Robust PSS Design under Multioperating Conditions Using Differential Evolution

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Abstract—A power system stabilizer (PSS) design method, which aims at enhancing the damping of multiple electromechanical modes in a multi-machine system over a large and pre-specified set of operating conditions, is introduced in this paper. With the assumption of normal distribution, the statistical nature of the eigenvalues corresponding to different operating conditions is described by their expectations and variances. A probabilistic eigenvalue-based optimization problem used for determining PSS parameters is then formulated. Differential evolution (DE) is applied for solving this highly nonlinear optimization problem. Different strategies for control parameter settings of DE have been studied to verify the robustness of DE in PSS optimization problems. The performance of the proposed PSS, with a conventional lead/lag structure, has been demonstrated based on two test systems by probabilistic eigenvalue analysis and nonlinear simulation.

I. Introduction

With the growth of interconnected power systems and particularly the deregulation of the industry, problems related to low frequency oscillation have been reported, including major incidents [1]. Power system stabilizers (PSSs) have been widely used to suppress the low frequency oscillation and enhance the system dynamic stability [2-16]. The basic function of a PSS is to produce an electrical torque component in phase with the rotor speed variation and add damping to the rotor oscillations by controlling its excitation using an auxiliary stabilizing signal [2]. Many approaches have been proposed for PSS tuning such as the damping torque approach [2], eigenvalue sensitivity analysis [3], nonlinear optimization [4], robust H_∞ controller design method [5] and some of them have been applied to real power systems [6, 7]. However, these conventional PSS (CPSS) designs are determined based only on a few specified operating conditions so they cannot guarantee the overall system performance if the operating conditions vary significantly. Besides, it is still questionable if some approaches for PSS coordination, such as the decoupled and sequential tuning method, can achieve an optimal overall performance and adequately handle adverse interactions among controls [8].

The probabilistic approach has been successfully applied for power system dynamic research studies under multioperating conditions [11-13]. With nodal voltages regarded as basic random variables and determined by probabilistic load flow calculation, the probabilistic distribution of each eigenvalue is obtained from the probabilistic attributes of nodal voltages, and described by its expectation and variance under the assumption of normal distribution. References [14-16] extended the probabilistic eigenvalue analysis to PSS design in multimachine systems for the purpose of including a wide range of system load conditions. However this optimization problem of the probabilistic PSS design is highly nonlinear and the solution is difficult to be obtained based on the conventional optimization technique.

Evolutionary Algorithms (EAs) have attracted a great deal of attention recently and have been found to be a robust approach for solving non-linear, non-differentiable and multi-modal optimization problems. EAs are evoked by an analogy with biology, in which a group or population of solutions evolves generation by generation through natural selection. In their implementations, a population of candidate solutions, referred to as the chromosomes, evolves to an optimum solution through the operation of genetic operators such as reproduction, crossover, and mutation. In recent years, some evolutionary methods such as Genetic Algorithm (GA) [9] and Particle Swarm Optimization (PSO) [10] have been applied to the problem of PSS design. Unlike the conventional methods, these methods can finally reach the optimal solution regardless of the initial PSS settings. The canonical PSO has been primarily applied to the problem of probabilistic PSS design as well [23]. Since PSO performance is affected significantly by the selection of the control parameters (swarm size, neighborhoods, and some coefficients), simple classic or canonical PSO might suffer from the problem of convergence stagnation when the optimization model is very complicated [24].

As a new branch of EAs, differential evolution (DE) has the ability to overcome some drawbacks of classic GA, such as non-isomorphic search strategies and susceptibility to coordinate rotation [17]. It is distinguished from other EAs by its reproduction operation, which drives mutation with the differences of randomly sampled pairs of chromosomes. This self-adjusting property of DE uses few control mechanisms when compared to other approaches, making DE both effective and easy to use, thus the control parameters of DE is easy to determine and the balance between the convergence speed and the population diversity can be reached with less effort than other EAs. In light of these advantages, a novel DE-based approach to probabilistic PSS design is proposed in this paper.

The paper is organized as follows: In section II, a probabilistic eigenvalue analysis approach is first reviewed. In section III, the probabilistic PSS design problem is then formulated as a probabilistic eigenvalue based optimization model. The DE algorithm is introduced in section IV and the procedure for solving the probabilistic PSS design problem is outlined. In section V, the effectiveness of the proposed probabilistic PSS design scheme is demonstrated on two test systems by DE robustness testing, eigenvalue analysis and nonlinear simulation. Finally, the paper is concluded in section VI.

II. PROBABILISTIC EIGENVALUE ANALYSIS

Under the multioperating conditions of a power system, all nodal injections, nodal voltages and eigenvalues are regarded as random variables. Statistical attributes of nodal injections are determined from system operating samples. Probabilistic distributions and stability probabilities of all eigenvalues can be obtained by means of the probabilistic eigenvalue analysis [13].

Under the assumption of normal distribution, the statistical nature of an eigenvalue can be described by its expectation and variance. For a particular eigenvalue $\lambda_k = \alpha_k + j\beta_k$, having an expectation $\overline{\alpha}_k$ and standard deviation σ_{α_k}, the distribution within $\{-\infty, \overline{\alpha}_k + \kappa\sigma_{\alpha_k}\}$ with a distribution constant κ over [3.5, 4] has a probability from 0.99977 to 0.99997, which is very close to unity. To ensure the stability of α_k, this distribution range should be located on the left-hand side in the complex plane as illustrated by the curves of probability density function (pdf) in Fig. 1.

Thus, the upper limit of this distribution range α_k' in (1) can be regarded as an extended damping coefficient from which the robust stability of multioperating conditions can be estimated. Correspondingly, the damping ratio $\xi_k = -\alpha_k / \sqrt{\alpha_k^2 + \beta_k^2}$ with expectation $\overline{\xi}_k$ and standard deviation σ_{ξ_k} has an extended value ξ_k' in (2),

$$\alpha_k' = \overline{\alpha}_k + \kappa\sigma_{\alpha_k} \tag{1}$$

$$\xi_k' = \overline{\xi}_k - \kappa\sigma_{\xi_k} \tag{2}$$

To ensure the system dynamic performance, all the eigenvalues need to satisfy the requirement of damping constant and damping ratio in (3) and (4) respectively. In other words, all the eigenvalues should be located in the shadowed D-shape region S^* in Fig. 2.

$$\alpha_k' \le \alpha_C \tag{3}$$

$$\xi_k' \ge \xi_C \tag{4}$$

where α_c and ξ_c are acceptable limits for damping constant and damping ratio, respectively.

