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Dynamic genetic algorithms for robust design of multimachine power system stabilizers

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ABSTRACT

Genetic Algorithms (GAs) are the most popular used methods of the evolutionary algorithm family. GA effectiveness highly depends on the choice of the search space range for each parameter to be optimized. The search space being a set of potential solutions may contain the global optimum and/or other local optimums. Being often a problem-based experience, a bad choice of search spaces will result in poor solutions. In this paper, a novel optimization approach based on GAs is proposed. It consists in moving the search space range during the optimization process toward promising areas that may contain the global optimum. This dynamic search space allows the GA to diversify its population with new solutions that are not available with fixed search space. As a result, the GA optimization performance can be improved in terms of solution quality and convergence rate. The proposed approach is applied to optimal design of multimachine power system stabilizers. A 16-machine, 68-bus power system is considered. The obtained results are evaluated and compared with other results obtained by ordinary GAs. Eigenvalue analysis and nonlinear system simulations demonstrate the effectiveness of the proposed approach in damping the electromechanical oscillations and enhancing the system dynamic stability.

1. Introduction

The extension of interconnected power systems is continually increasing because of the constantly growth in electric power demand. At the same time, the power systems are almost operated ever closer to their transient and dynamic stability limits. With heavy power transfers, such systems exhibit inter-area modes of oscillation of low frequency (0.1–0.8 Hz). The stability of these modes has become a source of preoccupation in today's power systems. In some cases, the related oscillatory instability may lead to major system blackouts [1,2].

Due to their flexibility, easy implementation and low cost, Power System Stabilizers (PSSs) stay the most used devices to damp small signal oscillations (0.1–2 Hz) and enhance power system dynamic stability [2,3]. PSS parameter setting is commonly based on the linearization of power system model around a nominal operating point. The purpose is to provide an optimal performance at this point as well as over a wide range of operating conditions and system configurations [4,5].

The past two decades have seen an explosion of metaheuristic optimization methods. Most of these methods are inspired by nature and can be classed in two important categories that are evolutionary algorithms and swarm intelligence. Numerous algorithms based on these methods have been widely applied to the problem of multimachine PSS design.

Genetic Algorithms (GAs), the most popular evolutionary algorithms, have been used in numerous research works concerning the optimum design of PSSs [6–13]. The authors, in [6–8], developed new approaches based on GAs to optimize the PSS parameters in multimachine power systems. Wang et al. [9] used a GA based-approach, taking several oscillation modes into consideration for avoiding suboptimal damping performance in other modes. GAs are used to design fuzzy logic PSSs in [10] and neuro-fuzzy logic PSSs in [11]. A GA-based PSS design in a multimachine power system is presented in [12]; the PSS parameters are tuned via simulation experiments based on nonlinear model of the system. In [13], Non-dominated Sorting GA (NSGA-II) is employed to search the optimal tuning of PSS parameters.

Particle Swarm Optimization (PSO), a quite popular method of the swarm intelligence family, is suggested in [14–17] to design robust PSSs. An algorithm of PSO-based fuzzy logic PSSs is proposed in [18] to damp the multimachine power system oscillations. In [19], the authors developed three PSO algorithms based PSSs for an interconnected power system composed of three stand alone-power systems. Hussein et al. [20] introduced a PSO based-indirect adaptive fuzzy PSS to damp inter-area modes of oscillation following disturbances in power systems. In [21] a hybrid optimization technique is presented for optimum tuning of PSS parameters in a multimachine power system. The hybrid technique is derived from PSO by adding the passive congregation model. A Modified

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PSO algorithm (MPSO) is proposed in [22] for optimal placement and tuning of PSSs in power systems. The MPSO integrated the PSO with passive congregation (to decrease the possibility of a failed attempt at detection or a meaningless search) and the chaotic sequence (to improve the global searching capability).

A Bacteria Foraging Algorithm (BFA) based optimal neuro-fuzzy scheme is developed in [23] to design intelligent adaptive PSSs for improving the dynamic and transient stability performances of multimachine power systems. In [24], a modified algorithm of BFA, named Smart Bacteria Foraging Algorithm (SBFA), is presented for optimal tuning of PSSs.

In [25], an Artificial Bee Colony (ABC) algorithm is employed for better stability of the power system, while an ABC algorithm based rule generation method is proposed in [26] for automated fuzzy PSS design to improve power system stability and reduce the design effort.

A Differential Evolution (DE) algorithm is applied in [27] to solve the problem of PSS coordination design based on the nonlinear time-domain simulation. A new hybrid DE algorithm, called gradual self-tuning hybrid DE, is developed in [28] for rapid and efficient searching of an optimal set of PSS parameters. A DE algorithm is employed in [29] to tune multiband PSSs in a portion of the high voltage Mexican power grid.

A novel method of PSS design using the multiobjective optimization approach named Strength Pareto Evolutionary Algorithm (SPEA) is introduced in [30].

The Harmony Search (HS), one of modern heuristic optimization algorithms, is employed in [31] for optimal parameter tuning of PSSs in multimachine power systems.

GAs are powerful global optimization methods. Their fundamental concept is based on natural selection in the evolution process, which is completed by two genetic operations (crossover and mutation) [32]. Independent of the problem complexity, the only GA requirements are to specify an appropriate objective function and to place finite bounds on the parameters to be optimized.

Several approaches are reported in the literature to improve GA performance in searching for the global optimum, such as self-adaptive GA operators, self-adaptive GA population size, parallel GAs, and others [33–43].

