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Power system stabilizer design using Strength Pareto multi-objective optimization approach

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ABSTRACT

Power system stabilizers (PSSs) are the most well-known and effective tools to damp power system oscillation caused by disturbances. To gain a good transient response, the design methodology of the PSS is quite important. The present paper, discusses a new method for PSS design using the multi-objective optimization approach named Strength Pareto approach. Maximizations of the damping factor and the damping ratio of power system modes are taken as the goals or two objective functions, when designing the PSS parameters. The program generates a set of optimal parameters called Pareto set corresponding to each Pareto front, which is a set of optimal results for the objective functions. This provides an excellent negotiation opportunity for the system manager, manufacturer of the PSS and customers to pick out the desired PSS from a set of optimally designed PSSs. The proposed approach is implemented and examined in the system comprising a single machine connected to an infinite bus via a transmission line. This is also done for two familiar multi-machine systems named two-area four-machine system of Kundur and ten-machine 39-bus New England system. Parameters of the Conventional Power System Stabilizer (CPSS) are optimally designed by the proposed approach. Finally, a comparison with famous GAs is given.
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1. Introduction

Ever increasing complexity of electric power systems has increased research interests in developing more suitable methodologies for power system stabilizers (PSSs). PSSs are the most effective devices for damping low frequency oscillations and increasing the stability margin of the power systems [1]. In fact, a PSS provides the excitation system with a proper supplementary signal in-phase with the rotor speed deviation resulting stable operation of the synchronous generator.

In the last two decades, various types of PSSs have been introduced. Fuzzy Logic Based PSS (FLPSS) and adaptive controller-based PSS with some capabilities have been developed in recent years [2–6]. Conventional power system stabilizers (CPSS) are one of the premiere PSSs composed by the use of some fixed lag–lead compensators. CPSSs still are widely being used in the power systems and this may be because of some difficulties behind using the new techniques.

To overcome the difficulties of PSS design, intelligent optimization based techniques have been introduced [7–15]. These techniques can be divided into two categories: time domain [7,8] and frequency domain methods. In the time domain design, generally after applying a disturbance to the power system, some of the main signals are optimized. However, disturbances at various locations may excite dominant modes with quite different specifications, leading to different PSS tuning parameters. Also this method may require heavy computational burden for big power systems' simulation. Abdel-Magid and Abido [9] and Zhang and Coonick [14] have proposed frequency domain based techniques that seem more complete than the others. Ref. [9] formulates the robust PSS design as a multi-objective optimization problem and employs GA to solve it. Improving damping factor and damping ratio of the lightly damped or un-damped electromechanical modes are two objectives. It has been shown that taking just one of the objectives into account may yield to an unsatisfactory result for another one. To overcome this, a weighted sum of the objectives has been assumed as a goal function for the optimization problem. In this method, weight assignment for damping factor and damping ratio is normally a complicated problem. Ref. [14] proposes a technique based on the method of inequalities for the coordinated synthesis of PSS parameters in multi-machine power systems to enhance overall system small signal stability. This paper presents a list of objectives and applies GA to optimize them.

In the present paper, the PSS design scenario is treated as a multi-objective optimization task, where improving the damping factor and damping ratio of the oscillatory modes of the system are two individual objectives. The Strength Pareto, an evolutionary multi-objective optimization approach, is employed to solve the

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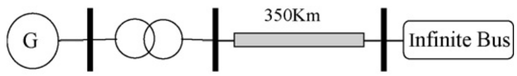

Fig. 1. Single line diagram of SMIB system.

problem. A set of values of one optimum designed PSS parameters is called a Pareto optimal set. Each Pareto set can be chosen as a favorite set of design parameters by the power system designers according to their own particular technical issues and contemplations. This method except proper descriptions of the existing constraints does not require any further interfering like that of weight assignment in the optimization problem.

This paper is constructed as follows: in Section 2, three familiar power systems are given. The first system is a single-machine connected to an infinite bus which the parameters have been given in the previous articles [16]. The second one is the Kundur's two-area four-machine system [17] and the other is ten-machine 39-bus New England system [18]. A common PSS structure named CPSS is employed in each power system. The Strength Pareto approach and related concepts are explained in Section 3. This method is applied for optimally tuning of the abovementioned PSSs structure of three different power systems. The capabilities of the new method are shown in abovementioned systems by comparing the simulation results with the results obtained by the GA technique. Simulation results are illustrated in Section 4. The Pareto fronts provide valuable information about the relationship between the two objectives' indexes. In the end, Section 5 concludes the paper.

2. Power systems and modeling

2.1. Single-machine infinite-bus system

The first aim of any PSS installation is the local mode [19], so the single-machine infinite-bus (SMIB) model of a power system for evaluating the proposed designing method is considered. In SMIB model, a typical 500 MVA, 13.8 kV, 50 Hz synchronous generator is connected to an infinite bus through a 500 MVA, 13.8/400 kV transformer and 400 kV, 350 km transmission line [16]. The system is shown in Fig. 1 and the mathematical model of each element is given individually in Ref. [16].

2.2. Two-area four-machine system

PSS design for a multi-machine system with a strong inter-area mode is of interest for power system researchers. First multi-machine system studied in this paper is the Kundur's Two-Area Four-Machine (TAFM) system consisting of two fully symmetrical areas linked together by two 220 km, 230 kV transmission lines [17]. This power system typically is used to study the low frequency

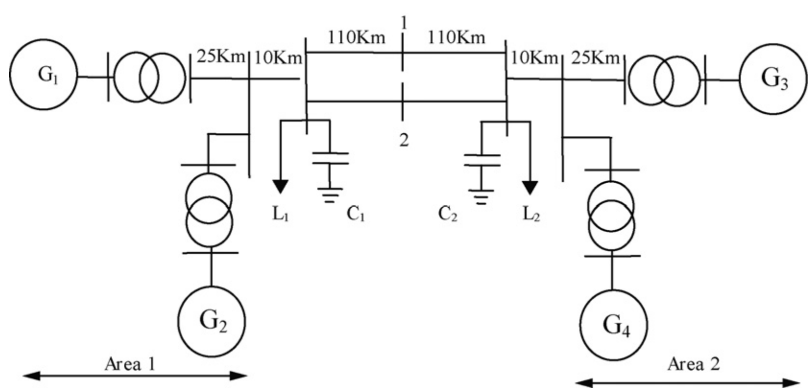

Fig. 2. TAFM system.