III. Problem Formulation of Probabilistic PSS Design

A. PSS Structure

A typical PSS structure with two lead/lag stages will be adopted in this study as follows:

$$F_i(s) = K_i \cdot \frac{pT_w}{1+pT_w} \cdot \frac{1+pT_{1i}}{1+pT_{2i}} \cdot \frac{1+pT_{3i}}{1+pT_{4i}} \tag{5}$$

where $i \in \{1,\ldots,N_{\mathrm{PSS}}\}$ and N_{PSS} is the total number of PSS to be tuned; K_i is PSS gain constant with positive value for speed input signal and negative value for power input signal; T_w is washout time constant; T_{1i}/T_{2i} and T_{3i}/T_{4i} are lead/lag time constants. It should be noted that the time constants T_{2i} and T_{4i} should not be less than 0.04s to avoid excessive amplification of input signal noise. In this study, T_w is fixed as 10s and 5s for speed and power input signals respectively. The ranges of the PSS parameters are set as follows: [0.1p.u., 20p.u.] for K_i of PSS with speed input signal and [-20p.u., -0.1p.u.] with power input signal, [0.06s-2.0s] for T_{1i} and T_{3i}, [0.04s-0.2s] for T_{2i} and T_{4i} [19].

B. Parameter Optimization

For optimization purposes, it is more convenient to introduce the standardized expectations of the damping constant and damping ratio α_k^* and ξ_k^*, derived from (1) and (2) and termed as $\kappa\sigma$ criteria, are defined as:

$$\alpha_k^* = -(\overline{\alpha}_k - \alpha_C)/\sigma_{\alpha_k} \geq \kappa \tag{6}$$

$$\xi_k^* = (\overline{\xi}_k - \xi_C)/\sigma_{\xi_k} \geq \kappa \tag{7}$$

After the standardization in (6) and (7), α_k^* and ξ_k^* are per-unit variables and can be directly compared. Thus, an optimization problem is formulated in (8) and only those "weak" eigenvalues ($\alpha_k^* < \kappa$ or $\xi_k^* < \kappa$) are included so that those unstable or poorly damped electromechanical oscillation modes are relocated to a more stable region. If problem (8) is solvable (i.e. a feasible solution exists), all the eigenvalues should be located in the D-shape region S^* in Fig. 2 and the value of the objective function will be equal to zero; otherwise, it will be greater than zero.

$$\text{Minimize } f(\boldsymbol{P}) = \sum_{\alpha_k^*<\kappa}(\alpha_k^* - \kappa)^2 + \sum_{\xi_k^*<\kappa}(\xi_k^* - \kappa)^2 \tag{8}$$

s.t. $K_{i,\min} \leq K_i \leq K_{i,\max}$

$T_{1,\min} \leq T_{1i} \leq T_{1,\max}$

$T_{2,\min} \leq T_{2i} \leq T_{2,\max}$

$T_{3,\min} \le T_{3i} \le T_{3,\max}$

$T_{4,\min} \le T_{4i} \le T_{4,\max}$

where ***P*** stands for the PSS parameter vector; $K_{i,\min}$, $T_{1i,\min}$, $T_{2i,\min}$, $T_{3i,\min}$ and $T_{4i,\min}$ are the minimum limits of PSS parameters; $K_{i,\max}$, $T_{1i,\max}$, $T_{2i,\max}$, $T_{3i,\max}$ and $T_{4i,\max}$ are the maximum limits of PSS parameters.

IV. PROBABILISTIC PSS DESIGN USING DIFFERENTIAL EVOLUTION

DE is a kind of intelligent search technique suitable for optimizing nonlinear, non-differentiable and multi-modal continuous space functions. It has been widely studied and shown its excellent performance on a large variety of benchmark problems and practical problems [17]. Similar to other EAs, in DE's implementation, a population of randomly generated and real-encoding candidate solutions evolves to an optimal solution through the reproduction operation and selection. This section describes the principal components of DE and its application in solving the problem of probabilistic PSS design in (8). The pseudo-code of the proposed method is given in Table I.

A. Principal Components of DE

The principal components of the DE algorithm are introduced as follows:

(i) *Chromosomes*: A chromosome can be taken as an array holding a candidate group of PSS parameters. The parameters are encoded using floating-point numbers and are set as elements in the chromosomes.

(ii) *Population initialization*: The initial DE population with *NP* (population size) candidate solutions or individuals is generated at random from the parameter domains according to:

$$x_{i,j}^{(0)} = p_j^{\min} + r \cdot (p_j^{\max} - p_j^{\min}) \tag{9}$$

where $i \in \{1,..., NP\}$; $j \in \{1,..., M\}$ and M is the total number of PSS parameters to be decided in (8); $x_{i,j}^{(g)}$ denotes the value of the *j*-th PSS parameter of the *i*-th individual at the *g*-th generation, i.e. *g* = 0 for the first generation; $p_j^{\max}$ and $p_j^{\min}$ denote the upper and lower bounds of parameter *j*; and *r* is a uniformly distributed random value over the range of [0, 1].

(iii) *Reproduction operation*: The classical DE operator and its derivative operators could provide tailored candidate schemes for solving different domain problems, in which a tradeoff between the convergence speed and the population diversity could be achieved [17]. Each parent x_i will produce one offspring u_i in every generation. The reproduction operator used in this study called DE/rand-to-best/1/bin, which is designed to be easy to understand and simple to use and with no sacrifice to effectiveness [20], is given as,

$$u_i^{(g)} = x_i^{(g)} + K(x_{best} - x_i^{(g)}) + F(x_{r_1}^{(g)} - x_{r_2}^{(g)}) \tag{10}$$

where $r_1, r_2 \in \{1,..., NP\}$ are randomly selected number with $r_1 \neq r_2 \neq i$; x_{best} is the up-to-date best individual; K and F are scale coefficient of crossover and mutation, respectively; $K(x_{best} - x_i^{(g)})$ and $F(x_{r_1}^{(g)} - x_{r_2}^{(g)})$ play a role of crossover and mutation operation, respectively. The impact of the scale coefficients K and F on the performance of DE in the probabilistic PSS design will be investigated in Section V. DE's reproduction strategy by (10) can be viewed as a "greedy" reproduction since it exploits the information of the best individual to guide the search. This can speed up the convergence because the way the best individual being utilized here is a kind of "population acceleration" [21], whilst the diversity of the whole population can be held by the diffuse effect of mutation item. Unlike other EAs that rely on a predefined probability distribution function, the reproduction of DE is driven by the difference between randomly sampled pair of individuals in the current population. This reproduction scheme, though simple, endows DE with the features of self-tuning and rotational invariance, which are crucial for an efficient EA scheme and have long been pursued in the EA community. In ES, they are realized by complicated approaches using strategy vectors and matrices [18].