In [33], a Self-Adaptive Migration Model GA (SAMGA) is proposed, where the population size, the number of points of crossover and the mutation rate are adaptively determined over each generation. Further, the migration of individuals between populations is decided dynamically. A Self-Organizing GA (SOGA) is investigated in [34]. In this algorithm, a new dominant selection operator is introduced that enhances the action of the dominant individuals, along with a new cyclical mutation operator that periodically varies the mutation rate during the optimization processes. In [35], a second selection step after reproduction is proposed. This self-adaptive selection mechanism, referred to as offspring selection, is closely related to the general selection model of population genetics. In [36], new variants of the uniform crossover operator that adaptively introduce selective pressure on the recombination stage are proposed, while a new variant of adaptive population sizing is discussed in [37] that depends on the actual ease or difficulty of the algorithm to generate new child chromosomes that outperform their parents. The authors discussed in [38] the problem of the self-adaptive GA parameters. The control of GA parameters is encoded within the chromosome of each individual. The values of the control parameters are thus entirely dependent on the evolution mechanism and on the problem context. In [39], a novel GA, entitled Self-adaptive GA (SaGA), is proposed. During the optimization process, the whole populations are classified into subgroups. Self-adaptive mechanism updates the subgroups and adjusts the control parameters to assure an optimal balance between exploration and exploitation. In [40], an adaptive algorithm that can adjust the control parameters of GAs according to the observed performance is investigated. The parameter adaptation occurs in parallel to the running of the GA. An Efficient Parallel GA (EPGA) is presented in [41] for the problem of large-scale optimal power flow. The length of the original chromosome is successively reduced based on the decomposition level and adapted with the topology of the new partition. An Improved Dynamic GA (IDGA) is presented in [42]. During the evolution process, the crucial parameters, including mutation and crossover rates, are dynamically adjusted in order to get the optimal global solution. Togan et al. discussed [43] two new self-adaptive member grouping strategies (to reduce the size of the optimization problem), and a new strategy to set the initial population (to reduce the number of search to reach the optimum design in the solution space).

Good results may be obtained by these kinds of optimization approaches. However, if the sought global optimum is being outside the proposed search space of the problem, none of these approaches can thus allow the GA to find this optimum. Other optimization approaches based on the idea of dynamically reducing the search space size, like dynamic search-space reduction strategy [44–49], are also proposed in the literature. These approaches can be only interesting in local optimum search.

The high dependence of GA performance on the choice of the problem's search space range makes the optimization more difficult, in particular when the parameters to be optimized are numerous and different in nature. Furthermore, if the search space size is too small, it is evident that the GA will converge to a local optimum, unless the sought global optimum is already being in this search space. On the other hand, if the search space size is too large, the optimization tends to be easily got trapped in a local optimum. To resolve this problem, we propose an approach consisting in moving the search space range over the GA generations toward new areas, but only when it is necessary. Consequently, the GA can diversify its population with new solutions that are not available in the case of fixed search space. Thus, these dynamic search spaces can significantly improve the GA performance in terms of solution quality and convergence rate.

The proposed approach is applied to optimal design of multimachine PSSs. The power system considered is the 16-machine, 68-bus New England/New York interconnected system [50]. Eigenvalue analysis and nonlinear system simulations are carried out to assess the effectiveness of the optimized PSSs to damp the electromechanical modes of oscillations and enhance the system dynamic stability. The performance of the proposed approach is also compared to that of ordinary GAs reported in the literature.

2. Problem statement

2.1. Power system model and PSS structure

A power system can be modeled by a set of nonlinear differential–algebraic equations. In damping control design, small-signal model obtained by linearizing the system around an operation point is commonly used [51]. For a power system with n machines and N_{PSS} stabilizers, the state equation of the linearized system model can be expressed as:

$$\Delta\dot{X} = A \cdot \Delta X + B \cdot \Delta U \tag{1}$$

where X is the vector of the system state variables, A is system state space matrix, B is system input matrix, U is the vector of the PSS output signals.

The well-known Heffron–Phillips linearized model, a commonly used model in damping control design, is employed to represent the multimachine power system. The small-perturbation transfer function bloc-diagram of the ith machine is given in Fig. 1. In this

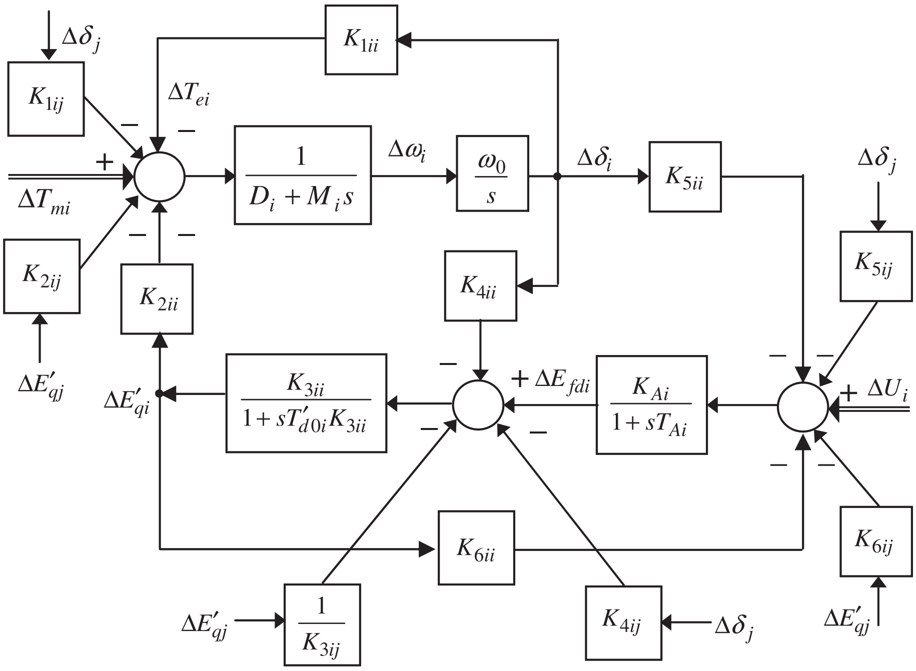

Fig. 1. Heffron–Phillips block diagram of multimachine power system.

