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Parameter optimization of multimachine power system conventional stabilizers using CDCARLA method

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ABSTRACT

In this paper, a novel Combinatorial Discrete and Continuous Action Reinforcement Learning Automata (CDCARLA) based approach for optimal design of multimachine power system stabilizers (PSSs) is presented. The proposed CDCARLA based design approach is a combined procedure of two optimization stages in discrete and continuous spaces for fast convergence and high optimization efficiency. The potential of the proposed approach in seeking the optimal settings of the widely used conventional lead-lag PSSs' parameters is investigated and assessed in multimachine power systems. The performance and robustness of the proposed CDCARLA based PSS is evaluated under different power system disturbances. The performance of the proposed stabilizer is also compared with other stabilizers reported in the literature including the multi-band PSSs for a two-area four-machine power system. Simulation results show the effectiveness and robustness of the proposed CDCARLA PSS in damping local and inter area oscillation modes under various disturbances, and confirm its superiority in comparison with other types of PSSs.

1. Introduction

Due to the increasing complexity of power systems the need for enhancing the stability margin has also increased. Generally, power systems experience a variety of disturbances that can result in low-frequency electromechanical oscillations, which take place among rotors of synchronous generators connected to the power system [1–3]. In a multimachine power system characterized by a weak structure, e.g. a weak connection between two or more coherent power generation area, these oscillations may sustain and grow leading to loss of synchronism and system separation if no adequate damping is available [4].

Dynamic instability in the form of low frequency oscillations was first observed in 1977 in Hong Kong power system [5]. This problem was resolved by desensitizing the excitation responses on the main generation units. In 1984, by connecting this system to South China power system, severe oscillations in tie line have been recorded. One of the worst oscillations had a 90 MW amplitude, and a duration of 50 s while nominal transmission power of tie line was 120 MW.

Such dynamic instabilities impose unnecessary limitations on power systems operation. However, the stability margin of the power systems can be greatly enhanced by increasing the system damping characteristics at the low frequency oscillations. Therefore, the maximum capacity of transmission lines and energy corridors can be reached [6]. In the last decades, several methods for power system stabilization have been proposed. One of the cost-effective and efficient methods is using power system stabilizers, (PSS) which introduce a supplementary signal in the generator excitation system in-phase with the rotor speed deviations.

In recent years, several approaches based on modern control theory have been applied to the PSS design problem, such as optimal control, adaptive control, variable structure control, and intelligent control [7–11]. Despite of the merits of such techniques, power system utilities still prefer the conventional lag-lead PSS (CPSS) structure [12,13] because of its fixed structure, ease of online tuning, and the lack of assurance of stability related issues of some of the optimal, adaptive, or variable structure techniques [14].

It is generally agreed that the PSS significantly improve the stability of power system, however the optimum tuning of its parameters is still a serious problem; because the inadequate setting of PSS parameters may not only fail to stabilize an unstable power system, but may also reinforce the instability.

In this paper, a novel numerical optimization method based on *Reinforcement Learning Automata* is proposed and utilized for the optimum tuning of PSSs parameters in a multimachine multi-area power system. The preliminary form of the proposed optimization

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method was first introduced by Howell et al. [15], which was called *Continuous Action Reinforcement Learning Automata* (CARLA) and has been successfully applied to numerous applications [16–18]. The universalized form of CARLA which is proposed in this paper is *Combinatorial Discrete and Continuous Action Reinforcement Learning Automata* (CDCARLA) which is composed of two successive learning algorithms. In the first algorithm, the total variation limit of each decision variable is divided into large enough number of sub-limits and then, the optimum sub-limit for each variable will be determined based on a pre-specified cost function. In the second algorithm, the decision variables optimum value will be obtained using a cost function that is often selected the same as the previous algorithm. In fact, both algorithms operate through interaction with a random or unknown environment by selecting actions, i.e. discrete or continuous, in a stochastic trial and error process.

In this paper, an application of the CDCARLA technique is applied to the PSS optimal parameters tuning for a two-area four-machine power system. The performance and effectiveness of the proposed stabilizer are compared to the conventional power system stabilizer (CPSS) as well as the multi-band PSSs.