(iv) Selection Strategy: A one-to-one replacement strategy is employed for the DE' selection as follows:

$$x_i^{(g+1)} = \begin{cases} u_i^{(g)} & \text{if } f(u_i^{(g)}) < f(x_i^{(g)}) \\ x_i^{(g)} & \text{otherwise} \end{cases} \tag{11}$$

It is an elitist strategy because the current best vector of the population can only be replaced by a better vector.

B. Design Procedure

With the principle components described above, the probabilistic PSS design problem can be solved by the following procedure:

Step 1 Initialization: Initialize *NP* individuals/chromosomes in the population according to (9), which act as the initial parent population. By decoding each chromosome into a group of PSS parameters, the objective function value of each individual in the initial population is evaluated according to (8) and thus the best individual $x_{best}^{(0)}$ is obtained.

Step 2 Reproduction: For each parent chromosome, a child chromosome is generated by performing the reproduction operation in (10) so that a *NP*-size children population is prepared. A midway fine-tuning strategy [18] will be applied if the boundary limit is violated. The objective function value of the child chromosome will be evaluated in succession. Repeat the reproduction step until *NP* child chromosomes are formed.

Step 3 Selection: Each child will compete with its corresponding parent according to (11) and all the survivors will constitute the parent population of next generation.

Step 4 Evolution: Repeating Steps 2 and 3 until the objective function becomes zero or the specified maximum number of generations is reached.

V. APPLICATIONS

In this section, two test systems will be employed to demonstrate the effectiveness of the proposed method. In the studies, the criteria for the damping ratio and damping constant are chosen as $\xi_C = 0.1$ and $\alpha_C = -0.1$ for both systems. The distribution constants for the two systems are set to 4.0 and 3.5, respectively.

A. Three-machine Power System (System I)

The three-machine nine-bus system is shown in Fig. 3. All machines are represented as fourth-order models and equipped with fast-acting static exciter [19]. All dynamic parameters are given in the Appendix. The loads are modeled as constant impedances. Normal operation values of nodal powers and PV bus voltages shown in Fig. 3 are regarded as their expectations. Each nodal power and PV bus voltage is assigned with standardized daily operating curves as shown in [13]. From these curves, 480 operating samples are created and covariances of nodal injections are determined. The statistical characteristics can be captured by the probabilistic eigenvalue analysis. 480 system operating samples are created and the worst scenario is very marginally stable with $\xi < 0.005$. The probabilistic eigenvalue analysis is performed by the method in [14, 15] and the worst damped modes are listed in Table II. As discussed in Section III, if the standardized expectations of both α_k^* and ξ_k^* are larger than 4, the corresponding mode is regarded as adequate for robust stability, otherwise inadequate. In this case, two eigenvalues of the system in Table II are "inadequate" with α_1^*, α_2^*, ξ_1^* and ξ_2^* equal to 2.88, 1.67, 0.36 and 0.38, respectively. Modal analysis [15] on eigenvalue expectation shows that these two eigenvalues are electromechanical modes: eigenvalue 1 is the oscillation between G1 and G2 + G3, and eigenvalue 2 between G2 and G1 + G3. Following the result of probabilistic sensitivity analysis on these two modes, two speed-based PSSs are installed at G1 and G2; and in total 10 parameters of PSSs need to be decided. The population size (*NP*) and the maximum generation for DE in this case study are set to be 100 and 50 respectively.

1) DE Robustness

Studies on the selection of DE control parameters and its robustness are first conducted. It has been revealed in (10) that *K* controls the strength of the contractive pressure of the population, while *F* controls the strength of the diffuse pressure of the population. The larger the value of K or F, the stronger the contractive or diffuse is. High ratio of K to F may lead to premature convergence, while low ratio of K to F may make the convergence too slow. So, K and F must be coordinately set in order to achieve the best performance. One strategy recommended by K. V. Price [18] is choosing K randomly from the range of [0, 1] for every individual at each generation, which is found to be frequently very effective, while setting the F to be some fixed value within [0, 1]. Another simpler strategy of setting K=F has been validated to be widely effective and applied to aerodynamic optimization, digital filters design, etc [20]. The influence of these two parameter setting strategies on the performance of the proposed method will be investigated thoroughly in two experiments: (1) Setting K randomly for every individual of each generation; and then increasing the F from 0.1 to 0.9; (2) Setting K=F and then increasing them from 0.1 to 0.9. Based on 50 trial simulations, the average convergence curves of two cases are presented in Figs. 4 (a)-(b). From Fig. 4 (a), it is shown that the algorithm is nearly insensitive to F control parameter over the ranges [0.5, 0.9] when K is randomly determined. Fig. 4 (b) shows that keeping K=F has the similar characteristics; however, setting K=F between 0.5 and 0.9 performs prominently. These observations indicate that DE is not remarkably sensitive to its control parameters over specified ranges. Thus, their values are relatively easy to choose, which is consistent with the experimental conclusions in [18]. Hence the setting K=F=0.85 will be kept for DE in the remaining study.

2) Tuning Results

Based on the proposed method in Section IV, the final PSS settings are determined in the DE-PPSS portion of Table III, and the probabilistic eigenvalues as shown in Table IV are adequate for robust stability. When compared with the original values in Table II, the system stability is much improved. The eigenvalue distribution of the closed-loop system under 480 operating conditions is also plotted in Fig. 5, in which all eigenvalues have been shifted into the area with $\xi > \xi_C$ and $\alpha < \alpha_C$, compared with the original open-loop eigenvalues.