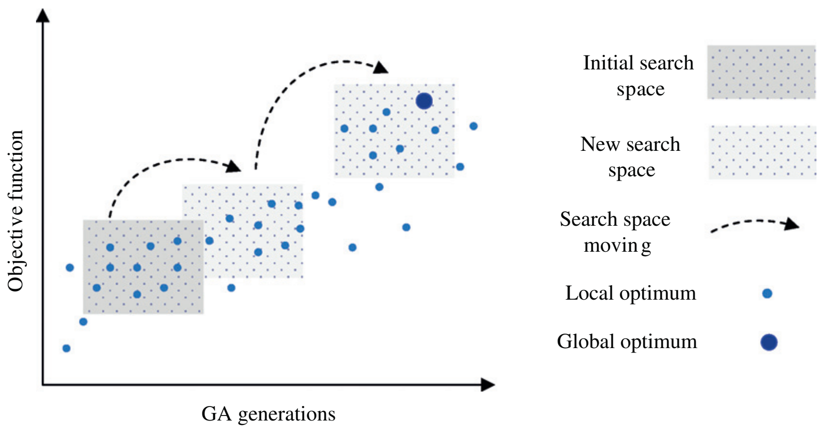

Fig. 2. Dynamic GA schematic.

configuration, the third-order model is employed to represent the system synchronous machines [52], and so:

$$\Delta X = [\Delta\delta_i, \Delta\omega_i, \Delta E'_{qi}, \Delta E_{fdi}]^T \tag{2}$$

The equations of the system linear model are the following:

$$\Delta\dot{\omega}_i = \frac{1}{M_i}\left(-D_i\Delta\omega_i - \sum_{j=1}^{n}(K_{1ij}\Delta\delta_j) - \sum_{j=1}^{n}(K_{2ij}\Delta E'_{qj})\right) + \frac{1}{M_i}\Delta T_{mi} \tag{3}$$

$$\Delta\dot{\delta}_i = \omega_0\Delta\omega_i \tag{4}$$

$$\Delta\dot{E}'_{qi} = \frac{1}{T'_{doi}}\left(-\sum_{j=1}^{n}(K_{4ij}\Delta\delta_j) - \sum_{j=1}^{n}\left(\frac{1}{K_{3ij}}\Delta E'_{qj}\right) + \Delta E_{fdi}\right) \tag{5}$$

$$\Delta\dot{E}_{fdi} = \frac{1}{T_{ai}}\left(-K_{ai}\sum_{j=1}^{n}(K_{5ij}\Delta\delta_j) - K_{ai}\sum_{j=1}^{n}(K_{6ij}\Delta E'_{qj}) - \Delta E_{fdi}\right) + \frac{K_{ai}}{T_{ai}}\Delta U_i \tag{6}$$

where for the ith machine, δ_i and ω_i are the rotor angle and speed respectively; E'_{qi} is the internal voltage behind the d-axis transient reactance; E_{fdi} is the equivalent excitation voltage; M_i and D_i are the machine inertia coefficient and damping coefficient respectively; ω_0 is the synchronous speed; T'_{doi} is the d-axis open-circuit transient time constant; T_{mi} is the mechanical torque; K_{ai} and T_{ai} are the automatic voltage regulator gain and time constant respectively; U_i is the PSS output signal at the machine; K_{1ij}–K_{6ij} are the linearization constants.

The fast-acting high-gain excitation systems used to improve the transient stability limit of synchronous machines lead at the same time to degradation in the system damping. This conflicting performance of the excitation control loop was resolved by introducing a component of supplementary damping torque proportional to the machine rotor speed deviations. PSS is one of the most cost-effective systems to produce the aimed stabilizing signals. A widely used conventional lead–lag PSS is considered in this study [52]. For the ith PSS in a multimachine power system, the transfer function, as given in (7), consists of an amplification block with a control gain K_i, a washout block with a time constant T_{wi}, and two lead–lag blocks for phase compensation with time constants T_{1i}, T_{2i}, T_{3i}, and T_{4i}:

$$V_{PSSi}(s) = K_i \cdot \frac{sT_{wi}}{1+sT_{wi}} \cdot \left[\frac{(1+sT_{1i})}{(1+sT_{2i})} \cdot \frac{(1+sT_{3i})}{(1+sT_{4i})}\right] \cdot \Delta\omega_i(s) \tag{7}$$

The PSS output signal V_{PSSi} is a voltage added to the generator exciter input. The generator speed deviation $\Delta\omega_i$ is typically used as the PSS input signal. The time constants T_{wi}, T_{2i}, and T_{4i} are usually predetermined [53]. However, the stabilizer gain K_i and time constants T_{1i} and T_{3i} still remain to be optimized.

2.2. Objective function

To ensure a well damping system over a wide range of operating conditions and system configurations, a robust PSS tuning must be designed. The PSS design problem is formulated as an optimization problem with eigenvalue-based multiobjective function.

The optimization problem can be stated as:

$$\begin{aligned} &\text{maximize} \quad f(x); x \in \Re^n \\ &x_i^{\min} \leqslant x_i \leq x_i^{\max}; \ i = \{1,2,\ldots,n\} \end{aligned} \tag{8}$$

– *f(x)* is the problem's objective (or multiobjective) function. The multiobjective function employed, given in (9), is formulated to optimize a composite set of two eigenvalue-based objective functions; comprising eigenvalue real part (σ) and damping factor (ζ) of the system dominant electromechanical modes.

$$f(x) = -\max(\sigma) + \min(\zeta) \tag{9}$$

The use of this multiobjective function will shift the system modes into a *D*-shape sector in the complex *s*-plane; and thus the system damping can be furthermore improved [54]. The *D*-shape sector criteria that can guarantee a good stability operating area for a wide range of operating conditions are chosen as following: $\sigma_{cr} = -1$, $\zeta_{cr} = 10\%$.