The structure of the paper is as follows: In Section 2, the control structure of synchronous generator and model of the CPSS are presented. In Section 3, the multimachine power system considered for performance evaluation, is illustrated. Details of the CDCRLA design method is described in Section 4, and application of this method for the PSS optimal tuning is explained in Section 5. Simulation results to evaluate the proposed method are given in Section 6. Section 7 includes the conclusion.

2. Power system stabilizers

Increasing the rotor damping of a synchronous generator is the main objective of the power system stabilizer. This objective is realized by introducing appropriate supplementary control signals to the generator excitation system. Fig. 1 shows a schematic of a synchronous generator control components.

In this paper, the change in the rotor speed is considered as an input to the PSS. Fig. 2 shows the structure of the conventional PSS.

The above structure is composed of three main blocks: phase compensator, washout filter, and gain block:

- The phase compensator block provides the necessary phase lead characteristics for lag compensation between excitation input and electrical torque (air gap torque).
- The washout filter acts as a high pass filter with time constant T_w, consequently, PSS only responds to rotor speed deviation, while steady-state operation does not affect the generator terminal voltage. The value of the time constant T_w must be selected large enough to pass required PSS signals intact.
- The gain unit indirectly determines the damping ratio of the PSS; however its value is restricted by practical considerations.

In addition to the above block, there is a limiting block at the output of the PSS to prevent over excitation. The nominal bounds of the limiting block are usually selected from ±0.12 to ±0.15 pu.The transfer function of the conventional PSS is given by

$$G_{PSS}(s) = K_s \frac{T_w s(1+sT_1)(1+sT_3)}{(1+T_w s)(1+sT_2)(1+sT_4)} \tag{1}$$

The PSS parameters that can be optimized are K_s, T_1, T_2, T_3, and T_4 which are referred to as decision variables in the optimization problem. Analytically a linearized incremental model of the power system around an equilibrium point is derived and these parameters are set so that power system and the PSS have acceptable performance in the frequency domain.

3. Multi machine power system model

In this paper, the two-area four-machine test power system model [6] shown in Fig. 3 is selected for evaluating the performance of the designed PSSs using the proposed approach. This model consists of two similar power generation areas that are connected by a 220 km two-circuit tie line. Beside of its simplicity this model mimics various behaviors of real power systems.

Each area contains two identical 20 kV, 900MVA synchronous generator. All generator s' electrical and mechanical parameters, except inertia constants, are the same. Moreover, for Area 1 generators, H = 1 s., and for Area 2 generators, H = 6.175 s.

Load flow calculation shows that Area 1 transfers 413 MW of power to Area 2. Because of the fact that the surge impedance loading (SIL) of transmission lines approximately reach 140 MW, therefore the system is normally under stressful conditions.

In this work, it is assumed that each generator in the power system is equipped with a PSS. Since each PSS has five parameters to be tuned; hence there are 20 parameters or decision variables to be optimized using the proposed method.

4. Design methodology

Generally, when dealing with a large number of decision variables in complex computational optimization methods, the number of iterations for obtaining optimum solution may increase significantly. In the proposed method, this concept is taking into account, thus, design procedure is divided into two successive steps to speed up the optimization procedure. In the first step, the total variation limit of each decision variable is divided into sub-limits of usually equal length, and then the *Discrete Action*

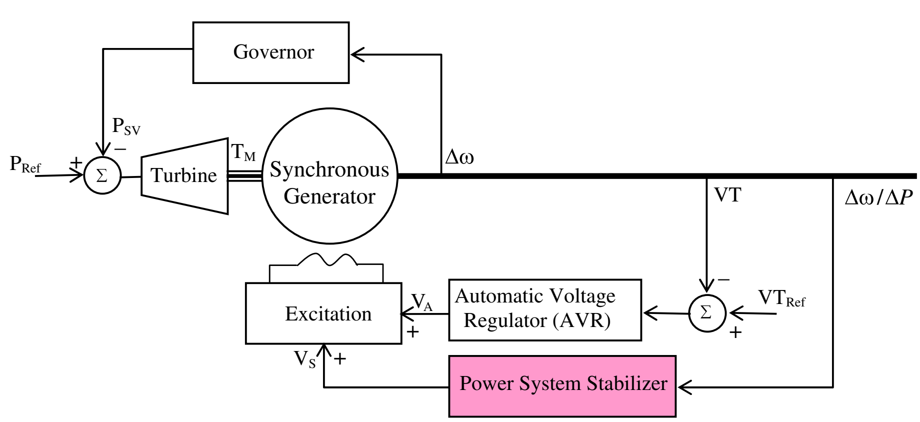

Fig. 1. Control diagram of synchronous generator.