3) Effectiveness Validation

The performance of the proposed PSS design approach is evaluated and compared with that of the conventional PSS (CPSS) [4], which is designed under the worst scenario of the 480 operating conditions by pushing all the eigenvalues into the stability region. In addition, the same damping criteria are used in CPSS design for fair comparison. The results of CPSS parameters are listed in the CPSS portion of Table III.

To simulate a large disturbance imposed on the system, a six-cycle three-phase-to-earth fault happens near bus 6 at t = 0.2 s as shown in Fig. 3. The fault is then cleared by line isolation without reclosure. The study system with the large disturbance impulsion will be tested under 480 sampled operation conditions with DE-PPSS (probabilistic

PSS design with DE) and CPSS independently installed. A nonlinear time domain simulation will be conducted for each case. The output limits of field voltage are set to ±5 p.u. respectively. The output limits of PSSs are set to ±0.1 p.u. Investigation on the following physical variables is performed:

(i) Rotor angle of G1, G2 (relative to G3) in degree

(ii) Field voltage of G1, G2 and G3 in p.u.

(iii) Terminal voltage of G1, G2 and G3 in p.u.

Following the techniques employed in the automatic control theory, the quality of transient process, such as the settling time and overshoots, can quantitatively be estimated by its deviation characteristics and therefore this idea is now adopted in evaluating the transient stability performance of the obtained PSSs under wide operation conditions. Two performance indices (PI) on the basis of multi-operating conditions are defined here in this study to measure the averaged total variation (ATV) of signal [22],

$$PI_1 = \frac{1}{N}\sum_{n=1}^{N}\int_{t=0}^{t=t_{sim}} \left|\Delta\varepsilon(t)\right| dt \tag{13}$$

$$PI_2 = \frac{1}{N}\sum_{n=1}^{N}\int_{t=0}^{t=t_{sim}} t\cdot\Delta^2\varepsilon(t) dt \tag{14}$$

where $\varepsilon(t)$ represents all the time response of the selected physical variables and $\Delta\varepsilon(t)=\varepsilon(t)-\varepsilon(t-1)$; N is the total number of samples; and t_{sim} is the total simulation time. It is obvious that the lower the values of these indices, the smaller deviation of the signal will present in response to disturbance.

The ATV values for DE-PPSS and CPSS are listed in Table V, where D_{PI} and C_{PI} denote the corresponding scenarios respectively. Most of ATV values of DE-PPSS are less than those of CPSS. Indeed, it is well expected that DE-PPSS outperforms CPSS because the proposed DE-PPSS method is derived from probabilistic eigenvalue analysis; and multi-operating conditions and certain nonlinear characteristic of the system have been taken into account in the PSS design. However, CPSS is designed based only on a linearized model under a stressed operating condition and its performance may be unsatisfactory when the operating environment varies significantly due to large disturbances.

Due to space limit, only transient response curves at light, medium and heavy load conditions of the daily operating curve are shown in Fig. 6, Fig. 7 and Fig. 8 respectively. Although CPSS stabilizes the system, DE-PPSS exhibits better damping properties generally and this result is consistent with the performance index analysis.

B. Eight-machine Power System (System II)

The test system showed in Fig. 9 is a three-area system consisting of 8 machines and 24 buses. All generators are represented as fifth-order models and equipped with speed governors and IEEE-Type I exciters [19], with exciter parameters given in the Appendix. System loads are represented by constant impedance models. Details of network parameters, nodal powers and generator parameters can be referred to in [14].

Similarly, the statistical characteristics of the system can be captured by the probabilistic eigenvalue analysis based on sampled 480 operating conditions. Modal analysis shows that an inter-area mode involving machines in different areas is a lightly damping mode. There are seven unsatisfactory electro-mechanical oscillation modes and the details of these modes are listed in Table VI. By means of probabilistic sensitivity analysis [15, 16], a scheme of installing PSSs at G1, G2, G3, G5, G6, and G7 is tentatively developed. Besides, the probabilistic sensitivity analysis shows that these oscillation modes are much more sensitive to PSSs with electrical power input than with speed signal input. So for this system, power input PSS will be adopted hereinafter. Totally, 30 parameters of PSSs need to be decided. The population size and the maximum generation for DE in this case study are set to be 200 and 100 respectively. With the proposed DE-PPSS approach, the resulting PSS parameters are listed in the DE-PPSS portion of Table VII and compared with the CPSS parameters in the CPSS portion of Table VII. The electro-mechanical modes are listed in Table VIII, with the system damping effectively enhanced. Based on 15 simulation trials, the average evaluation number (i.e. population size x average generation number) of the DE method is 2730 and each DE process lasts 60.35 minutes on average in an Intel P4 2.66 GHz CPU and 1G RAM computer; while the values for the canonical PSO in [23] is 3240 and 71.6 minutes. From these simple comparisons, the DE can converge faster than the canonical PSO in [23]. Besides, the performance and the convergence of PSO are significantly affected by the control parameters in PSO [24]. In larger-scale power systems, DE's convergence performance mainly depends on the number of PSSs considered in the optimization problem, which should be limited to those most effective generators or areas in power systems. It is expected that the computing time of DE will increase with the increment of PSS number. Fortunately, DE is very amenable to parallel implementation by nature so that computation time can be greatly reduced. The same case study has been performed on a master-slave PC-cluster, which consists of one control node and 30 working nodes with 61 processors. Each processor is configured with 1G RAM and dual Intel Xeon 2.66GHz CPUs. It has been found that the time consumption of the DE for this eight-machine test system is reduced to less than 2 minutes.

For transient performance checking, a six-cycle three-phase fault is applied to the tie-line 8-15 near bus 15 at t =

0.2 s as shown in Fig. 9. The fault is then cleared by line isolation without reclosure, making the tie-line out of operation. The system responses are simulated under typical wide operating conditions, which are composed of one operating condition of every hour (totally 24 operating conditions) in the operating curve. The maximum and minimum limits of field voltage are set to 12 p.u. and −10 p.u. respectively. The deviations of generators' electrical power in p.u. are investigated and the performance indices are presented in Table IX; and the electrical power responses of generators with PSS under different operating conditions are plotted in Fig. 10. Again, DE-PPSS is superior to CPSS in terms of damping ability under a wide range of operating conditions.