– $x_i^{\min}$ and $x_i^{\max}$ are the search space boundaries of the x_i parameter to be optimized. In our problem, the parameters to be optimized are:

$$\begin{aligned} &K_i^{\min} \leqslant K_i \leq K_i^{\max} \\ &T_{1i}^{\min} \leqslant T_{1i} \leq T_{1i}^{\max} \\ &T_{3i}^{\min} \leqslant T_{3i} \leq T_{3i}^{\max}; \quad i = 1,2,\ldots,N_{PSS} \end{aligned} \tag{10}$$

3. Proposed approach

In effect, during the optimization running, the values of one or more parameters to be optimized may reach one of the associated search space boundaries. This may happen after many generations or even from the beginning of the optimization. However, the optimal parameter values may exist outside the proposed search space boundaries. As a result, the objective function evolution will decelerate converging to a local optimal solution. Thus, it will be interesting if the problem's search space can move over the optimization process toward the global optimum area.

The principle of our proposed approach consists in releasing the search space boundaries, during the GA running, and allowing them to attain different values depending on the optimization process needs. These dynamic search spaces can then assure an efficient and fast convergence to the global optimum, Fig. 2.

The flowchart of the proposed approach is given in Fig. 3. The GA optimization is initialized with fixed search space boundaries

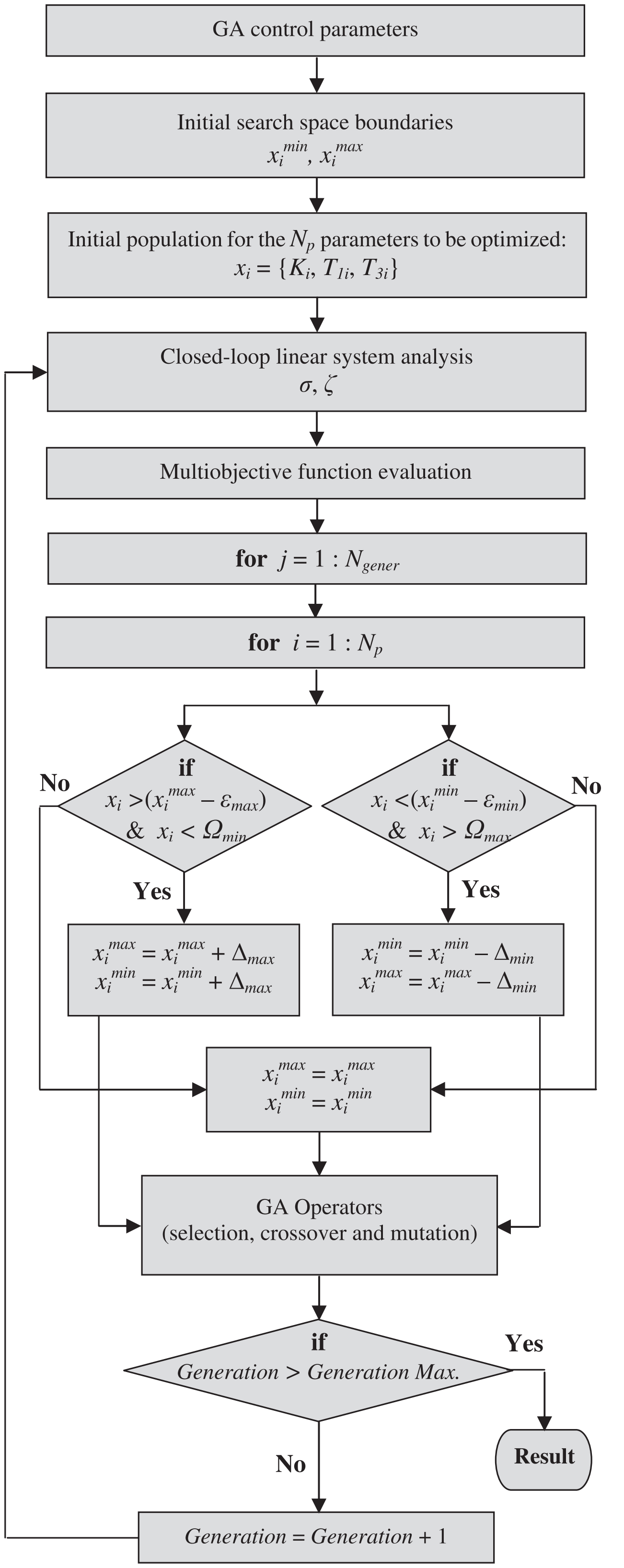

Fig. 3. Dynamic GA flowchart.

$[x_i^{\min}, x_i^{\max}]$. Tolerance margins ($\varepsilon_{\min}$, $\varepsilon_{\max}$) are set for both boundaries of search spaces. The tolerance margin can be determined as 1–5% of the associated search space size. When the value of a parameter to be optimized attains the range of the associated tol-

