on heuristics, are applied, in order to determine the parameters of the controllers that guarantee a robust performance. The performance of heuristic optimization techniques is studied when applied to the design of Power System Stabilizers (PSS), based on H_∞ criterion to robustness. The New England – New York benchmark, a reasonably complex, and coupled classical case study, is chosen to compare the performance of the designed PSS with these heuristic techniques. In this way, the paper presents a methodology for the design and allocation of PSS, and the same performance criteria are applied to the three methods in order to determine the one that presents a superior response in the process of tuning of the controllers.*
Keywords: PSS tuning, Robustness, Heuristic optimization, Multi-machine system

1. **Introduction.** Most of the large electrical systems in the world are highly interconnected. This configuration may result in the appearance of weakly or non-damped, low-frequency electromechanical oscillations [1]. These oscillations are harmful because they reduce the stability margins of the power system and even impose constraints in the power transmission. Therefore, the damping of these oscillations has become a requisite for safe operation of an electrical system and the concern of engineers and operators [2].

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To effectively control these oscillations, it is essential of the analysis and knowledge of characteristics such as the nature, types, and frequencies of the most disturbing oscillations, among others. Therefore, the most efficient way to mitigate these oscillations is applying robust control techniques that considers the complexity inherent to the system, such as variations in operating conditions, change of system parameters due to failures, and also uncertainty in the system model parameters [3-6]. Interconnected power systems cannot operate without an adequate control system, requiring the presence of controllers that damp the electromechanical oscillation modes [2]. For this reason, a common alternative in power systems is the inclusion of decentralized lead-lag compensators, called Power System Stabilizers (PSS), that provide additional stabilizing signals in the generator excitation control systems. Frequency domain methods are constantly used in the analysis and design of these stabilizers.

Since traditional classical control techniques perform poorly because they do not consider variations in operating conditions, an alternative is the robust control design according to the H_∞ criterion which consists in minimizing the peaks of frequency responses of a closed-loop system when subject to exogenous inputs, which corresponds to the maximum singular value of a system of Multiple Inputs and Multiple Outputs (MIMO) [7]. Such a project involves solving the H_∞ norm minimization problem in the definition of the controller parameters, requiring the use of computational and numerical methods for the best solution. Since the minimization problem is not an explicit function of the controller parameters, optimization methods that do not require the calculation of the function derivatives are well suited for this purpose.

The three stochastic methods tested are known for their ability to cope with hard optimization problems, as they do not require objective function gradient evaluations, and consequently there is no need to calculate the derivative of the functions. These methods are Simulated Annealing (SA) and two evolutionary algorithms: Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) [8].

Other key reasons for choosing these methods are that they were already verified to perform well when applied to Power System Stabilizers (PSS) for different system models. In [9], GA is used to tune the parameters of the PSS, as well as the Automatic Voltage Regulator (AVR) of the synchronous generator with the purpose of minimizing the speed offset of the generator. In [10], PSO is applied in order to tune the parameters of the PSS controller with a Thyristor-Controlled Series Capacitor (TCSC), used in a multi-machine system. This system remains stable, under the influence of the controller, even in the face of system failures. In [11], GA is applied to PSS controllers, although in a system with a single machine connected to an infinite bus their performance is compared to controllers which have been tuned using PSO. GA also performs well when applied to PSS tuning, including when using H_∞ robust control techniques, as can be seen in [12]. SA, although less conventional in this type of application, presented satisfactory results in obtaining PSS parameters, used in multi-machine systems, as described in [13]. Thus, this work aims to analyze the performance of the three previously mentioned methods in the tuning of low order robust PSS applied to a large system such as the New England (NETS)/New York (NYPS) and to compare the efficiency of the methods in tuning the robust controllers for the system.

This paper is organized as follows. In Section 2, the problem statement is presented, together with the mathematical formulation regarding the robust control H_∞ criteria and how it can be applied to the tuning of robust PSS. In Section 3, the controller positioning and tuning procedure are applied to the NETS/NYPS benchmark system. Subsequently, in Section 4, the setup of the heuristic optimization methods is presented. In Section 5, the results are presented and finally in Section 6, the conclusions are stated.