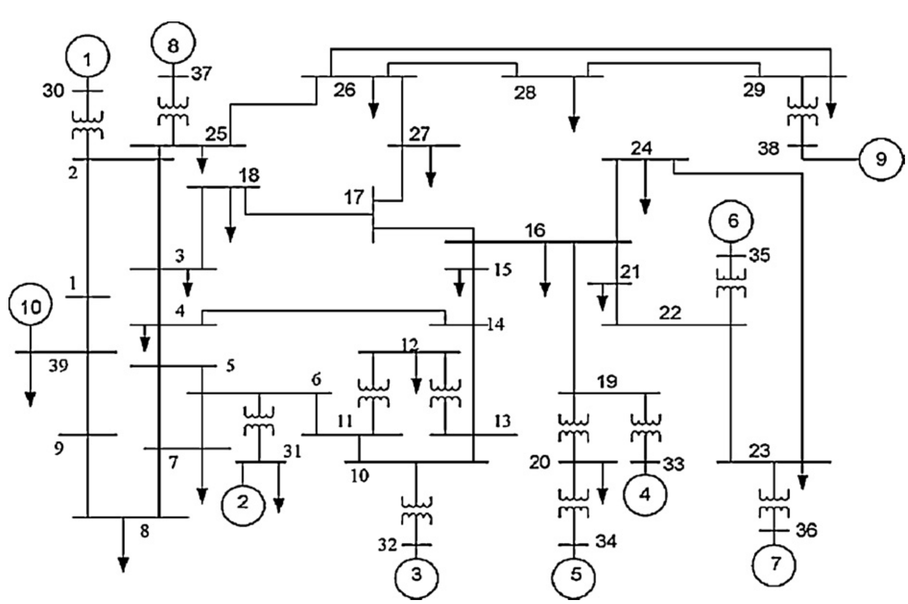

Fig. 3. New England test system.

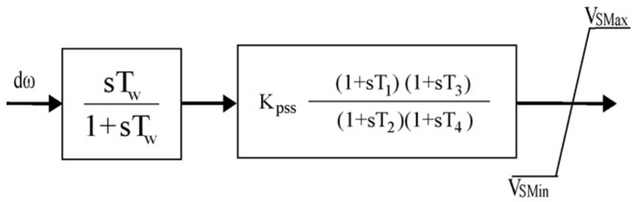

Fig. 4. Power system stabilizer.

electromechanical oscillations of a large interconnected system. The system is shown in Fig. 2 and its data are available for anyone in Matlab software's demo.

2.3. Ten-machine 39-bus New England system

New England power system with 10 machines and 39 buses as shown in Fig. 3 is the last PSS design methodology test system considered in this paper. All generators except G_{10} are equipped with CPSS. This system is modeled using Power System Toolbox 3 (PST). The system data can be found in [18].

2.4. Power system stabilizer

Fig. 4 illustrates model of the CPSS. The CPSS consists of two phase-lead compensation blocks, a signal washout block, and a gain block. Value of the parameter T_w of washout block is commonly chosen ten [17] while six other constant coefficients of the model (i.e., T_1, T_2, T_3, T_4, V_{Smax} and K_{PSS}) have to be designed optimally. The upper and lower limits of the limiter are assumed to be the same.

3. Multi-objective optimization

3.1. Main concepts

One way of handling a multi-objective or vector objective problem is to combine the goals of the optimization problem and to construct a scalar function and then to use a common scalar optimization approach to solve the problem. The major dilemma of this methodology is unavailability of any straightforward method for combining the objectives or goals of the problem while they vary constantly.

Generally, a multi-objective optimization problem can be represented as:

$$\text{Min/max}: \quad y = f(x) = f_1(x), \ldots, f_i(x), \ldots, f_k(x). \tag{1}$$

Subjected to:

$$x = (x_1, x_2, \ldots, x_n) \in X \quad \& \quad y = (y_1, y_2, \ldots, y_k) \in Y$$

where x is the decision vector, X is the parameter space, y is the objective vector and Y is the objective space.

Game theory concept is applicable for a multi-objective optimization problem in its own original status needless to any modifications or combinations of the objectives, but of course it requires an evolutionary method to reach globally optimum results [20–24]. Some advanced evolutionary methods are as [24]:

Niched Pareto Genetic Algorithm (NPGA).
Hajela's and Lin's Genetic Algorithm (HLGA).
Vector Evaluated Genetic Algorithm (VEGA).
Non-dominated Sorting Genetic Algorithm (NSGA).
Strength Pareto Evolutionary Algorithms (SPEA).

One of the most successful multi-objective optimization approaches is the SPEA [24] which is based on Pareto optimality concept.

Definition. Concept of Pareto optimality can be described mathematically as below:

The vector a in the search space dominates vector b if:

$$\begin{aligned} &\forall_i \in \{1, 2, \ldots, k\}: \quad f_i(a) \geq f_i(b) \\ &\exists_j \in \{1, 2, \ldots, k\}: \quad f_j(a) > f_j(b) \end{aligned} \tag{2}$$

if at least one vector dominates b, then b is considered dominated vector, otherwise it is called non-dominated. Each non-dominated solution is regarded optimal in the sense of Pareto or called Pareto optimal. Obviously, any Pareto optimal solution is comparatively the most optimal one in terms of at least one of the objective functions. The set of all non-dominated solutions is called Pareto Optimal Set (POS) and the set of the corresponding values of the objective functions is called Pareto Optimal Front (POF) or simply Pareto front.