VI. CONCLUSIONS

A probabilistic PSS design for multi-machine system under multi-operating conditions using DE is proposed in this paper. A comprehensive comparison between the probabilistic PSS and a CPSS is conducted on two test systems and the results have indicated that the probabilistic PSS is more robust than the CPSS, which is partly because the probabilistic PSS design has considered a wide range of operation conditions in the design process and the DE is able to tune the PSS parameters in a coordinated way. The studies have also showed that DE is not remarkably sensitive to its control parameters over specified ranges. This makes it easy to select its parameters for the probabilistic PSS design problem.

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IX. APPENDIX

Table A-1
Dynamic parameters of three-machine system

Parameters	Machine		
	G1	G2	G3
Capacity (MVA)	250	250	1200
H (pu)	3.20	3.01	1.97
D (pu)	0.01	0.01	0.01
x_d (pu)	1.796	1.9688	1.752
x_q (pu)	1.725	1.8867	1.1628
x'_d (pu)	0.2396	0.272	0.7296
x'_q (pu)	0.2396	0.272	0.7296
T'_{do} (s)	6.00	5.89	8.96
T'_{qo} (s)	0.535	0.6	0.31
K_a (pu)	100	100	100
T_a (s)	0.05	0.05	0.05
T_r (s)	0.02	0.02	0.02

* Generator’s per unit data are on its capacity base

Table A-2
Parameters of exciters in eight-machine system

	Machine							
	G1	G2	G3	G4	G5	G6	G7	G8
K_a (pu)	50	50	50	20	20	50	50	50
T_a (s)	0.05	0.03	0.01	0.02	0.02	0.04	0.03	0.03
K_f (pu)	0.023	0.04	0.05	0.0	0.0	0.04	0.1	0.2
T_f (pu)	0.8	0.715	0.715	0.0	0.0	0.715	0.715	0.715
T_e (s)	0.5	0.5	0.5	0.05	0.05	0.5	0.5	0.5
T_r (s)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

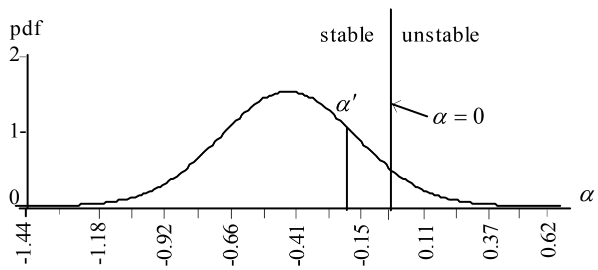


Fig. 1. Probabilistic eigenvalue distribution

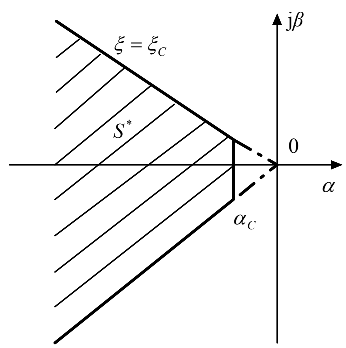


Fig. 2. Desired eigenvalue distribution region

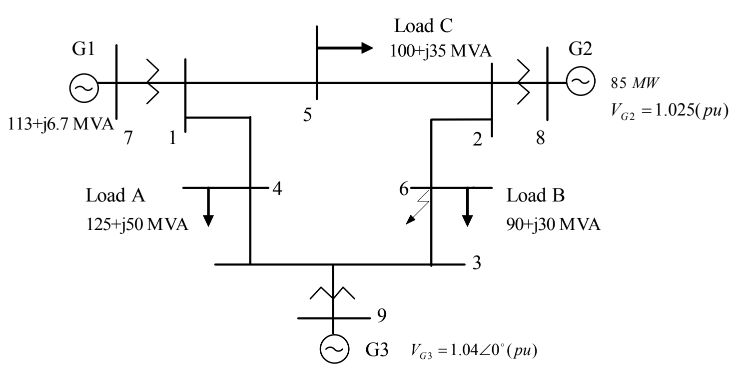
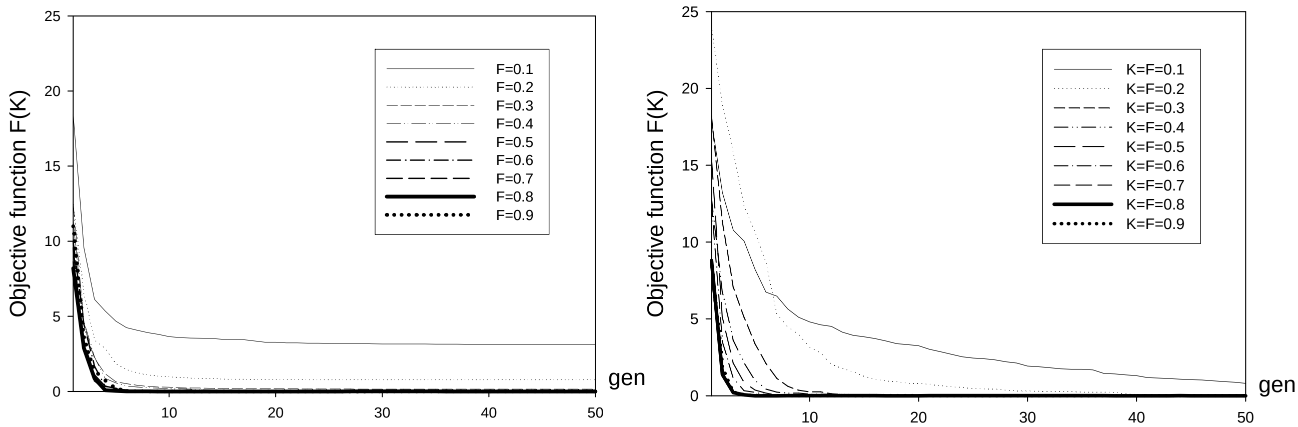