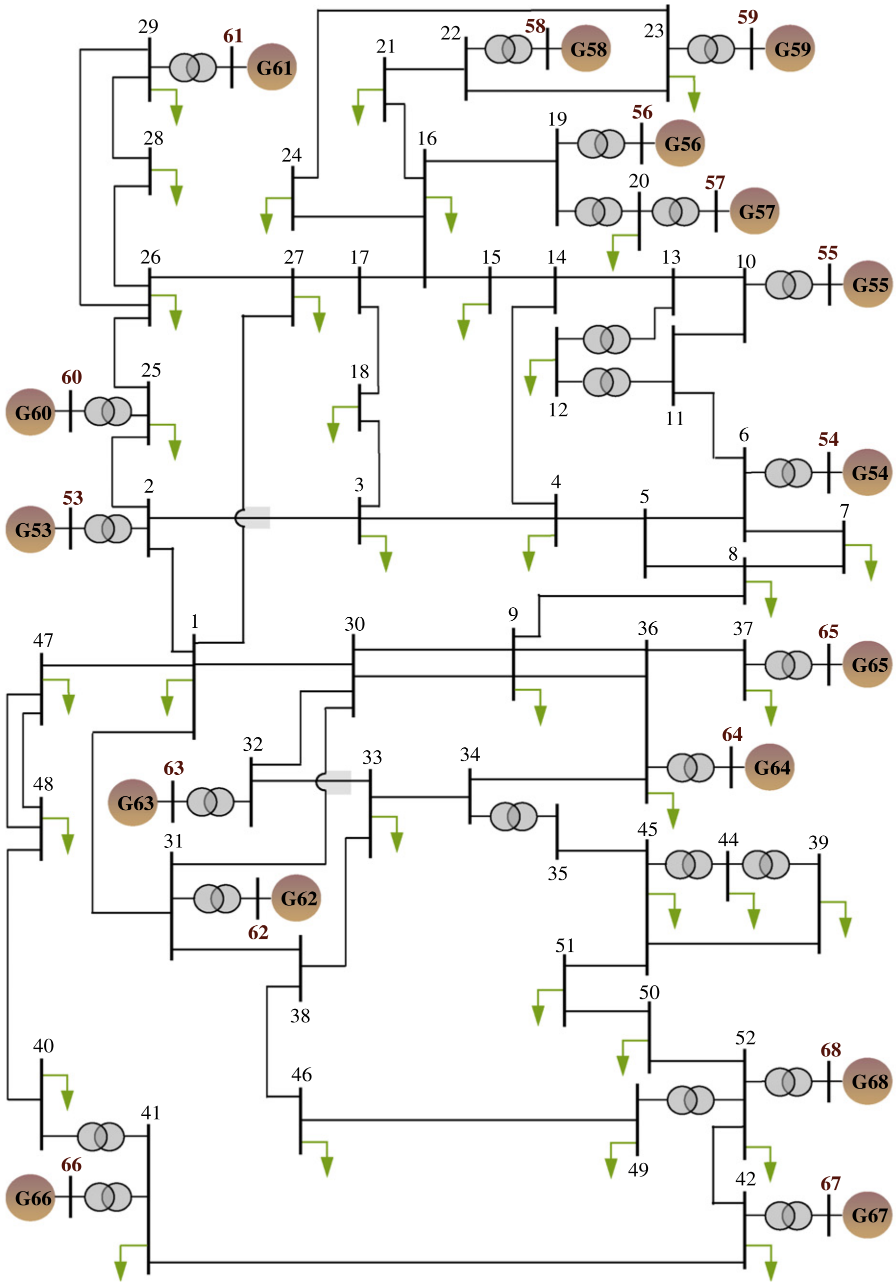

Fig. 4. A single line representation of a 16-machine 68-bus power system.

erance margin, for many consecutive generations (N_{gener}), this may mean that the optimal value may exist beyond the initial boundary. In this case, the related boundary will be modified by predetermined values (Δ_{min}, Δ_{max}) that can be determined as 1–5% of the associated search space size. As a result, the search space range can dynamically moves by always keeping its initial size. This process can be occurred several times in the course of the optimization while it is necessary. Finally, in order to keep the search space as feasible solution area, the decrease and increase of search space boundaries should be limited to minimum and maximum limits (Ω_{min}, Ω_{max}).

4. Results and discussion

To validate the effectiveness of the proposed approach, many applications on several multimachine power systems having different sizes have been performed. In this paper, the results obtained with a relatively large power system which is the New England/New York interconnected system (16-machine, 68-bus), Fig. 4, are presented. Details of the system data can be found in [50].

The obtained results of the proposed approach have been evaluated and compared to ordinary GA results [55].

4.1. System analysis without PSSs

A linear representation of the system without PSSs is formed around the studied nominal operating point. The repartition of the system dominant electromechanical modes in the complex *s*-plane is given in Fig. 5. It clearly shows that the system is unstable.

The first conventional step in PSS design is to identify the best effective generators for PSS locations. The participation factor method is widely used to find the optimum PSS locations. The application of this method demonstrates that 14 generators are

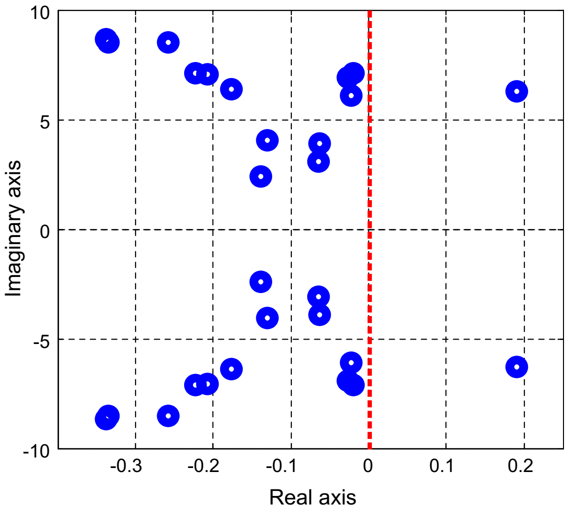

Fig. 5. System electromechanical modes without PSSs.

mainly involved in the system dominant modes and they must be equipped with PSSs.

4.2. Ordinary GA-based PSS design

The coordinated synthesis of PSS parameters is optimized using an ordinary GA with fixed search spaces, as developed in [55], case A. The GA control parameters and the fixed PSS parameters' values are given in Tables 1 and 2, respectively. The search space boundaries of the optimized 42 PSS parameters stay fix over the optimization process. They are given as following:

$$\begin{aligned} &1 \leqslant K_i \leq 40 \\ &0.01 \leqslant T_{1i} \leq 1 \\ &0.01 \leqslant T_{3i} \leq 1; \quad i = 1, 2, \ldots, N_{PSS}; \quad N_{PSS} = 14 \end{aligned} \tag{11}$$

The final values of the optimized PSS parameters are listed in Table 3.