2. **Problem Statement and Preliminaries.** As previously stated, the purpose of this work is to compare the performance of three optimization methods in the tuning of power system stabilizers, applied in the NETS/NYPS system. The three methods will be applied in the design of robust controllers according to the H_∞ criterion.

Robust control theory assumes that the models used to design control systems contain modeling errors. Fundamentally, it is assumed that there is uncertainty or error between the real plant and its mathematical model and includes this uncertainty or error in the design of the control system to guarantee the objectives established in the project [7].

The H_∞ theory uses the limits of uncertainties in the design of controllers. In the robust control design, a real model is adopted, which consists of the nominal model plus the uncertainties. The nominal model is linear and valid for a point of operation. However, the controller must be designed to stabilize a set of models valid for common operating points.

When the uncertainties associated with the models are generic, including all forms of errors and variations, including those due to the non-consideration of part of the system's dynamics, these are called unstructured uncertainties.

A valid approach to describe this class of uncertainties is the frequency domain, which gives rise to complex normalized disturbances $||\boldsymbol{\Delta}(s)||_\infty \leq 1$. It is also possible to use an approach that consists of one or more sources of uncertainties gathered in a single concentrated uncertainty, that is, a complex matrix $\boldsymbol{\Delta}$ of uncertainty is used, normally with dimensions compatible with those of the plant where, for any $\boldsymbol{\Delta}(j\omega)$, the relation of the maximum singular value $\bar{\sigma}(\boldsymbol{\Delta}i(j\omega)) \leq 1$ is satisfied.

In the system adopted in this work, a closed loop system model $\boldsymbol{M\Delta}$ described in [6] is applied, where the block of uncertainties $\boldsymbol{\Delta}_0$ has been isolated and where $\boldsymbol{M}$ is the transfer function matrix of the controlled system, given by

$$\boldsymbol{M}(s) = -\boldsymbol{W}_0(s)\boldsymbol{T}(s)\boldsymbol{H}(s) \tag{1}$$

where $\boldsymbol{T} = \boldsymbol{SG}$ is the matrix of closed-loop transfer functions of the system and $\boldsymbol{S}$ is the sensitivity matrix of the system, which transfer functions matrix is $\boldsymbol{G}$, and is defined as $\boldsymbol{S} = (\boldsymbol{I} + \boldsymbol{GH})^{-1}$. Matrix $\boldsymbol{H}$ is a diagonal matrix with the controller models and $\boldsymbol{W}_0$ is a diagonal matrix representing the upper limits of the uncertainties in the model.

This is a generic way of representing uncertainties and the most appropriate way to design H_∞ controllers for controlling the excitation of generators.

Considering for this model the multiplicative unstructured uncertainties described in [7], the following equation may be obtained:

$$\boldsymbol{\Delta}_0\boldsymbol{W}_0(s) = (\boldsymbol{G'} - \boldsymbol{G})\,\boldsymbol{G}^{-1} \tag{2}$$

where $\boldsymbol{G'}$ represents the real system transfer function matrix, which results in

$$\boldsymbol{G'}(s) = (\boldsymbol{I} + \boldsymbol{\Delta}_0\boldsymbol{W}_0)\boldsymbol{G}(s) \tag{3}$$

If $\boldsymbol{S'} = (\boldsymbol{I} + \boldsymbol{G'H})^{-1}$ is the sensitivity matrix of the real system, then

$$\boldsymbol{S'} = \left[\boldsymbol{I} + (\boldsymbol{I} + \boldsymbol{\Delta}_0\boldsymbol{W}_0)\boldsymbol{GH}^{-1}\right]^{-1}[\boldsymbol{I} + \boldsymbol{GH}]\boldsymbol{S} \tag{4}$$

Defining $\bar{\sigma}$ as the highest singular value, $\underline{\sigma}$ as the lowest one and the ratio, $\gamma = \bar{\sigma}/\underline{\sigma}$ as the condition number and assuming that the range of frequencies of the greatest interest occurs if $\underline{\sigma}(\boldsymbol{GH}) >> 1$, results in

$$\bar{\sigma}\left(\boldsymbol{S'}\right) \leq \frac{\gamma(\boldsymbol{G})\gamma(\boldsymbol{H})}{\underline{\sigma}(\boldsymbol{I} + \boldsymbol{\Delta}_0\boldsymbol{W}_0)}\bar{\sigma}(\boldsymbol{S}) \tag{5}$$

Usually, the $\boldsymbol{W}_0(s)$ matrix is represented by $\omega_0(s)\boldsymbol{I}$, where $\omega_0(s)$ is a weight, considering a single upper bound, representing the worst case, associated to all control channels [14].