Fig. 3. Three-machine system



(a) The random strategy for *K*

(b) *K=F*

Fig. 4. DE convergence performance experiments

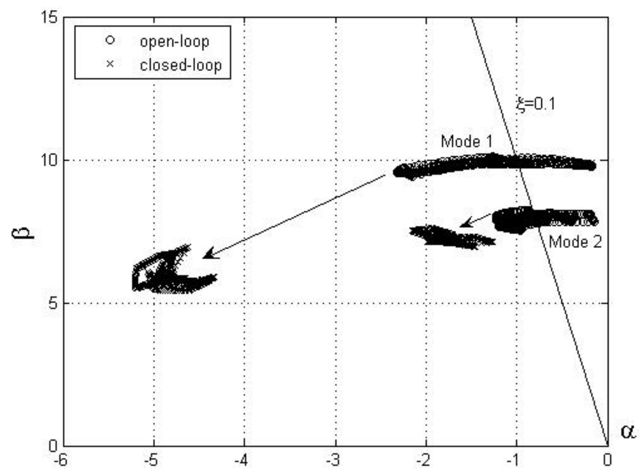


Fig. 5. Electromechanical modes distribution under 480 operating conditions

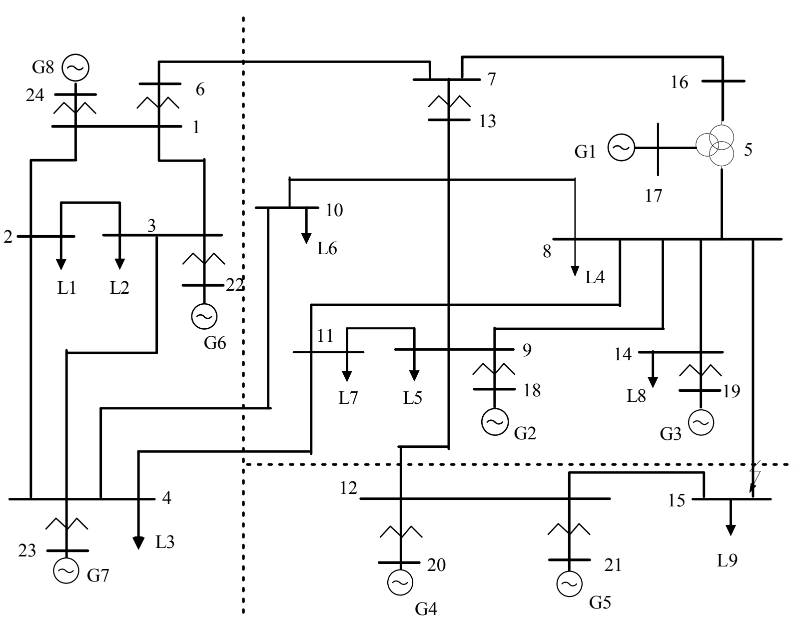


Fig. 9. Single line diagram of eight-machine system

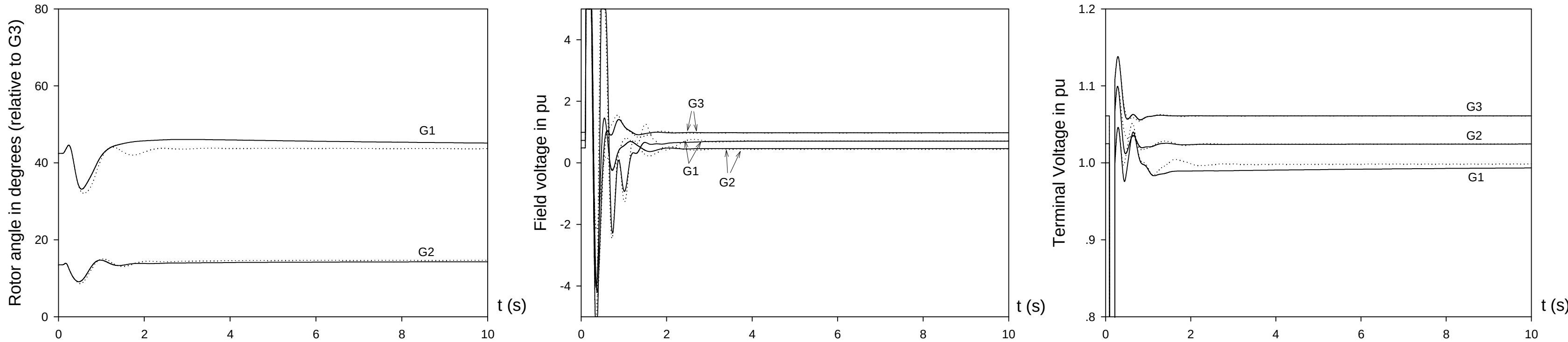


Fig. 6. System response at light load condition (solid lines for DE-PPSS and dotted lines for CPSS)

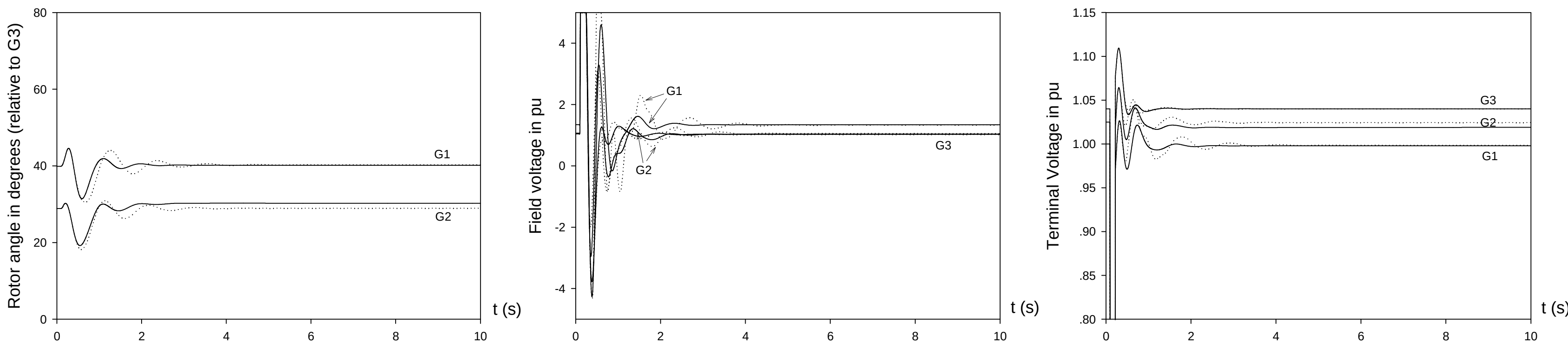


Fig. 7. System response at medium load condition (solid lines for DE-PPSS and dotted lines for CPSS)