3.2. Strength Pareto Evolutionary Algorithm (SPEA)

The SPEA which takes benefits from many features of some other approaches is used in this paper. Fig. 5 shows a flowchart of the approach which includes the following major steps [24]:

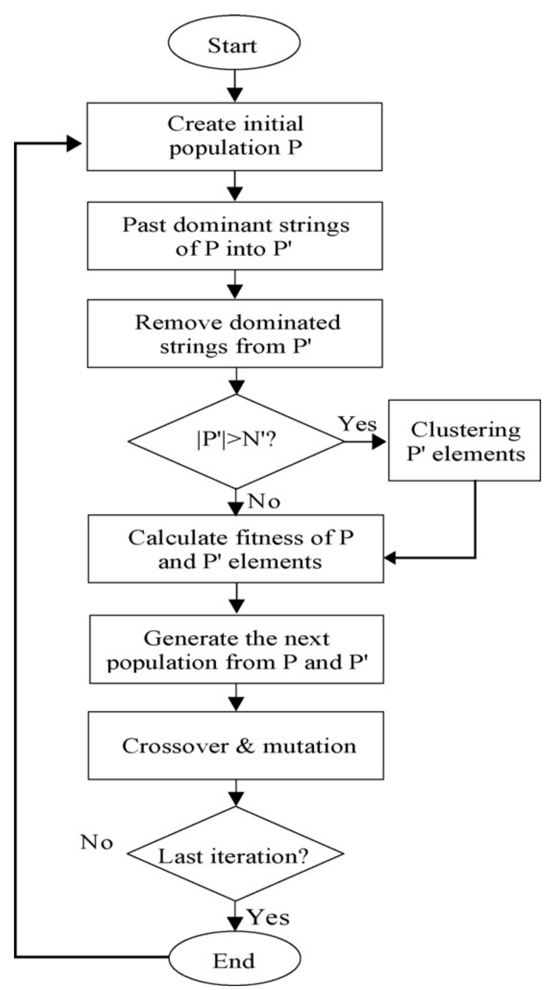

Fig. 5. Strength Pareto flowchart.

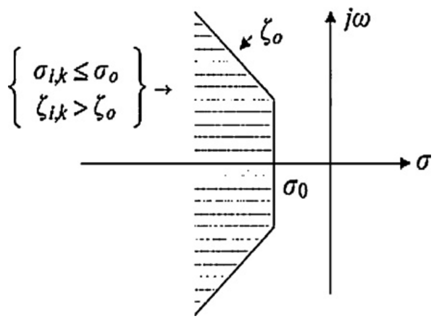

Fig. 6. Objectives' performance in [9].

Table 1
CPSS boundaries.

Parameter	T_1	T_2	T_3	T_4	V_{Smax}	K_{PSS}
Lower limit	0.01	0.01	0.01	0.01	0.05	10
Upper limit	1	1	10	10	0.5	100

3.2.1. SPEA algorithm

(1) Generate an initial population P and create the empty external non-dominated set P′.
(2) Paste non-dominated members of P into P′.
(3) Remove all solutions within P′ covered by any other members of P′.
(4) If the number of externally stored non-dominated solutions exceeds a given maximum N′, prune P′ by means of clustering.
(5) Calculate the fitness of all individuals in P and P′.
(6) Use binary tournament selection with replacement and select individuals from P and P′ until the mating pool is filled.
(7) Apply crossover and mutation operators as usual.
(8) If the maximum number of generations is reached, then stop, else go to Step 2.

Fitness evaluation is also performed in two steps. First, the individuals in the external non-dominated set P′ are ranked. Then, the individuals in the population *P* are evaluated. For more details, refer to [24].

3.3. Applying SPEA algorithm in power systems

As it said, [9,14] are two main references of CPSS design with GA. Ref. [9] minimizes

$$J = \sum_{j=1}^{n_p} \sum_{\sigma_{i,j} \ge \sigma 0} [\sigma_0 - \sigma_{i,j}]^2 + a \sum_{j=1}^{n_p} \sum_{\xi_{i,j} \le \xi_0} [\xi_0 - \xi_{i,j}]^2,$$

where n_p is the number of operating points considered in the design process, and $\sigma_{i,j}$ is the real part of the *i*th eigenvalue of the *j*th operating point. Moreover, $\xi_{i,j}$ is the damping ratio of the *i*th eigenvalue of the *j*th operating point. Fig. 6 shows this method's performance.

Ref. [14] tries to satisfy the three below inequalities:

For electro-mechanical oscillation modes:

(1) $\xi_k \ge \xi_{madr}$. Where $k = (1,2,\ldots\text{n-gen} - 1)$ and ξ_{madr} is the minimum acceptable damping ratio.

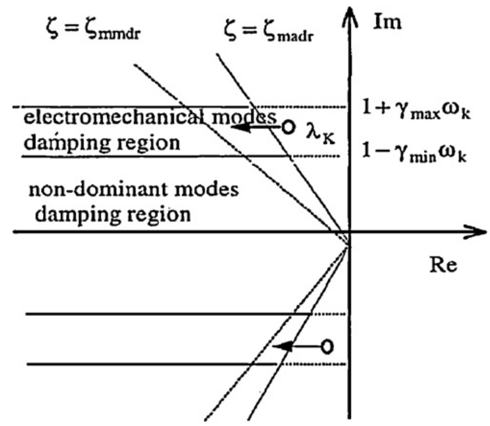

Fig. 7. Objectives' performance in [14].

Table 3
GA weights.

GA	w_1	w_2
GA_1	10	1
GA_2	1	1
GA_3	1	10

(2) $(1 - \gamma_{min})\omega_k \le \omega_k + \mathrm{Im}(\Delta\lambda_k) \le (1 + \gamma_{max})\omega_k$. Where ω_k is the frequency of *k*th mode and γ is defined according to system specifications.

For all other modes, including the original natural modes and the new modes:

(3) $\xi_i \ge \xi_{mmdr}$. While ξ_{mmdr} is minimum marginal damping ratio.

Fig. 7 explains the second technique's performance. More details could be found in [14].

In the present paper, to use advantages of the abovementioned Refs., the following objectives are considered:

Maximize: $y_1 = (\mathrm{Min}(\mathrm{abs}(\sigma_k)))$, σ_k is the real part of the *k*th electro-mechanical mode.

Maximize: $y_2 = (\mathrm{Min}(\xi_k))$, ξ_k is the damping ratio of the *k*th electro-mechanical mode.