Assuming that matrix $\boldsymbol{M}$ and uncertainties $\boldsymbol{\Delta}$ are stable, then the system $\boldsymbol{M\Delta}$ will be stable for all perturbations with $\bar{\sigma}(\boldsymbol{\Delta}) \leq 1$, $\forall\omega$, if and only if [7]

$$\mu(\boldsymbol{M}(j\omega)) < 1, \quad \forall\omega \tag{6}$$

where $\mu(\boldsymbol{M})$ is the singular structured value of $\boldsymbol{M}$.

It is known that $\mu(\boldsymbol{M}) \leq \bar{\sigma}(\boldsymbol{M})$ and that equality occurs when the uncertainty matrix $\boldsymbol{\Delta}$ is full. Therefore, it is considered as a necessary and sufficient condition for robust system stability, with $\bar{\sigma}(\boldsymbol{\Delta}) \leq 1$, $\forall\omega$, the following condition:

$$\bar{\sigma}(\boldsymbol{M}(j\omega)) < 1, \quad \forall\omega \tag{7}$$

In order to achieve robustness, the parameters of the $\boldsymbol{H}(s)$ controller are adjusted to solve the following H_∞ optimization problem:

$$\min\left[\sup(\bar{\sigma}(\boldsymbol{M}(j\omega)))\right] \tag{8}$$

From (1), consider $\boldsymbol{M} = \omega_0\boldsymbol{TH}$ (the negative sign does not affect the result). Then, (8) reduces to

$$\bar{\sigma}(\boldsymbol{M}) = \bar{\sigma}(\omega_0\boldsymbol{TH}) \leq \bar{\sigma}(\omega_0\boldsymbol{H}) \cdot \bar{\sigma}(\boldsymbol{T}) < 1 \tag{9}$$

or

$$\bar{\sigma}(\boldsymbol{T}) = \frac{1}{\bar{\sigma}(\omega_0\boldsymbol{H})}, \quad \forall\omega \tag{10}$$

Then, the objective is to optimize the function matrix $\boldsymbol{M}$, finding the values of the controller parameters that satisfy the robustness condition, which corresponds to (11). By minimizing the maximum singular value of $\boldsymbol{M}$, the peaks related to the oscillation modes are decreased, which, consequently, improves the stability of the system.

In [15], the minimization of the H_∞ norm as given by (11) was obtained by applying the GA optimization technique to a relatively simple system. In the present work, GA and two other well-known heuristics, SA and PSO, are employed and results are compared in a case study of much higher order and complexity, as it will be shown in subsequent sections.

3. **Controller Positioning and Tuning Procedure.** The procedure for tuning and positioning low-order PSS controllers in a large power system, with no reduction in the system model, requires modal analysis methods that are capable of analyzing the inputs and outputs as a whole and identifying the most efficient ones, enabling the optimized positioning of the controllers and reducing the number of PSS to be installed. In addition, it is proposed that these stabilizers should be tuned automatically, using heuristic optimization methods.

3.1. **The case study model.** The NETS/NYPS system, represented by the diagram shown in Figure 1, has 68 buses and is a reduced-order equivalent of the New England interconnected test system (containing generators G_1 to G_9) and the New York power system (containing generators G_{10} to G_{13}). The whole system contains five areas of which NETS and NYPS are represented by its own group of generators and the other neighbouring areas are represented by equivalent generator models (G_{14} to G_{16}). G_{13} also represents a small sub-area within NYPS.