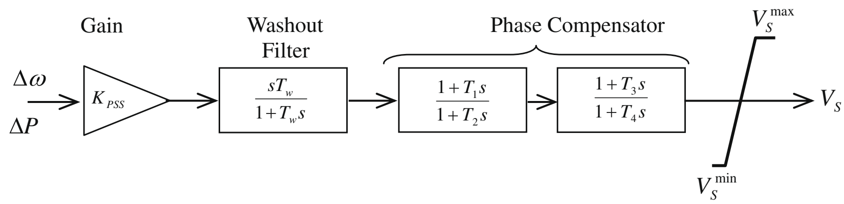

Fig. 2. Conventional PSS structure.

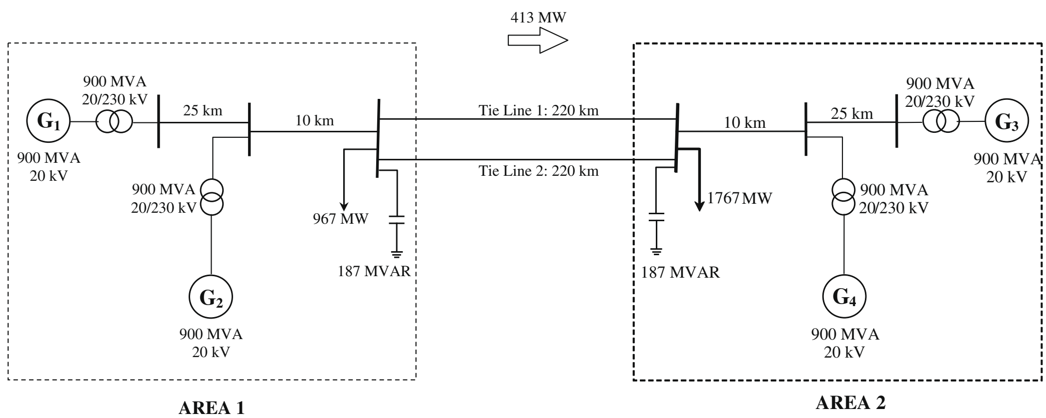

Fig. 3. Two-area four-machine test power system.

Reinforcement Learning Automata (DARLA) algorithm determines the optimum sub-limit of each decision variable. In the second step, the *Continuous Action Reinforcement Learning Automata* (CARLA) algorithm searches for the optimum value of each decision variable in the predetermined optimal sub-limit. Both algorithms find the optimum values of decision variable using a predefined cost function. Details of the above algorithms are as follows.

4.1. DARLA optimization algorithm

In DARLA optimization algorithm the total variation limit of each decision variable divided into numbers of usually equal length sub-limits. Following this step, the DARLA algorithm can be applied as shown in Fig. 4.

For each decision variable, an individual DARLA is considered which runs in a parallel implementation with other DARLAs. The only interconnection between DARLAs is through the environment and via a shared cost function. The computational flow of DARLA can be described as follows.

Discrete Probability Distribution Function: DARLA considers a discrete probability distribution function (DPDF) for each decision variable which is initially uniform and can be defined as:

$$f_i^{(0)}(d_i) = \begin{cases} \frac{1}{N_i} & d_i = 1, 2, \ldots, N_i \\ 0 & \text{other} \end{cases} \qquad (2)$$
$$i = 1, 2, \ldots, n$$

where, N_i is the number of sub-limits of ith decision variable and n is the number of decision variables.

Stochastic Selection: In each iteration of DARLA, a cumulative probability distribution function is computed for each decision variable. Then, a discrete action based on this function is stochastically expressed as:

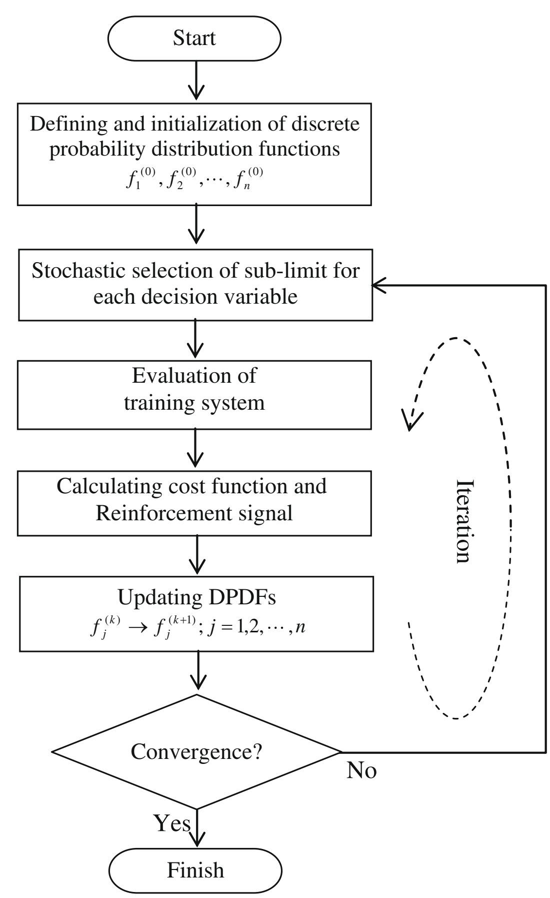

Fig. 4. DARLA flow diagram.

$$\sum_{1}^{d_i} f_i^{(k)}(d_i) = z_i^{(k)} \tag{3}$$

where z is a random number varies uniformly in the range [0,1].

Cost Function: The objective of DARLA algorithm is to find the optimum sub-limit for each decision variable that minimizes a predefined cost function. Often, the cost function is constructed from the weighted combination of the performance criteria as:

$$J^{(k)} = G_1 P_1(Y) + G_2 P_2(Y) + \cdots + G_m P_m(Y) \tag{4}$$

where, $J^{(k)}$ is the cost function of the kth DARLA iteration, $G_1, G_2, \ldots, G_m$ are the weighting coefficients, $P_1(.), P_2(.), \ldots, P_m(.)$ are the performance criteria, and $Y = [y_1, y_2, \ldots]^T$ is the model output vector. In iterations, the center of selected sub-limits is used for calculating of cost function value.

Reinforcement Signal: The reinforcement signal is the performance index of selected sub-limits in each iteration and it indicates the relative suitability of selected action. In other words, the lower value of reinforcement signal implies that the selection of sub-limit was poor while a higher value indicates a good selection. One of the common mappings between the cost function and the reinforcement signal can be expressed as:

$$\beta^{(k)}(J) = \min\{1, \max\{0, \frac{J_{avg} - J}{J_{avg} - J_{\min}}\}\} \tag{5}$$

where J_{avg} and J_{min} are the average and minimum of previous cost values, respectively.

This definition of reinforcement signal performs a reward/inaction rule in DPDFs modification. In other words, if the current selected action is less than the mean value of the previous cost, i.e. $\beta = 0$, then no modification of CPDFs will be performed (inaction) and, if the selected action leads to a cost value less than the minimum of the previous cost, i.e. $\beta = 1$, then maximum reinforcement will be done (reward). The important property of the mapping defined in (5) is that the average value of the cost has descending behavior, which guarantees obtaining optimal results for large enough number of iterations.

Updating Discrete Probability Functions: At the end of each iteration, the DARLA algorithm learns about selection actions of that iteration. The learning logic is that: if selecting of a sub-limit leads to good performance, likelihood neighbor sub-limits have relative good performance. The updating rule of DPDFs can be described as:

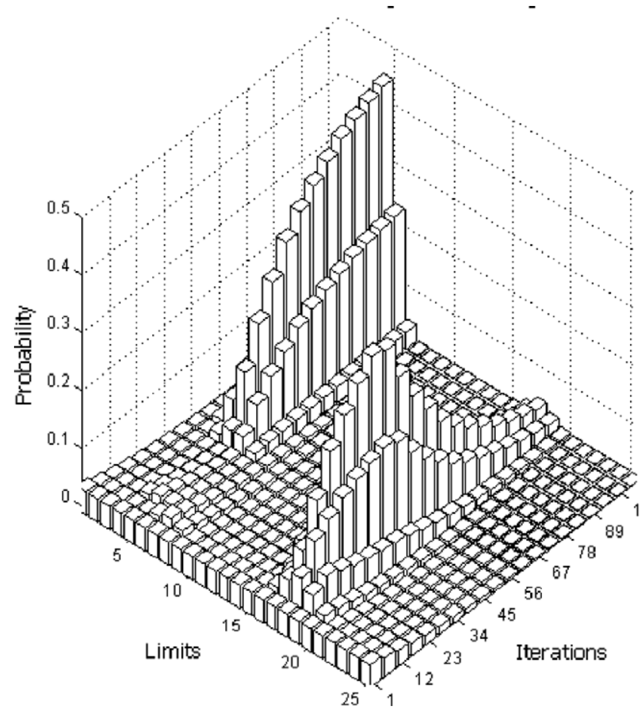

Fig. 6. Trend of DPDF variation.

$$\begin{aligned} &f_i^{(k+1)}(d_i) = \alpha_i^{(k)}[f_i^{(k)}(d_i) + \beta^{(k)} Q(d_i, \tilde{d}_i)] \\ &d = 1, 2, \ldots, N_i; i = 1, 2, \ldots, n \end{aligned} \tag{6}$$

where, $\tilde{d}_i$ is selected sub-limit of ith decision variable and, Q is a Gaussian function centralized in $\tilde{d}_i$ which is defined as (7).

$$Q(d, \tilde{d}_i) = q 2^{-(d - \tilde{d}_i)^2} \tag{7}$$

where, q is a positive constant and is considered as a learning factor. α in (6) is a normalization factor and is defined as (8).

$$\alpha_i^{(k)} = \frac{1}{\sum_{d=1}^{N_i} f_i^{(k)} + \beta^{(k)} Q(d_i, \tilde{d}_i)} \tag{8}$$

Now, the DARLA algorithm steps will continue with the new DPDFs.

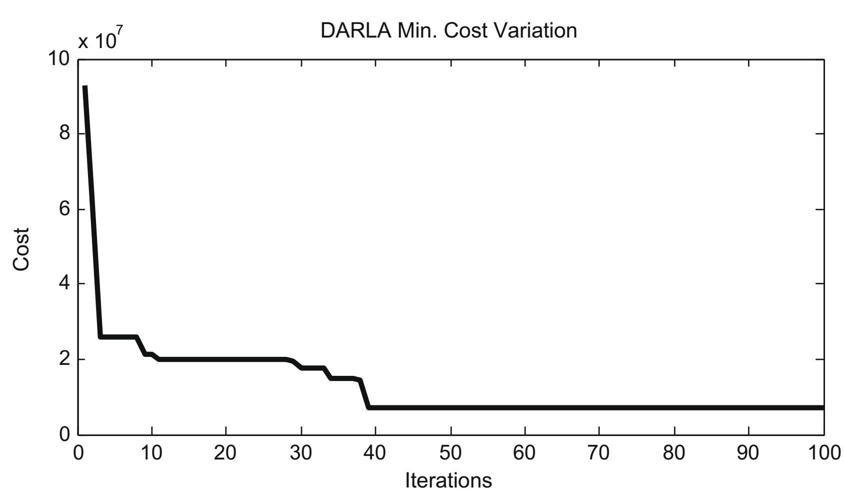

Fig. 5. Minimum of costs variation due to iterations for DARLA.

Table 1
Optimum sub-limits of decision variables.

	Parameter	Opt. Sub-limit		Parameter	Opt. Sub-limit
Generator 1	K_{PSS}	[14, 16]	*Generator 2*	K_{PSS}	[12, 14]
	T_1	[18, 20]		T_1	[8, 10]
	T_2	[2, 4]		T_2	[16, 18]
	T_3	[10, 12]		T_3	[10, 12]
	T_4	[18, 20]		T_4	[0, 2]
Generator 3	K_{PSS}	[14, 16]	*Generator 4*	K_{PSS}	[18, 20]
	T_1	[4, 6]		T_1	[8, 10]
	T_2	[4, 6]		T_2	[18, 20]
	T_3	[18, 20]		T_3	[14, 16]
	T_4	[22, 24]		T_4	[16,18]