The multiobjective function evolution as a function of generation number is shown in Fig. 6. We find that it attains at the end of optimization a value of 1.154. However, we can also notice that the convergence rate significantly decreases from the 150th generation.

Fig. 7 gives the repartition of the system dominant electromechanical modes with the optimized PSSs. We notice that almost modes are shifted in the *D*-shape sector. However, some of them remain very close to the sector limits with a maximum eigenvalue real part σ_{max} = –0.99 and a minimum damping factor ζ_{min} = 16.2%.

4.3. Dynamic GA-based PSS design

In this part of study, the proposed GA approach based on dynamic search spaces is applied. For the optimization initialization, the same search spaces used in the case of ordinary GA optimization, as given in (11) are used. The same GA control parameters and the same values of fixed PSS parameters (Tables 1 and 2,

Table 1
GA control parameters.

Population size	75
Variable number/PSS	3
Crossover probability P_c	0.9
Mutation probability P_m	0.005
Generation number	300

Table 2
Fixed PSS parameters.

T_{wi}	T_{2i}	T_{4i}
10	0.1	0.05

Table 3
Optimized PSS parameters with ordinary GA.

No. PSS	No. G	Ordinary GA-based PSS optimization		
		K	T_1	T_3
1	53	38.99	0.856	0.846
2	54	16.74	0.505	0.328
3	55	38.98	0.817	0.634
4	56	13.62	0.501	0.256
5	57	10.64	0.121	0.257
6	59	03.51	0.506	0.127
7	60	20.60	0.550	0.379
8	61	03.00	0.997	0.145
9	62	05.06	0.995	0.748
10	63	01.26	0.731	0.168
11	64	39.56	0.909	0.084
12	65	38.73	0.395	0.095
13	67	39.86	0.272	0.026
14	68	37.97	0.135	0.197

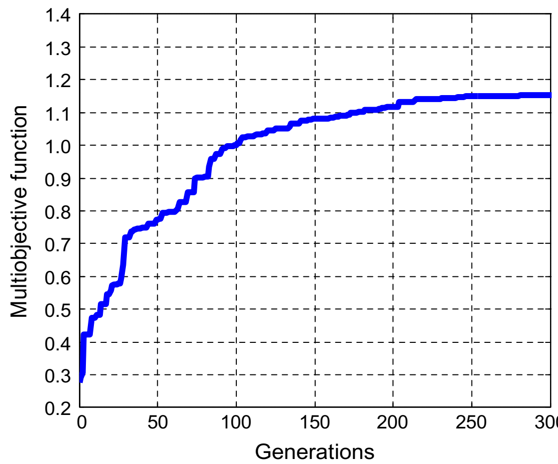

Fig. 6. Multiobjective function evolution with ordinary GA-PSSs.

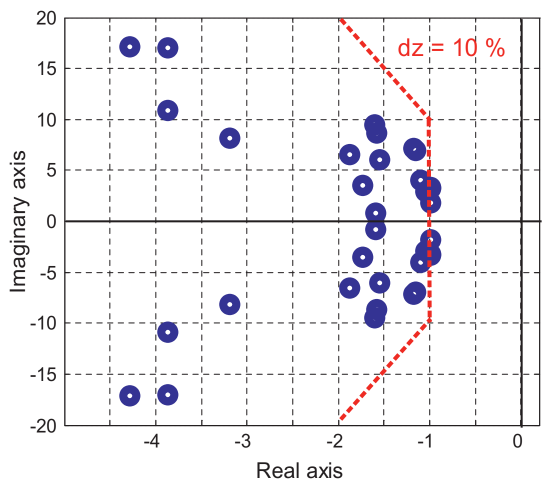

Fig. 7. System electromechanical modes with ordinary GA-PSSs.

respectively) are also used. The optimized PSS parameters' values are given in Table 4.

This application clearly shows that the expansion of some optimized parameters beyond their initial search space boundaries allows a well improving in the multiobjective function evolution, as shown in Fig. 8. In this case, we notice that the multiobjective function rapidly attains, at the 115th generation only, a value of 1.154 which is equal to the final value attained in the previous case. Then, it continues to improve attaining a value of 1.345 at the end of the optimization.

To illustrate the optimized parameters' evolution when using dynamic GA in comparison to the evolution when using ordinary GA, we present by way of an example the optimization evolution of the gain value of the 13th PSS $K_{(13)}$ (connected to the generator G.67), Fig. 9.

- On Fig. 9a, the PSS gain $K_{(13)}$ attains and remains, from the 125th generation, at values that are very close to the maximum boundary of the related search space.
- On the contrary, on Fig. 9b, the gain takes, from the 150th generation, new values that are higher than the initial maximum boundary. The final optimized value is 45.34.

This can clearly demonstrate the approach effectiveness in finding the optimal parameter values against the problem arisen when using fixed search spaces.

Table 4
Optimized PSS parameters with dynamic GA.