Subjected to:

(1) $\sigma_i < 0$, for all eigenvalues. This condition guarantees system small signal stability.
(2) For the electro-mechanical modes: $a \le \omega_k \le b$. While *a* and *b* are the empirically considered limits of frequency, presented in related figures.
(3) For all other modes: $\xi_i \ge \xi_{mmdr}$. Whereas ξ_{mmdr} is considered experimentally 0.2, 0.2 and 0.1 for SMIB, TAFM and New England, respectively.

No pre-specified value is considered σ_{min} or ξ_{min}. The PSS parameters construct the decision vector. For CPSS $x = (T_1, T_2, T_3, T_4, V_{Smax}, K_{PSS})$. These parameters are experimentally limited. These limitations reduce the computational times significantly. Table 1 shows the low and up boundaries of the parameters.

Major parameters of the population based algorithm SPEA are given in Table 2. As seen from the table, population size is 80 and external population size is 20 suggesting the ratio of 4:1. This ratio

Table 2
SPEA parameters.

Parameter	Generation number	Population size	Length of the chromosome	Selection	Recombination	Mutation
Value	50	$N = 80$ & $N' = 20$	5 for each variable	Roulette wheel	Single-point crossover	Discrete with probability of 0.035

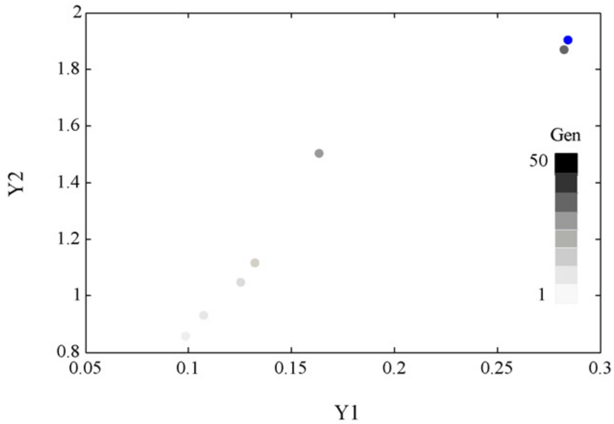

Fig. 8. Convergence characteristics of SPEA in SMIB.

is normally a common value employed to maintain an adequate selection procedure for elite solutions [23].

To have a comparison with SPEA, GA is employed, with the parameters similar to Table 2. This comparison helps us to have a better judgment. The goal is minimization of the following fitness function:

$$f = (w_1 y_1 + w_2 y_2)^{-1}$$

where y_1 and y_2 are objective functions described already. There different values for weights, w_1 and w_2 are assume to have comprehensive investigation. Table 3 lists them. The optimization constraints are like SPEA.

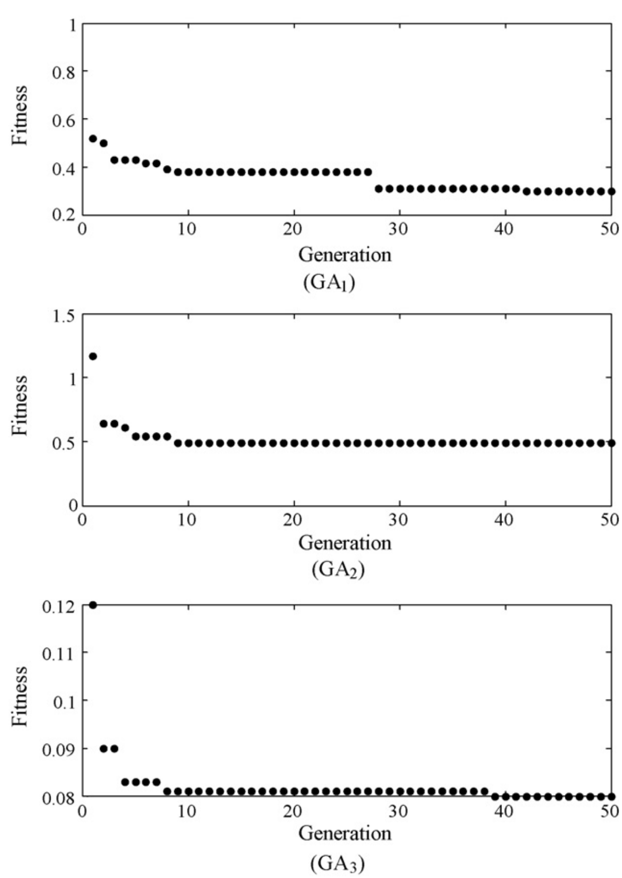

Fig. 9. Convergence characteristics of GA in SMIB.

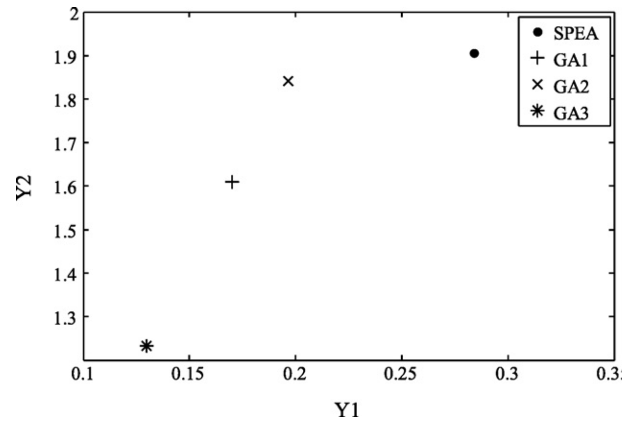

Fig. 10. SPEA against GA in SMIB.

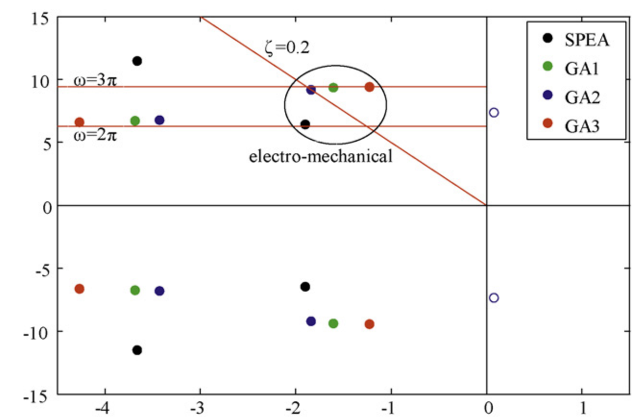

Fig. 11. Dominant modes of SMIB system comprising optimum PSSs.