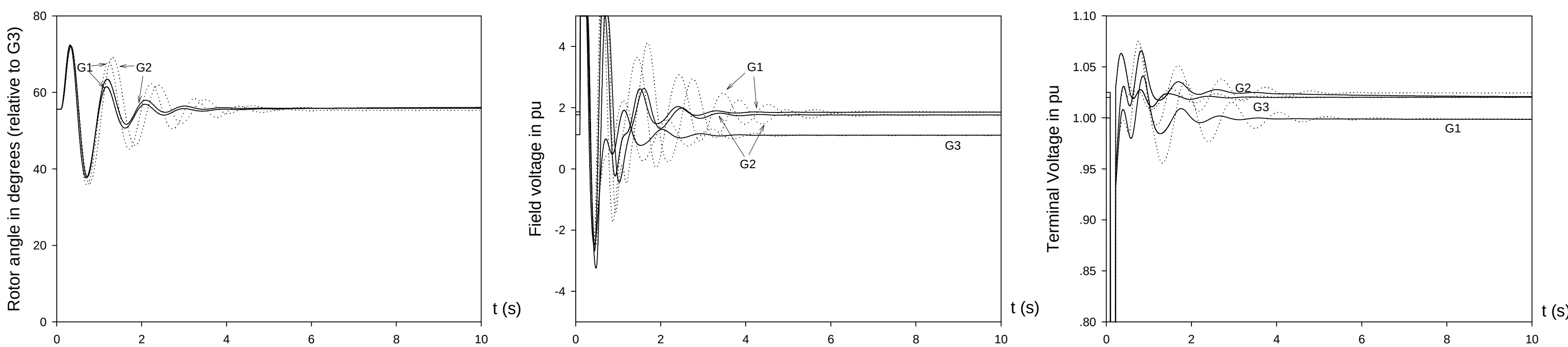


Fig. 8. System response at heavy load condition (solid lines for DE-PPSS and dotted lines for CPSS)

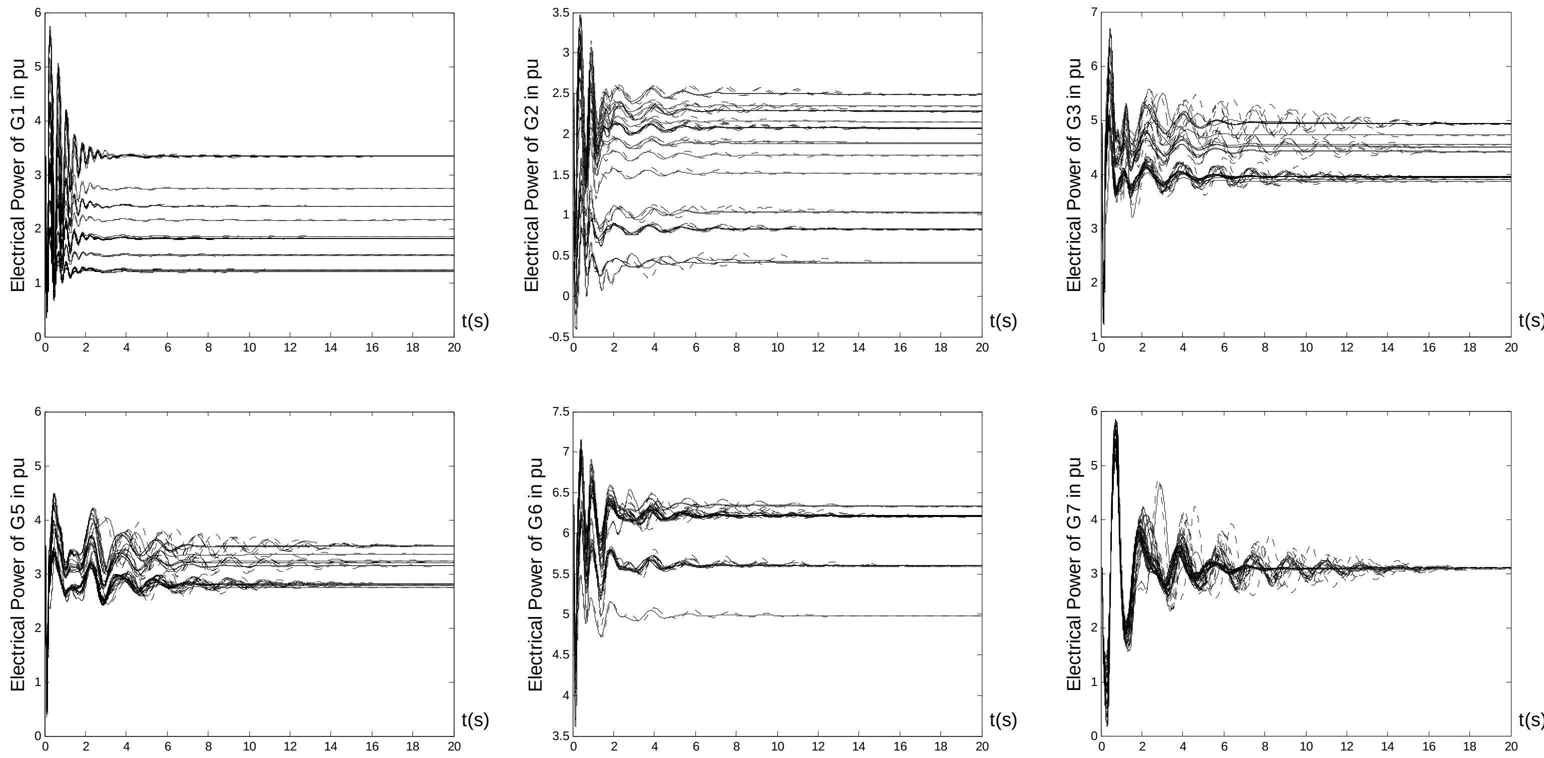


Fig. 10. Transient responses of generator G1, G2, G3, G5, G6 and G7 (solid lines for DE-PPSS and dotted lines for CPSS)