There are three major lines between the NETS and NYPS networks (between buses 60-61, 53-54 and 27-53). All three are double circuit lines. Generators G_1 to G_8 and G_{10} to G_{12} have DC excitation systems (DC4B); G_9 has fast static excitation (ST1A), whereas the remaining generators (G_{13} to G_{16}) have manual excitation since they are equivalent generator models rather than physical area generators. This system features slightly damped inter-area and local modes. In order to damp these modes, PSS controllers of

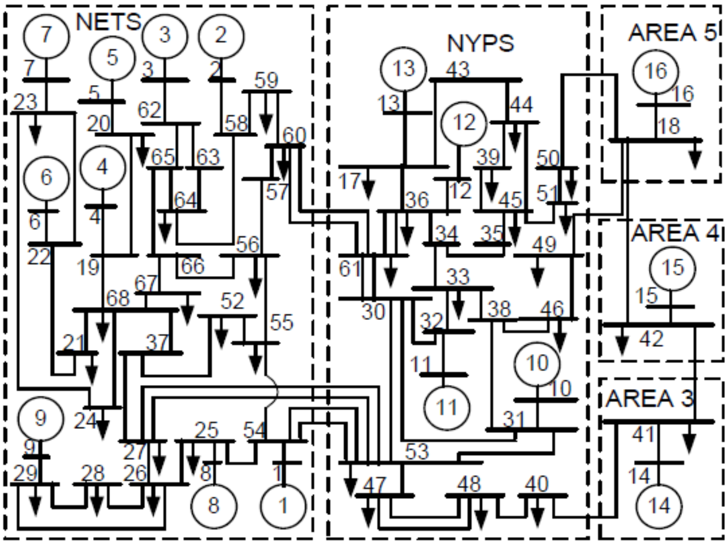

FIGURE 1. NETS/NYPS 68 buses system

the PSS1A type [16] will be used together with voltage regulators in the network shown in Figure 1.

In order to damp the oscillation modes of this system, it will be used, in conjunction with automatic voltage regulators, PSS1A type controllers [16], with the following simplified structure:

$$V_{ss} = K_{pss} \cdot \frac{sT_w}{(1 + sT_w)} \cdot \frac{sT_{11}}{(1 + sT_{12})} \cdot \frac{sT_{21}}{(1 + sT_{22})} S_m \tag{11}$$

where S_m is the rotor slip, T_w is the washout filter constant and T_{11}, T_{12}, T_{21}, and T_{22} are the lead and lag constants.

Before applying these stabilizers, it is necessary to select the generators where they will act, as well as perform the tuning of these controls so that they can damp most of the oscillation modes.

3.2. **Selection of generators.** Since only generators 1 through 12 belong to the system (the others are from neighbouring systems that are influenced by the main system, i.e., generators 13 to 16 do not correspond to actual generators but are only representative models), the generators to be controlled will be chosen among generators 1 to 12.

The procedure of selection of input and output pairs for controller application was illustrated in [15] and will use Relative Gains Array (RGA) and a combination with singular values to guarantee decentralization and more precise selection, if necessary.

Initially, an RGA matrix of the complete system is generated in steady state, considering all the inputs and outputs of all the units. From there, the input and output pairs that have the following characteristics are excluded:

- Pairs with $\lambda_{ij} < 0$;
- The output (s) with $\sum_{j=1}^{m} \lambda_{ij} << 1$;
- The pairs with large values of λ_{ij} ($\lambda_{ij} > 10$ was adopted).

The elimination of the input and output pairs that resulted in negative or very close to zero interactions in the RGA matrix led to a diagonal matrix with input and output pairs of generators 2 to 10, indicating a favourable system for decentralized control. After that, the condition number is calculated to verify that it is possible to apply the controller to the system with this arrangement. The result was $\gamma = 4.91$, i.e., less than 10, which indicates that the set of pairs of inputs and outputs is selected to be favourable for an application of the controls, according to [7].

3.3. **Tuning of the controllers.** After selecting the pairs of inputs and outputs, the decentralized controller is applied and the previously mentioned heuristic optimization methods are used to tune the parameters of the controllers. The objective is to minimize the norm using different optimization methods in order to obtain the best performance. The criteria to be analysed are the following:

- Satisfaction of the robustness criteria;
- Efficiency in damping the electromechanical modes;
- Shorter convergence time;
- Success in convergence, following the other criteria.

As already explained, the controllers must be efficient for a range of operation (robust control); therefore, a limit of unstructured uncertainties is associated to the model.