4. Simulation results

4.1. SMIB

Initially the design approach is employed to design a PSS for SMIB system. The convergence rates of the SPEA and GA are shown in Figs. 8 and 9, respectively. The optimum design of SPEA, shown with blue color, is extracted and shown in Fig. 10. The optimal results of GA are illustrated too. As seen from Fig. 8, SPEA proposes just one design as an optimum. So it seems that the objectives have not very clear conflict here. As we know, the damping factor is product of damping ratio and frequency. So, for one special mode, the objectives are inter-dependent. This is true for SMIB with just one electro-mechanical mode. But in the case of bigger systems, one electro-mechanical mode may have minimum damping ratio and another may have minimum damping factor. The next system's simulations may show this fact.

Fig. 10 compares SPEA with the results obtained from GA. It seems that using different weight in GA's fitness function results in different and sometimes non-optimum answers. So, to gain the

Table 4
Optimal PSSs' parameters in SMIB system.

Parameters	SPEA	GA_1	GA_2	GA_3
T_1	0.36	0.36	0.84	0.8
T_2	0.04	0.23	0.3	0.5
T_3	0.33	2.9	2.3	1.3
T_4	5.81	8.1	8.3	6.4
V_{Smax}	0.06	0.34	0.28	0.34
K_{PSS}	70.9	18.7	12.9	33.2

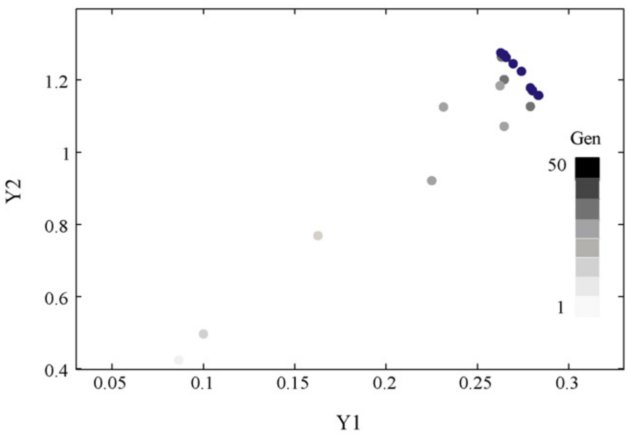

Fig. 12. Convergence characteristics of SPEA in TAFM.

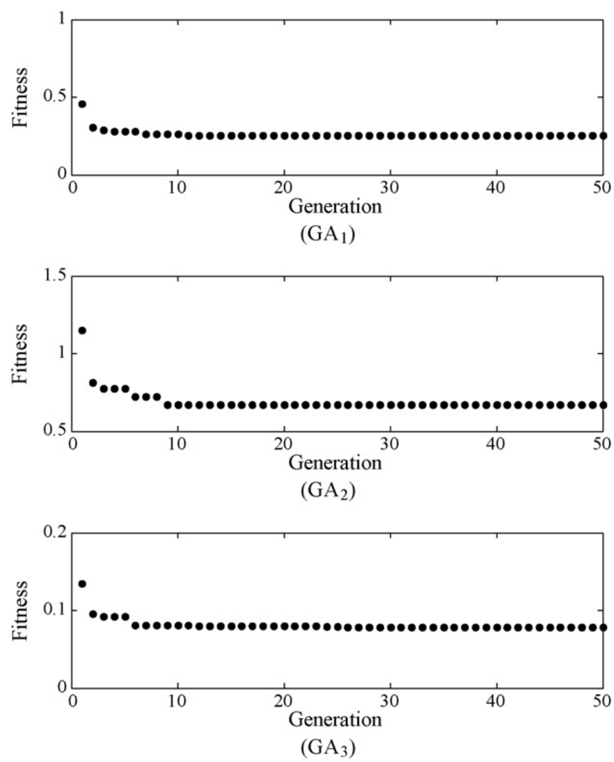

Fig. 13. Convergence characteristics of GA in TAFM.

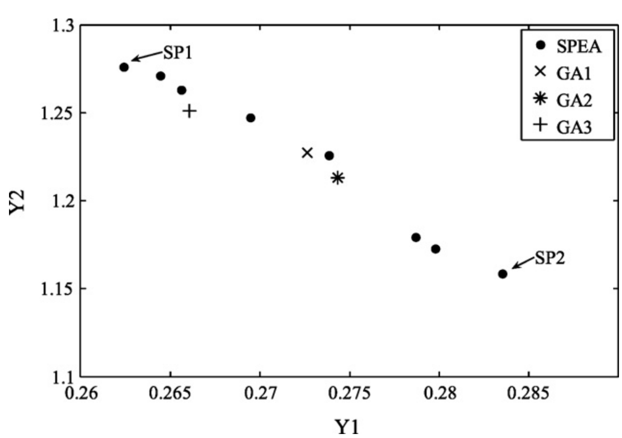

Fig. 14. SPEA against GA in TAFM.

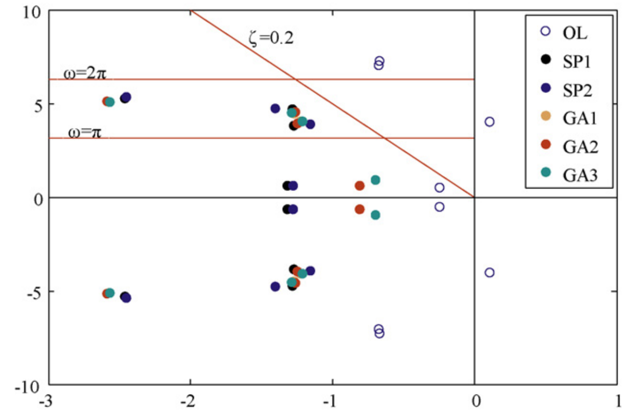

Fig. 15. Dominant modes of TAFM system comprising optimum PSSs.