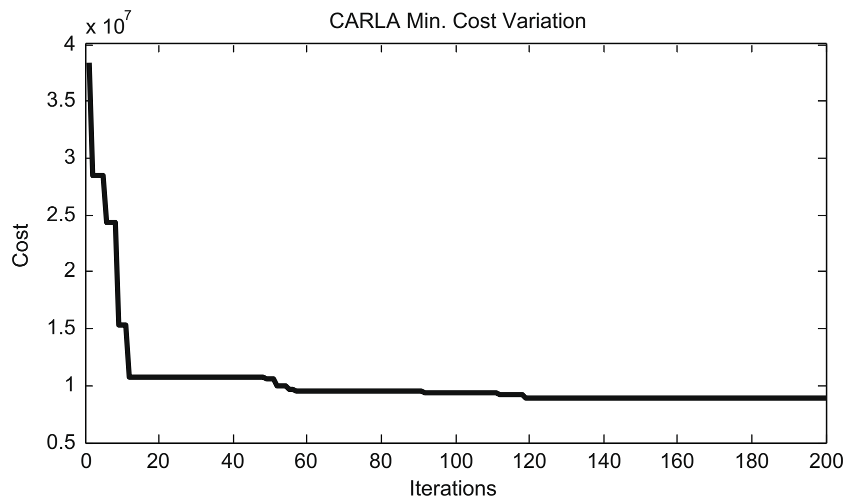

Fig. 7. Minimum of costs variation due to iterations for CARLA.

Convergence Criterion: The convergence criterion of the algorithm can be a specified number of iterations or the standstillness of selected actions, etc. After the algorithm is finished, it is expected that the DPDFs are maximized at corresponding decision variable optimal sub-limit.

4.2. CARLA optimization algorithm

After obtaining the optimum sub-limits by the DARLA algorithm, the CARLA searches for optimal values of decision variables in corresponding optimal sub-limits. The CARLA algorithm is similar to DARLA except that the DPDFs will change to *Continuous Probability Distribution Function* (CPDF). In fact, the only difference between CARLA and DARLA is that CARLA takes the actions in continuous space instead of discrete space.

In this algorithm, the probability distribution functions are initially defined uniformly in continuous space over the optimum sub-limit as:

$$f_i^{(0)}(x_i) = \begin{cases} \frac{1}{x_{i,\max}-x_{i,\min}} \ ; & x_i \in [x_{i,\min}, x_{i,\max}] \\ 0 \ ; & \text{other} \end{cases} \qquad (9)$$
$$i = 1, 2, \ldots, n$$

where, $x_{i,min}$ and $x_{i,max}$ are the lower and upper bounds of the ith optimal sub-limit, respectively.

The stochastic action selection, cost function and reinforcement signal calculation are similar to DARLA. CPDF updating in CARLA has the same philosophy, but differs slightly as:

$$f_i^{(k+1)}(x_i) = \alpha_i^{(k)}(f_i^{(k)} + \beta^{(k)} H_i(x_i, \tilde{x}_i)) \qquad (10)$$
$$i = 1, 2, \ldots, n$$

where, H is Gaussian function centralized in $\tilde{x}_i$ as defined in (11).

$$H_i(x_i, \tilde{x}_i) = \frac{g_h}{x_{i,\max}-x_{i,\min}} \exp\left(-\frac{(x_i-\tilde{x}_i)^2}{2(g_w(x_{i,\max}-x_{i,\min}))^2}\right) \qquad (11)$$

where, g_h and g_w are the height and width of H function and determine the speed and resolution of the learning algorithm. The normalization factor can be defined as:

$$\alpha_i^{(k)} = \frac{1}{\int_{x_{i,\min}}^{x_{i,\max}} f_i^{(k)}(x) + \beta^{(k)} H(x_i, \tilde{x}_i) dx} \qquad (12)$$

Similar to DARLA, by while satisfying the algorithm convergence criterion the optimum values of decision variables can be determined.

It is noticed that, the DARLA and CARLA algorithms do not require the knowledge of the system dynamics, but the designer should be aware of the system behavior in order to define an appropriate cost function.

In our implementation, the values of g_h and g_w are set as 1.0 and 0.003, respectively. The length of each sub-limit is equal to 2, and this interval has been divided to 2000 points in CARLA resulting in accuracy of 3 digits after zero.