In this model, these errors are considered adopting multiplicative uncertainties reflected in the output:

$$\omega_0 = \frac{10s}{100s + 3000} \tag{12}$$

where the numerical values were obtained experimentally. From this point, the three heuristic optimization methods are applied to test which one will have better performance in the controller tuning, satisfying the pre-established robustness criterion.

4. **Setup of Heuristic Techniques for Optimization.** As previously mentioned, three heuristic techniques, GA, PSO, and SA were employed. In GA, possible solutions to the problem correspond to individuals (chromosomes) that make up a population. Each individual will be submitted to genetic operators, such as selection, recombination (crossover) and mutation. The most common chromosome representation used is binary, that is, each solution is presented by a set of bit sequences (the genes). In the PSO algorithm, each candidate solution (called a particle) will be associated with a velocity, which in turn is adjusted through an update equation that takes account of the experience of the particle to which it is associated and the experience of the other particles of the population. It is as if the particle possessed a "memory" containing its best previous position (p_{best}), while the population has a kind of "collective memory", with the best position already reached by the group (g_{best}). The inertia factor, ω, allows to expand the exploration diversity of the search space. Higher values facilitate global search (exploration) in new regions, while smaller values favour local search (intensification) in a more promising region. In addition, there are the cognitive parameter, c_1, and the social parameter, c_2, which represent the acceleration with which the particles are taken to p_{best} and g_{best} values. At each iteration, there is an increase in the velocity of each particle (rate of variation of position), in all dimensions, causing a gradual evolution towards better historical values. SA is a method used to simulate the evolution of a solid in a boiler, towards the thermal equilibrium, in a sequence of decreasing temperatures. Each thermal level represents the solutions in the search space, where the energy of each state is the value of the objective function.

In order to apply the optimization methods, two criteria were used: find an optimum point that meets the robustness criteria and ensure that all eigenvalues are in the left half-plane. In all cases, identical controllers have been tuned for all selected generators, except generator 9, because it has a different mode of operation from the others. The search interval for these parameters was also limited by practical reasons, such as T_w (washout constant), which search space was restricted to the range of 10 to 20, which are the typical values when inter-area modes are present, such as in the system in question

[17]. Besides, minimum and maximum limits were set for the PSS output signal, which corresponds to -0.05 V_{ss} and 0.2 V_{ss}, respectively, following the recommendation given in [18]. The other parameters were limited so that no larger time constants or gains are generated.

For the application of GAs, an initial population of 20 individuals was defined, with a stopping criterion fixed in 200 generations. In the case of PSO, the values of the parameters were as follows: $c_1 = c_2 = 2$, since literature recommends that $c_1 + c_2 \leq 4$ should be considered in order to maintain a balance between the global and local search capability of the algorithm. For ω, the value of 0.3 was obtained through tests with the algorithm. It was also empirically determined the maximum particle velocity, 4, and the number of interactions and agents, 60 and 20, respectively. Finally, for SA, no restriction was determined beyond the search space limits. The only restriction is the simulation time that should not exceed 3 hours until convergence; otherwise the simulation is halted.

5. **Results and Comparative Analysis.** The comparative analysis between the three methods considered if it was possible to reach robustness, if there was damping of the modes, and how long it took for each method to tune the controller. Starting from a random population of solutions (or solution, in the case of simulated annealing), within the pre-established limits, 50 initial simulations were made for each method, in order to select the best result of each. This methodology was chosen so that there would be minimal intervention in the tuning process and methods such as GA and PSO do not depend exclusively on the initial population to reach good results. However, the best results of each method were used to make the comparison fairer. Among the third-order PSSs obtained by each method, the ones that presented the best performance are listed in Table 1.

Table 1. Controller parameters tuned by different heuristics

Method	Generator	K_{pss}	T_w	T_{11}	T_{12}	T_{21}	T_{22}
PSO	G9	10	10	0.0001	0.0001	5	0.0001
	Others	10	10	2.1687	0.0001	0.0001	0.0001
GA	G9	20.52	13.9	0.9870	0.3960	0.6236	0.2811
	Others	15.88	14.71	0.9742	2.3558	1.5945	0.0058
SA	G9	10.04	10.11	1.250	1.036	0.584	0.090
	Others	10.17	10.77	0.924	1.021	1.263	0.051

By using all of these controllers, it is possible to damp the oscillation modes, as shown by the singular values in Figure 2.