Table 5
Optimal PSSs' parameters of TAFM system.

Parameters	SPEA 1	SPEA 2	GA_1	GA_2	GA_3
T_1	0.26	0.26	0.52	0.5	0.36
T_2	0.01	0.01	0.04	0.04	0.04
T_3	4.5	4.2	0.65	0.65	1.6
T_4	9.7	10	5.8	5.5	7.1
V_{Smax}	0.44	0.33	0.31	0.34	0.3
K_{PSS}	42	45	100	94	68

optimal results we may need experiment, whereas SPEA could give all of possible optimums in a single run. Fig. 11 shows dominant oscillatory poles' map of the system. It is clear that the open-loop system is unstable. Constraints which have been satisfied are illustrated in this figure too. The numerical values of PSSs' parameters are shown in Table 4.

4.2. Kundor system (TAFM)

In the next step, the design technique is applied to TAFM system. Two PSSs with similar settings are installed at G_1 and G_4 while G_2 and G_3 are left without PSS. Anyway, G_1 and G_2 are the best locations for installation of the PSSs [25], providing a suitable discrimination between a very good and a moderately good PSS settings [19].

The convergence rates of the SPEA and GA are shown in Figs. 12 and 13. The final result of SPEA, Pareto front, is extracted and shown in Fig. 14. The optimal results of GA are illustrated as well. As seen, the Pareto front comprises 8 different designs. It seems

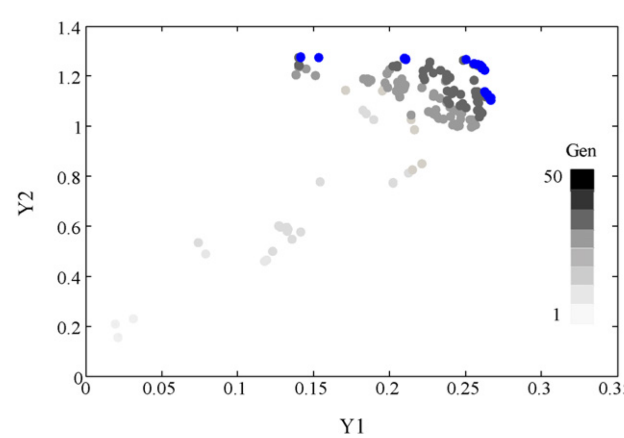

Fig. 16. Convergence characteristics of SPEA in New England system.

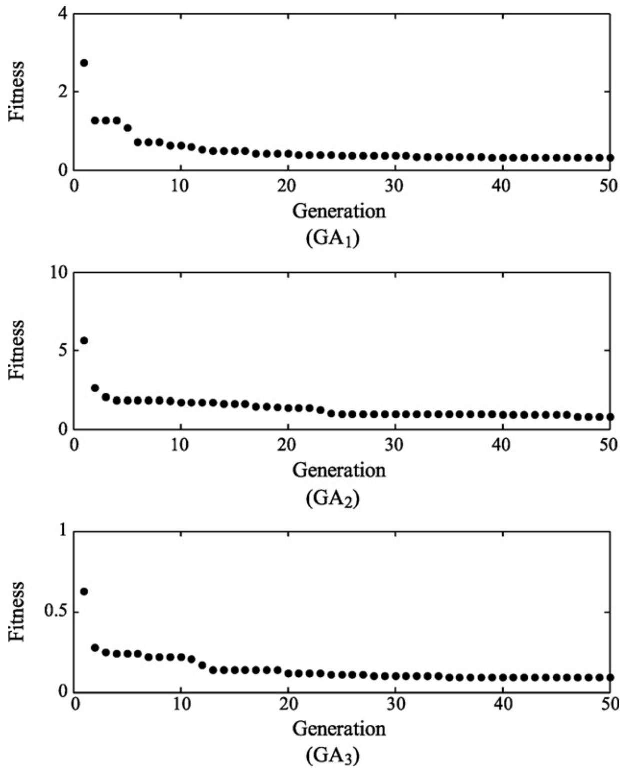

Fig. 17. Convergence characteristics of GA in New England system.

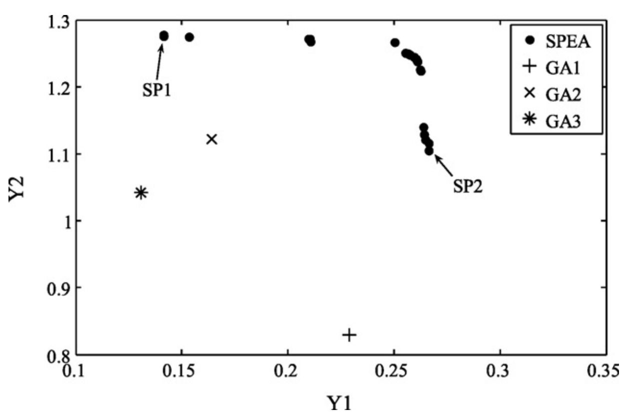

Fig. 18. SPEA against GA in New England system.

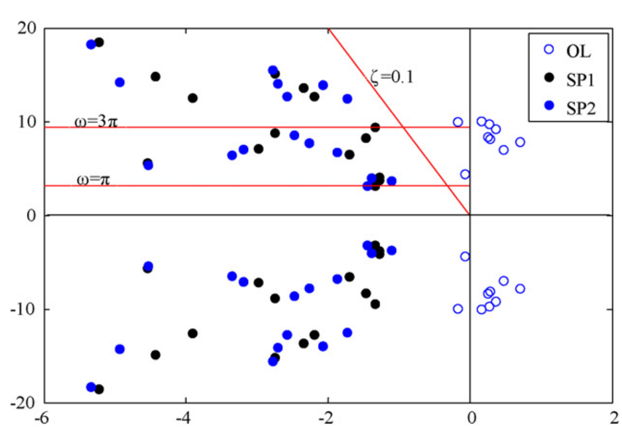

Fig. 19. Dominant modes of New England system comprising SPEA PSSs.