TABLE I Pseudo-code of the DE-based probabilistic PSS design

Set the iteration or generation counter *g* to 0;
Initialize population of chromosomes *P(g)* at generation *g*;
Evaluate the objective function values of chromosomes in *P(g)*;
While (not terminate) {
  Generate the child population *C(g)* from the parent population *P(g)* by reproduction operation;
  Evaluate the objective function values of *C(g)*;
  Perform the one-to-one selection and reproduce the *P(g+1)*;
  g = *g* + 1;
}

TABLE II Electromechanical modes of the open-loop system I

No.	$\overline{\alpha}$	$\overline{\beta}$	σ_α	α^*	P_α	$\overline{\xi}$	σ_ξ	ξ^*	P_ξ
1	-1.298	9.905	0.778	**1.54**	**0.938**	0.1299	0.0783	**0.38**	**0.649**
2	-0.910	7.895	0.316	**2.56**	**0.995**	0.1145	0.0402	**0.36**	**0.641**

Expectations: $\overline{\lambda} = \overline{\alpha} \pm j\overline{\beta}$ and $\overline{\xi}$;
Standard deviation: σ
Standardized expectation: $\alpha^* = -\overline{\alpha} / \sigma_\alpha$ and $\xi^* = (\overline{\xi} - 0.1) / \sigma_\xi$

TABLE III PSS parameters for system I

PSS		K_{PSS}	T_1	T_2	T_3	T_4
DE-PPSS	G1	1.732	0.186	0.098	0.692	0.127
	G2	2.931	0.226	0.045	0.406	0.158
CPSS	G1	0.655	1.00	0.08	1.10	0.08
	G2	0.272	1.00	0.08	1.10	0.08

TABLE IV Electromechanical modes of the closed-loop system I

No.	$\overline{\alpha}$	$\overline{\beta}$	σ_α	α^*	P_α	$\overline{\xi}$	σ_ξ	ξ^*	P_ξ
1	-4.912	5.801	0.186	25.91	1.00	0.6462	0.0228	23.92	1.00
2	-1.886	7.175	0.155	11.50	1.00	0.2542	0.0148	10.40	1.00

TABLE V Performance indices of system I

	δ_1	δ_2	v_{f1}	v_{f2}	v_{f3}	v_{t1}	v_{t2}	v_{t3}
C_{PI_1}	0.1226	0.1235	0.0565	0.0421	0.0253	0.0024	0.0032	0.0033
D_{PI_1}	0.0492	0.0586	0.0390	0.0291	0.0206	0.0022	0.0030	0.0033
C_{PI_2}	0.0202	0.0231	0.0024	0.00164	0.00059	0.00005	0.00012	0.00016
D_{PI_2}	0.0018	0.0032	0.0014	0.00069	0.00045	0.00005	0.00012	0.00016

TABLE VI Electromechanical modes of the open-loop system II

No.	$\overline{\alpha}$	$\overline{\beta}$	σ_α	α^*	P_α	$\overline{\xi}$	σ_ξ	ξ^*	P_ξ
1	-1.925	15.40	0.080	22.95	1.00	0.124	0.007	**3.40**	**0.9997**
2	-0.773	10.75	0.070	9.61	1.00	0.072	0.006	**-4.59**	**0.00**
3	-0.590	9.705	0.039	12.50	1.00	0.061	0.003	**-12.65**	**0.00**
4	-0.604	7.888	0.024	20.80	1.00	0.076	0.004	**-5.42**	**0.00**
5	-0.600	7.381	0.083	6.00	1.00	0.081	0.010	**-1.93**	**0.0268**
6	-0.365	6.420	0.046	5.72	1.00	0.057	0.007	**-6.05**	**0.00**
7	-0.033	3.854	0.007	**-9.76**	**0.00**	0.009	0.002	**-49.55**	**0.00**

TABLE VII PSS parameters for system II

PSS		K_{PSS}	T_1	T_2	T_3	T_4
DE-PPSS	G1	-0.086	0.107	0.192	0.194	0.199
	G2	-0.014	1.276	0.044	1.420	0.144
	G3	-0.824	0.169	0.121	0.135	0.054
	G5	-0.030	1.273	0.049	0.106	0.185
	G6	-0.019	0.951	0.064	0.612	0.110
	G7	-0.739	0.286	0.141	0.061	0.162
CPSS	G1	-0.063	0.091	0.165	1.621	0.041
	G2	-0.195	1.492	0.194	0.293	0.077
	G3	-0.064	1.827	0.066	1.132	0.192
	G5	-0.099	1.560	0.042	0.117	0.200
	G6	-0.226	0.593	0.044	0.624	0.087
	G7	-1.346	1.773	0.153	0.074	0.167

TABLE VIII Electromechanical modes of the closed-loop system II

No.	$\overline{\alpha}$	$\overline{\beta}$	σ_α	α^*	P_α	$\overline{\xi}$	σ_ξ	ξ^*	P_ξ
1	-2.020	15.07	0.094	20.54	1.00	0.133	0.007	4.44	1.00
2	-1.682	12.81	0.120	13.22	1.00	0.130	0.008	3.97	1.00
3	-1.546	11.31	0.073	19.73	1.00	0.135	0.003	11.06	1.00
4	-0.846	7.495	0.019	40.10	1.00	0.112	0.003	4.02	1.00
5	-4.498	4.931	0.252	17.47	1.00	0.674	0.023	25.08	1.00
6	-1.600	3.939	0.285	5.27	1.00	0.376	0.059	4.71	1.00
7	-0.853	3.028	0.153	4.91	1.00	0.271	0.038	4.57	1.00

TABLE IX Performance indices of system II

	P_{e1}	P_{e2}	P_{e3}	P_{e4}	P_{e5}	P_{e6}	P_{e7}	P_{e8}
C_{PI_1}	0.0770	0.0571	0.1414	0.0845	0.1208	0.0678	0.2051	0.4106
D_{PI_1}	0.0759	0.0428	0.0765	0.0607	0.0777	0.0519	0.1087	0.1385
C_{PI_2}	0.0066	0.0023	0.0146	0.0058	0.0124	0.0033	0.0175	0.1069
D_{PI_2}	0.0068	0.0020	0.0096	0.0047	0.0093	0.0029	0.0051	0.0121