The peaks of the singular values correspond to the slightly damped oscillation modes. The three methods reached robustness. However, the performance of the genetic algorithm was slightly better, even providing more damping to the existing modes. It is possible to observe this performance from the pole map generated by each of the methods, as shown in Figures 3 to 5. The system with the controller tuned with GA has fewer eigenvalues near the limit corresponding to a damping less than 0.05, compared to the other two methods.

As far as complying with the H_∞ norm, all three methods were able to satisfy this condition. Figure 6 shows the maximum singular value in relation to the limit given by $\frac{1}{\omega_0} \cdot \frac{1}{\bar{\sigma}(\boldsymbol{H})}$ (dashed line).

Finally, the time that each method took to converge to the optimal point was determined. On average, the GA needed 02h:10min to converge, the mean PSO time was

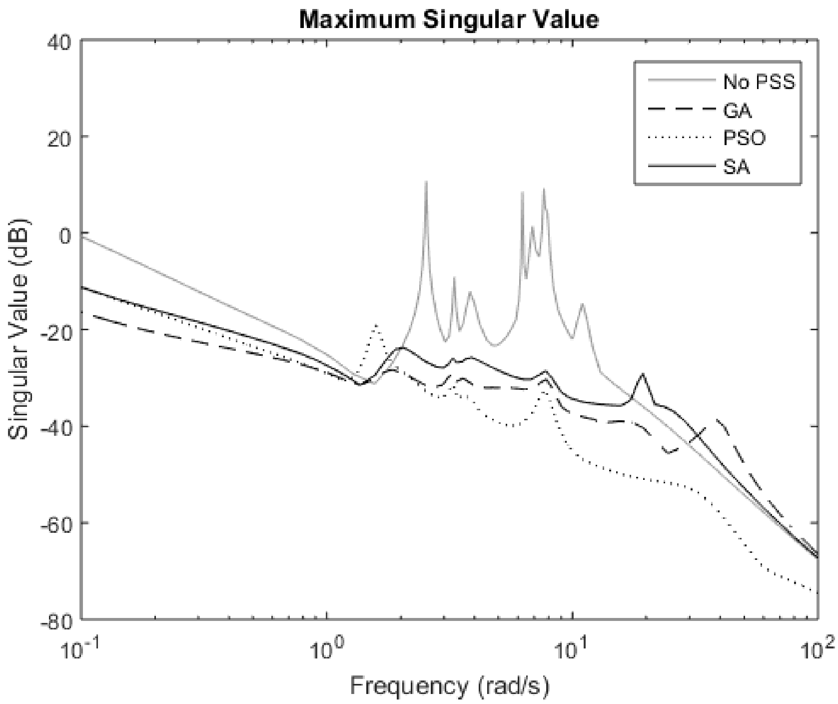

FIGURE 2. Maximum singular values of the system with controllers tuned by the 3 methods