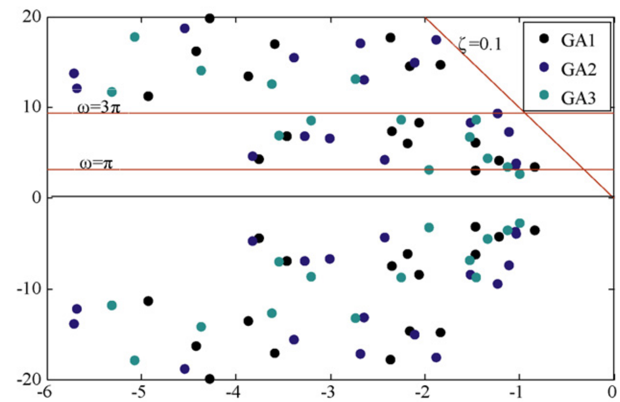

Fig. 20. Dominant modes of New England system comprising GA PSSs.

that the range of y_1 and y_2 variations is not very wide, indicating low conflict for objectives in TAFM system. However, this does not mean to use single objective optimization [9].

None of Pareto front designs dominate GAs and vice versa. Consequently, GA results are Pareto front member. Like SMIB system, minimization of the fitness function with different weight assigned to objectives, gives diverse answers. To have a better understanding, dominant oscillatory poles' maps of the system, comprising some optimum PSSs are shown in Fig. 15. This is done for two PSSs with different location in Pareto front as well as GA based PSSs.

This figure shows that the electro-mechanical modes are close together, but there is a higher difference in the other oscillatory mode of some PSSs. Also, instability of the open-loop system is obvious. Table 5 presents the designed PSSs' characteristics.

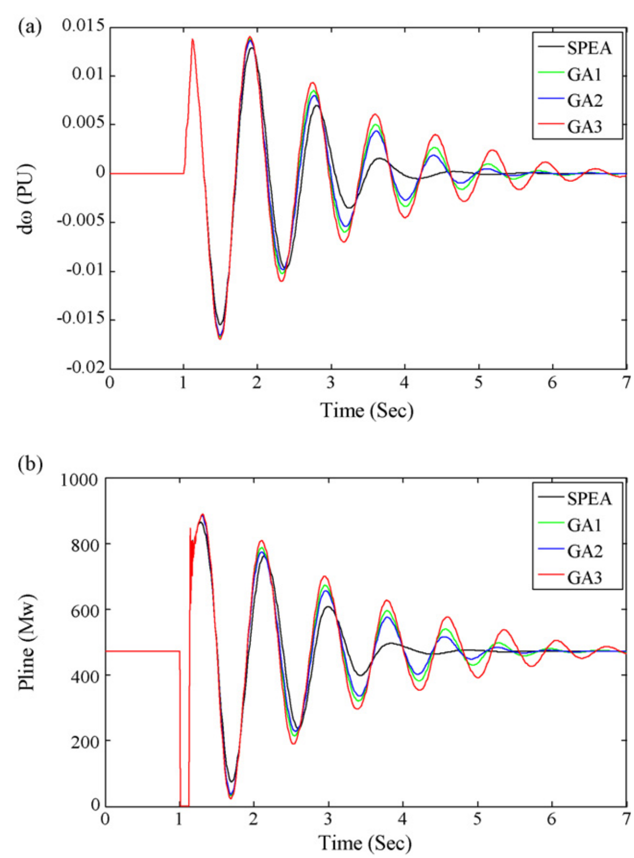

Fig. 21. SMIB results: (a) rotor speed deviation; (b) line power.

Table 6
Optimal PSS parameters for New England system.

Generator	SPEA 1			SPEA 2			GA_1			GA_2			GA_3		
	T_1	T_3	K_{PSS}	T_1	T_3	K_{PSS}	T_1	T_3	K_{PSS}	T_1	T_3	K_{PSS}	T_1	T_3	K_{PSS}
G_1	0.09	1.5	13	0.09	1.4	22.9	0.05	1.2	22.9	0.08	0.47	57.6	0.09	0.98	25.3
G_2	0.1	0.24	35.3	0.09	0.6	45.2	0.08	1.03	20.4	0.07	1.12	27.8	0.071	1.1	27.8
G_3	0.09	0.9	22.9	0.09	0.33	60.1	0.09	1.36	22.9	0.09	0.14	75	0.08	0.24	50.2
G_4	0.03	1.4	8	0.015	1.36	8	0.047	0.37	40.3	0.06	0.33	30.3	0.06	0.38	42.7
G_5	0.07	0.66	70	0.07	0.66	72.5	0.08	1.17	50.2	0.08	1.17	80	0.09	1.22	47.7
G_6	0.09	1.4	62.6	0.085	1.4	60.1	0.08	1.17	67.6	0.09	1.5	47.7	0.08	0.8	55.2
G_7	0.06	0.9	7.9	0.04	0.9	7.9	0.09	0.42	27.8	0.1	0.47	10.5	0.03	0.42	10.5
G_8	0.09	0.6	20.4	0.09	0.6	20.4	0.07	0.75	25.3	0.08	0.75	67.6	0.082	0.7	25.3
G_9	0.01	0.46	47.7	0.01	0.46	50.1	0.06	0.56	35.3	0.04	0.8	22.9	0.04	0.5	22.9

4.3. New England system

Normally it is of great importance to test the PSS design method in a large system. Therefore, the proposed PSS design technique is employed to design PSSs for New England system, showing the capability of the design approach. For reducing the computational time, V_{Smax} is assumed 0.2 and the values of T_2 and T_4 of all PSSs of the machines are kept constant at reasonable values of 0.1 and 0.05 respectively, thus the values of T_1, T_3 and K_{PSS} would be the only parameters designed optimally. The SPEA specifications and parameters' limits are as given in Tables 1 and 2.