No. PSS	No. G	Dynamic GA with large search space-based PSS optimization		
		K	T_1	T_3
1	53	25.10	0.914	1.070
2	54	16.21	0.879	0.455
3	55	21.79	0.847	0.200
4	56	05.70	0.253	0.443
5	57	10.56	0.133	0.249
6	59	08.54	0.198	0.161
7	60	21.36	0.937	0.492
8	61	12.90	0.708	0.041
9	62	22.13	0.716	0.055
10	63	09.78	0.065	0.321
11	64	13.04	0.433	0.200
12	65	41.48	0.453	0.086
13	67	45.34	0.162	0.004
14	68	47.20	0.012	0.228

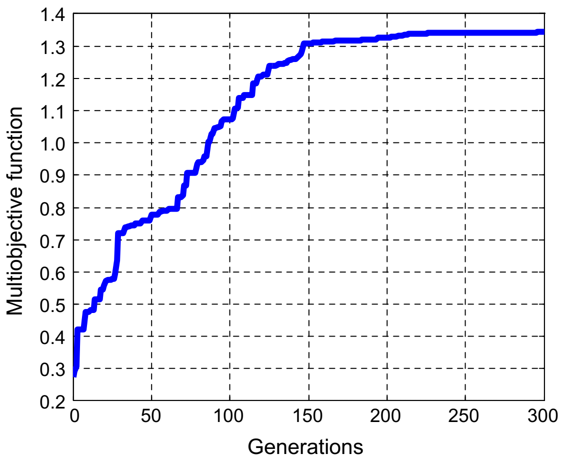

Fig. 8. Multiobjective function evolution with dynamic GA-PSSs.

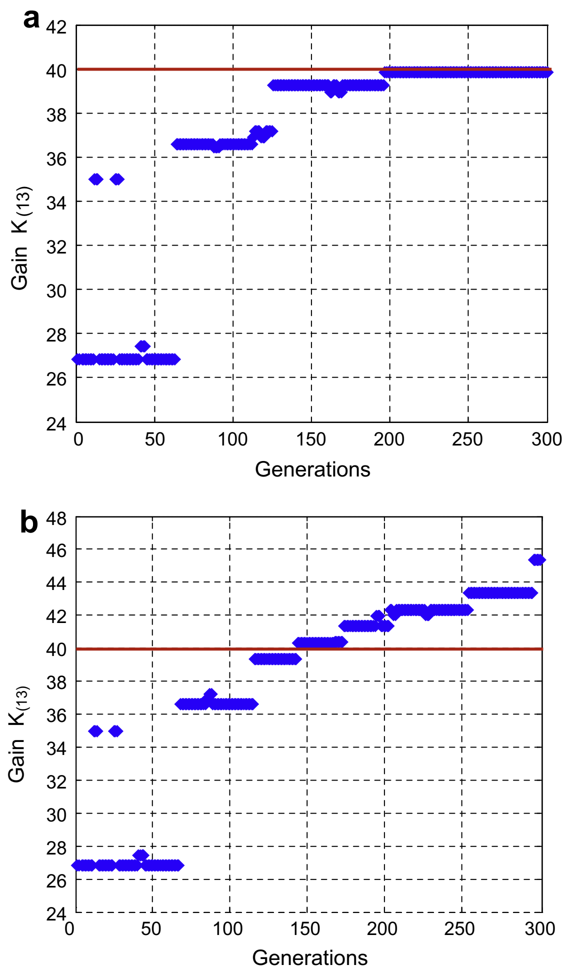

Fig. 9. Optimization evolution of the PSS parameter ($K_{(13)}$): (a) with ordinary GA-PSSs (b) with dynamic GA-PSSs.

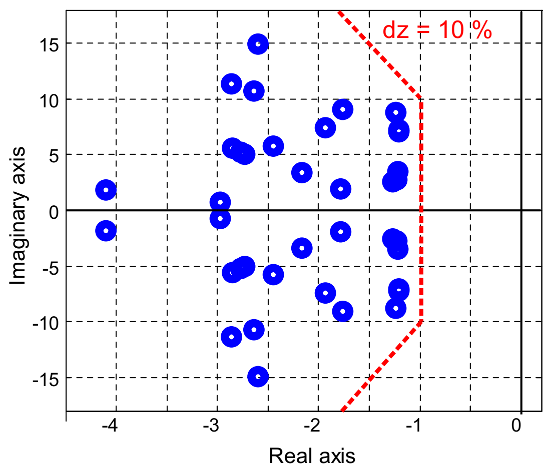

Fig. 10. System electromechanical modes with dynamic GA-PSSs.

Concerning the optimization effectiveness in enhancing the system dynamic stability, this can be confirmed by eigenvalue analysis and nonlinear system simulations.

The system damping enhancement based on eigenvalue analysis is illustrated in Fig. 10. It can be noticed that all the system modes are well shifted in the *D*-shape sector with $\sigma_{max} = -1.2$ and $\zeta_{min} = 14.48\%$.

The nonlinear time-domain simulations are carried out for a 6-cycle three-phase fault at bus 60 at the end of line 25#60, assuming also that the two lines (16#17 and 25#26) are out of service. The response of the system with PSSs tuned by dynamic GA is compared to the system response when using ordinary GA-PSSs. The rotor speed deviations of the generators G.53, G.59, G.60, G.61, and G.68, under the proposed severe scenario, are shown in Fig. 11. It can be seen that the system time-response and overshoot are well improved when using the dynamic GA optimization.

To assess the system response enhancement in nonlinear system simulations, the performance index, Integral Time Absolute Error (ITAE), is being used as:

$$ITAE = \int_0^{10} t \cdot (|\Delta\omega_1| + |\Delta\omega_2| + \cdots + |\Delta\omega_{16}|) \cdot dt \qquad (12)$$

It is worth mentioning that the lower the value of this index, the better is the system response in terms of time-domain characteristics.

Applying this index relation, we find for the dynamic GA optimization that $ITAE = 17.6$. On the other hand, the index value when using the ordinary GA optimization is $ITAE = 48.8$. Thus, it can be clearly proved the superiority of the system performance characteristics in terms of 'ITAE' index when using the dynamic GA optimization compared to the optimization based on ordinary GA.