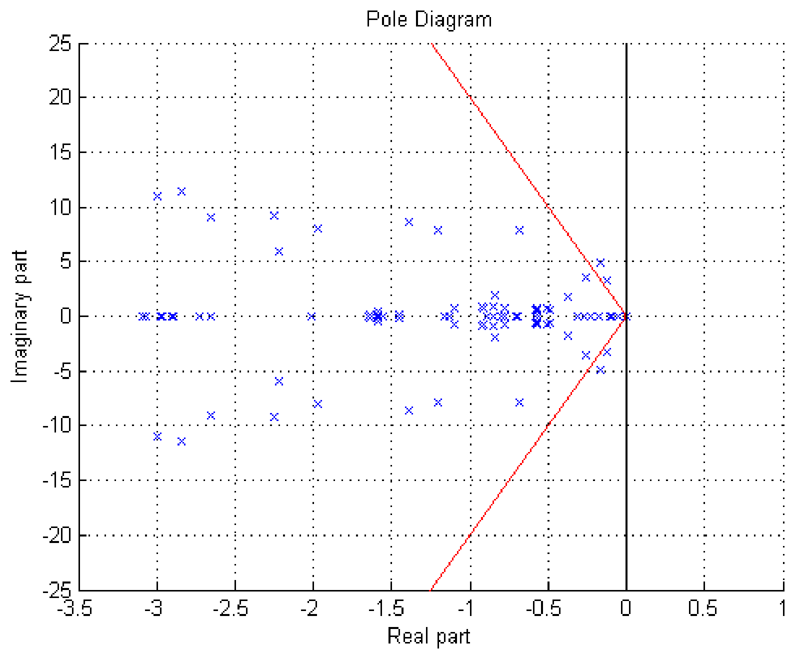

FIGURE 3. System poles diagram with GA-tuned controller

02h:23min, while for SA the convergence time was 01h:50min. All simulations were performed using MATLAB© 2012b software, on a computer with I3 Core processor, RAM memory of 4GB, and under Windows 7 operating system. Although it was faster, the SA method presented a tendency to reaching local minima, not resulting in a robust controller in some of the simulations.

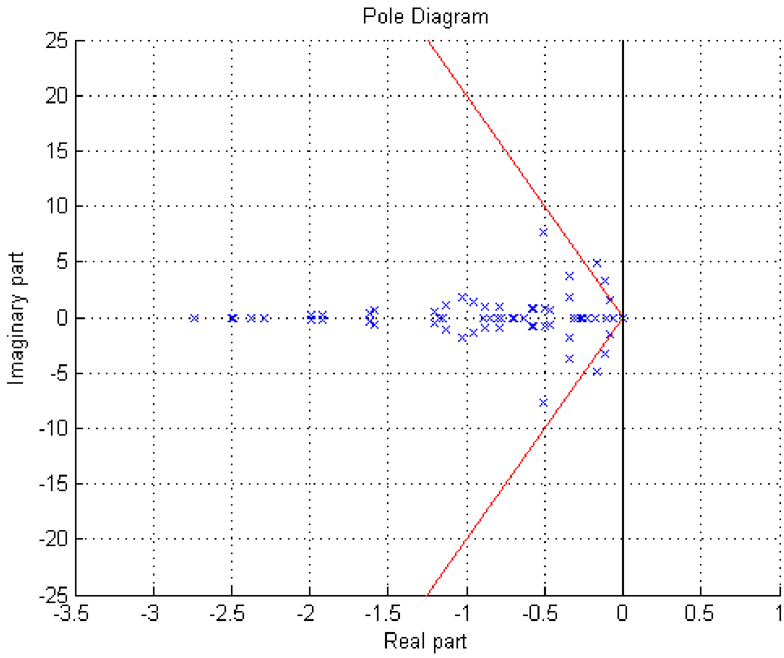

FIGURE 4. System poles diagram with PSO-tuned controller

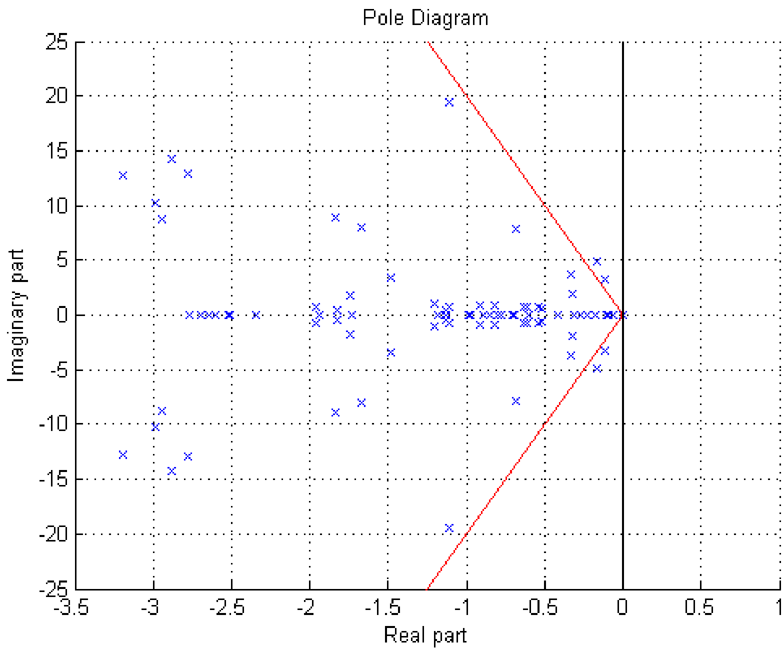

FIGURE 5. System poles diagram with SA-tuned controller

6. **Concluding Remarks.** The main objective of this work was to compare possible heuristic optimization methods for the tuning of power system controllers using the same criteria, in order to identify which one achieves the best performance. However, for that, applications of modal analysis methods, as RGA and singular values, were previously necessary to design and allocate the controllers. The controller project was based on the H_∞ robust criteria.