The convergence characteristic of SPEA is presented in Fig. 16, introducing acceptable improvement through generation increment. Moreover, the GA's fitness progress is shown in Fig. 17. Also, the Pareto optimal front is illustrated in Fig. 18, indicating domination of almost all of them against GA results. Note that using higher generations for GA may improve its final answer, but here the goal is to compare the algorithms in similar conditions. It can be seen from Fig. 18 that the Pareto front's range is wider, so, indicating more disagreement than aforementioned systems. Also after $y_1 = 0.25$, there is a high decrease in y_2. This means if we want to y_1 have a value more than 0.25, y_2 may not to be very favorable. Figs. 19 and 20 represent the system's dominant oscillatory poles' map with candidate SPEA and GA based PSSs while their parameters' numerical values are given in Table 6.

4.4. Time domain simulations

To investigate the performance of the PSSs under fault conditions, some large disturbances have been applied to the systems. Table 7 provides descriptions of three different faults applied to test the robustness of the controllers. There are many fault conditions, but because of the paper size limitation some major faults are considered here [9,19]. Variations of active power of a selected line

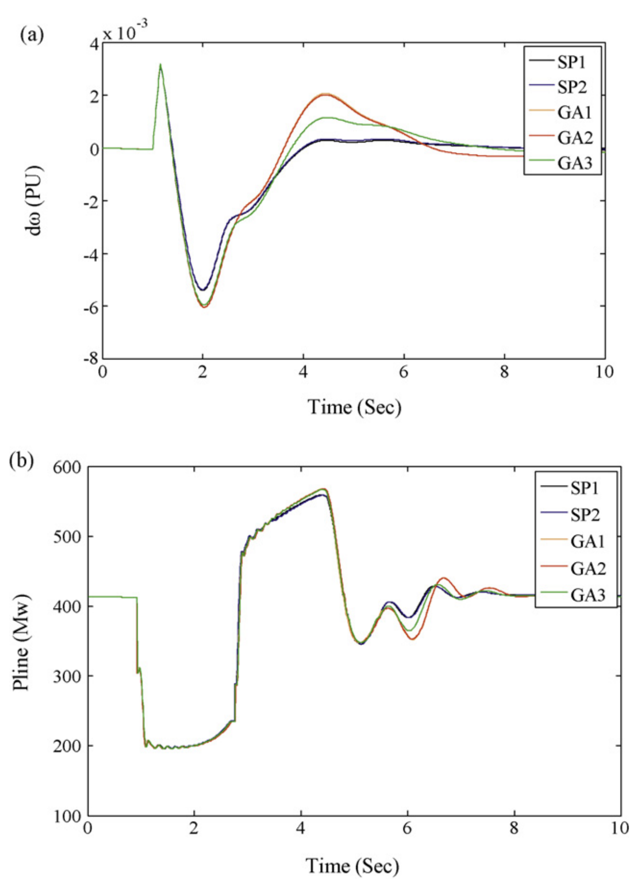

Fig. 22. TAFM results: (a) rotor speed deviation of G_1; (b) transmitting power from area 1 to area 2.

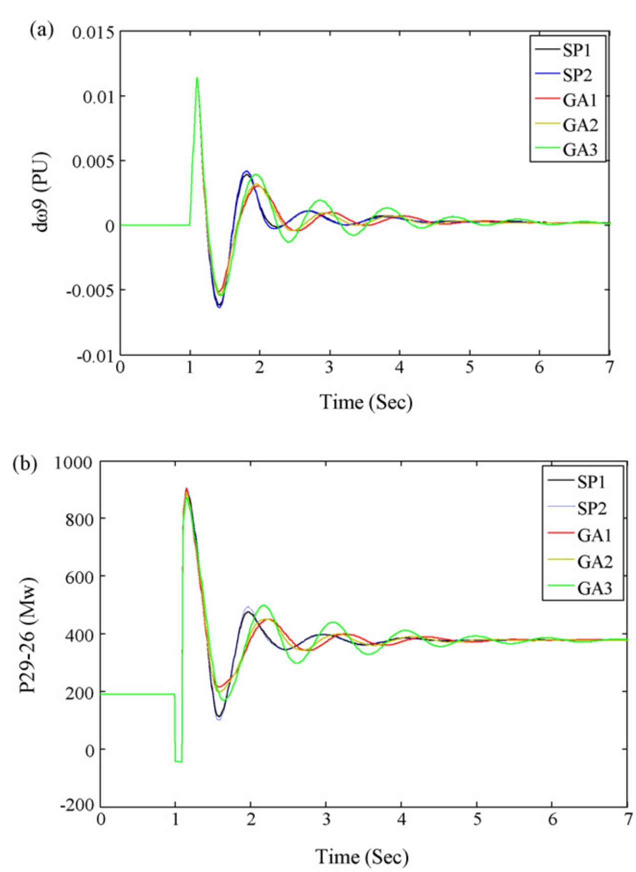

Fig. 23. New England system results: (a) rotor speed deviation of G_9; (b) power of line 26–29.

Table 7
Large disturbances tests.

System	Description
SMIB	6-cycle three phase ground fault at power plant bus cleared without equipment.
TAFM	9-cycle three phase ground fault at bus 1 cleared without equipment.
New England	6-cycle three phase ground fault at bus 29 at the end of line 26–29. The fault is cleared without equipment.

and rotor speed deviation of a generator located close to the fault position are plotted against time for various PSSs and the faulty operating condition as shown in Figs. 21–23. All of these figures present large signal stability of the test systems with optimum PSSs. Also it seems that, in SPEA PSSs has a better performance in most of the cases. However, more tests are needed to show the differences of the Pareto fronts' members clearly in future works.

5. Conclusion

In the present paper, a novel method of CPSS design named Strength Pareto Evolutionary Algorithm (SPEA) is introduced. The SMIB, TAFM and New England are three well-known power systems used to exercise the PSS design methodology. Maximizing the minimum damping ratio and minimum damping factor of dominant oscillatory modes of the aforementioned systems are employed as two objectives while the PSS parameters are optimization variables. Moreover in the present paper, we have reached some optimum answers which seem to dominate GA results. The designer is free to select any of the results. However, the present paper could not zoom on the differences of Pareto fronts' members very much, but recommends it for future works. Also the researchers may work on possible better objective functions.

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