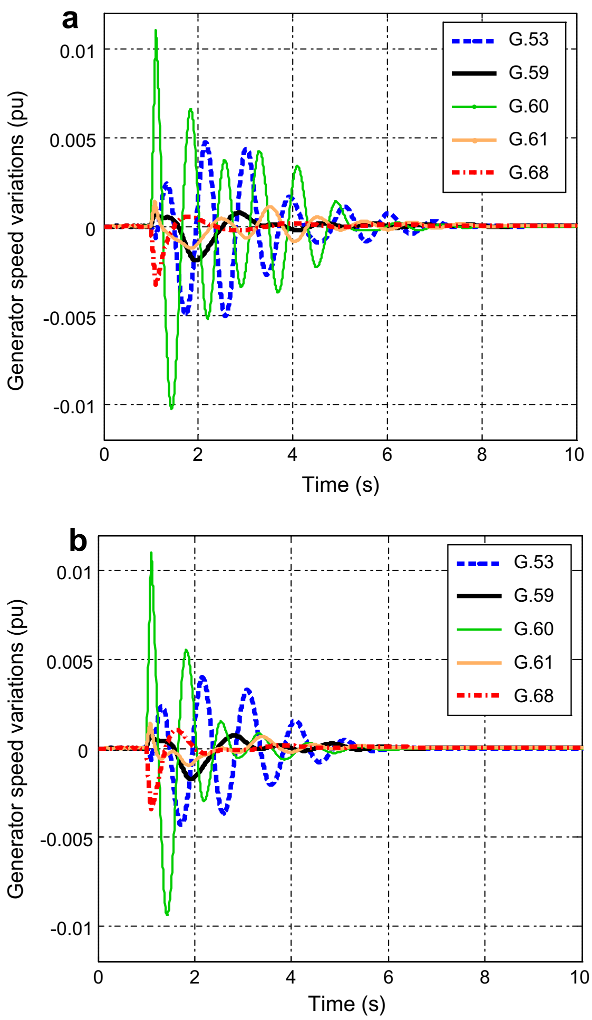

Fig. 11. Generator speed variations under severe scenario: (a) with ordinary GA-PSSs (b) with dynamic GA-PSSs.

For more demonstration of the dynamic GA robustness toward the size of the initial search space, the previous optimization is carried out with an initial small search space that is equal to the half of the search space given in (11). The GA control parameters are taken the same as in the previous case (Table 1). The optimized PSS parameters' values are given in Table 5.

The gradual moving of some parameters' search spaces constantly guides the optimization toward the global optimum area. We notice that the multiobjective function evolution, shown in Fig. 12, attains at the 180th generation a value of 1.153 which is equal to the final value in the case of ordinary GA. Then, it continues to advance and attains at the end of the optimization a value of 1.346. Thus, the principle of dynamic search space gratefully helps the optimization to be independent of the size of the problem's search space.

Table 5
Optimized PSS parameters with dynamic GA.

No. PSS	No. G	Dynamic GA with small search space-based PSS optimization		
		K	T_1	T_3
1	53	42.84	0.410	0.938
2	54	44.78	0.211	0.530
3	55	30.72	0.932	0.326
4	56	14.14	0.253	0.404
5	57	10.49	0.168	0.208
6	59	03.41	0.315	0.303
7	60	10.37	0.396	0.874
8	61	15.75	0.131	0.121
9	62	07.30	0.386	0.231
10	63	04.47	0.191	0.400
11	64	27.44	0.400	0.123
12	65	25.70	0.044	0.155
13	67	46.85	0.024	0.182
14	68	42.93	0.279	0.015

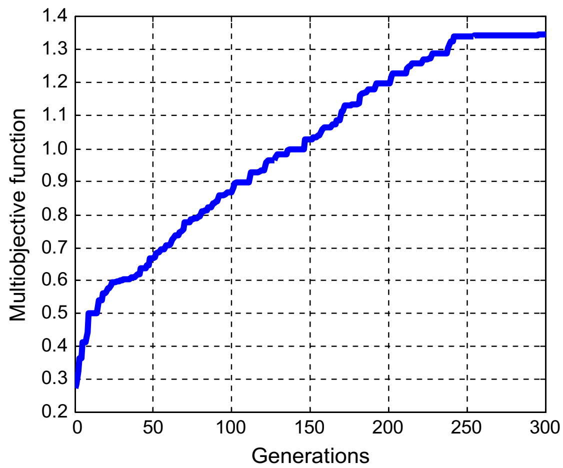

Fig. 12. Multiobjective function evolution with dynamic small search space GA.

Table 6
Result comparison.

	OGA	DLSSGA	DSSSGA
Optimization final-value	1.154	1.345	1.346
Relative optimization final-value% (compared to OGA)	–	16.5%	16.6%
Relative convergence rate% (compared to OGA)	–	62%	40%

Finally, to evaluate the optimization effectiveness, in terms of the optimal solution and convergence rate, we summarize, in Table 6, a comparison of the results obtained with:

- Ordinary GA (OGA).
- Dynamic Large Search Space GA (DLSSGA).
- Dynamic Small Search Space GA (DSSSGA).

5. Conclusion

In this paper, a new optimization approach based on dynamic search space GAs has been proposed. With ordinary GAs, the optimization performance is often restricted by the choice of the problem's search space. The sought global optimum may be located outside the chosen search space range. In this case, it is not possible to attain this optimum. In the proposed dynamic GA, we have proved that it is possible to overcome this problem by moving the search space range over the optimization process toward new areas. Consequently, it is possible to reach the global optimum regardless of the position of this optimum toward the initial search space. The approach effectiveness is validated on multimachine PSS design for enhancing power system stability. The performance of dynamic GA-PSSs design is compared to the results obtained with ordinary GA-based PSS design. It has been found that the optimization based on dynamic GA can attain better solutions even when using search spaces that are far form the global optimum position. The convergence rate is also more improved. In terms of power system stability, eigenvalue analysis has confirmed the efficiency of the proposed algorithm to provide good damping characteristics to electromechanical modes of oscillations. Nonlinear time-domain simulations have also demonstrated the robustness of the system with quick decay of system oscillations. In this way, the system dynamic stability can be well enhanced and the power transfer capability can also be extended.

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