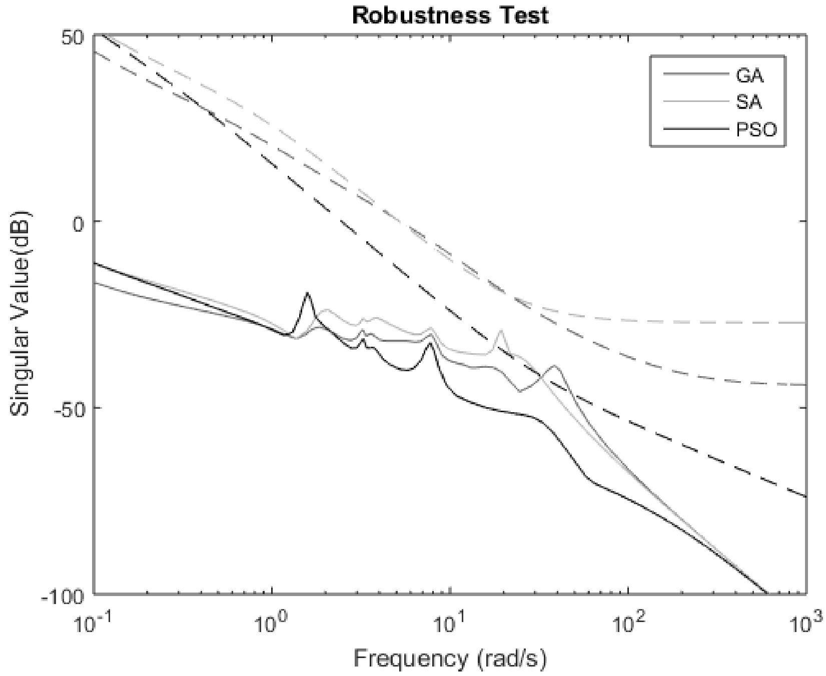

FIGURE 6. Robustness criterion checking for the three used heuristics

After more than fifty years of studies on PSS, the most commonly used ranges of values to tune their parameters are known, but the particularities of each system cannot be disregarded. Although more complex, computational techniques are still the most accurate methods to tune controllers when one has a good amount of system information, as is the case of the New England/New York system. With this data, the greatest difficulty would be how to tune in quickly and define where the application of the controllers would be most appropriate. Therefore, the set of modal techniques for selection of generators associated with evolutionary optimization methods, has the purpose of tuning these controllers so that they are robust. In this work, three of these methods were tested, since they have already been used in other power system applications. The three methods were capable of achieving robustness, however the GA had a better overall performance, even damping the existing oscillation modes. Apparently PSO-tuned controllers have damped the modes more effectively, although the peak of their maximum singular values at a frequency close to the range of the inter-area modes shows that it is very inefficient for these modes.

Despite being faster, the SA method showed a tendency to converge to local minima, therefore not meeting the criterion of robustness. There were situations where it did not converge even after many hours of simulation. Among the three methods, it was the only one that did not converge to an optimum point at all times, reaching robustness in only about 60% of the attempts. In addition, the SA method led to the worst performance regarding the purpose of damping the modes.

Considering all the parameters and tests analyzed, the GA technique presented an overall better performance, with more consistent results.

For future work, the authors plan to improve the solution methods adopted in this work especially with the purpose of making the process of tuning the parameters of the controllers faster. This may probably be reached by moving from the MATLAB© platform to a programming language that allows a faster execution. Another suggestion for future work is the use of other heuristic methods, such as the bat algorithm, for instance, or the employment of other attributes of the methods used in this work, such as elitism in GA. Another trend for future work is the use of hybrid methods, where aspects of different well-established heuristic methods are combined.

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