5. PSS design using CDCARLA

The described CDCARLA optimization procedure has been implemented and applied to select the optimal settings of PSSs parameters for the multimachine power system considered. The total variation limits of all 20 decision variables are selected between 0 and 50. Moreover, these variation limits are divided into 25 sub-limits. The training system in DARLA and CARLA algorithms

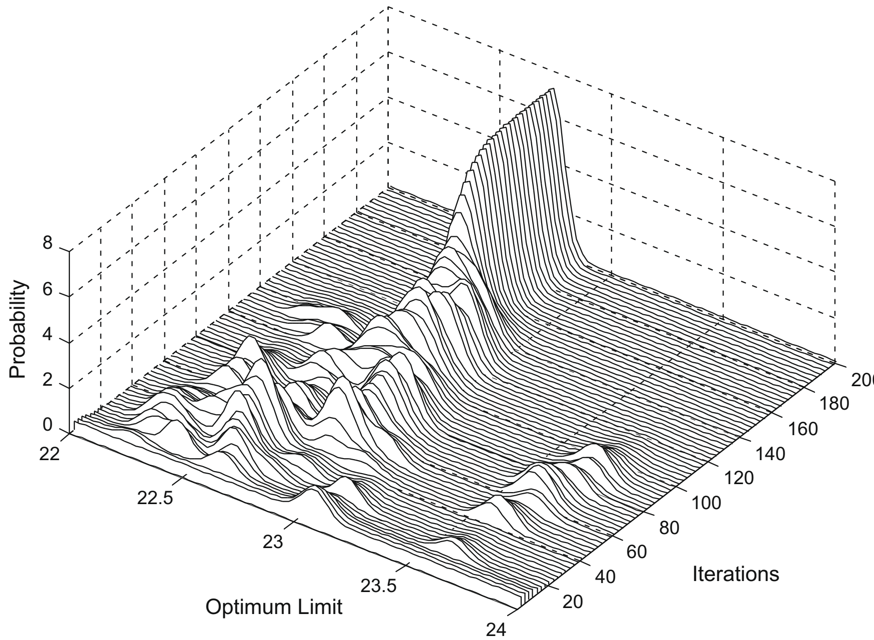

Fig. 8. Trend of CPDF variation.

is considered with a three-phase fault disturbance. The fault occurred at $t = 1.0$ s. in the middle of Tie-Line2 for 8 cycles. The fault is cleared by tripping Tie-Line 2.

A cost function that minimizes the overshoots and settling time of the system response is employed in this study. It can be defined as:

$$J = G_1 \sum_{j=2}^{4} \int_{t=0}^{T} t|\Delta\omega_{j-1}|dt + G_2 \sum_{j=2}^{4} \sup|\Delta\omega_{j-1}| + G_3 \sum_{j=2}^{4} E_{\Delta\omega_{j-1}} \quad (13)$$

where, $\Delta\omega_{j-1}$ is the relative rotor speed of the jth generator relative to the first generator, i.e. $\Delta\omega_{j-1} = \Delta\omega_j - \Delta\omega_1$, sup(.) is the supreme operator, and $E\Delta\omega_{j-1}$ is the steady state value of the relative rotor speed. T in (13) is the simulation time and should be large enough, e.g. $T = 7$ s.

Fig. 5 shows the variation of minimum of costs due to iterations for DARLA algorithm for 100 numbers of iterations, $G_1 = 1$, $G_2 = 5$, $G_3 = 20$ and $q = 0.5$.

Moreover, the trend of the DPDF for the PSS parameters typically is shown in Fig. 6.

Table 1 summarizes the optimum sub-limits of decision variables.

After obtaining the optimal sub-limits, the CARLA algorithm is applied. The cost function and its weighting coefficients are selected the same as the DARLA algorithm. Figs. 7 and 8 show the trend of the minimum cost function, and the trend of the CPDF variation for the decision variables, respectively. Table 2 shows the optimal settings of decision variables after 200 iterations. It is worth mentioning that the observed time per iteration of the design process is 41.2 s on 1.8 GHz PC.

Table 2
Optimum values of decision variables.

	Parameter	Opt. Value		Parameter	Opt. Value
Generator 1	K_{PSS}	14.79	*Generator 2*	K_{PSS}	13.98
	T_1	18.98		T_1	9.70
	T_2	3.17		T_2	17.80
	T_3	10.71		T_3	11.46
	T_4	18.07		T_4	1.45
Generator 3	K_{PSS}	14.28	*Generator 4*	K_{PSS}	18.91
	T_1	4.57		T_1	8.66
	T_2	5.09		T_2	19.22
	T_3	19.36		T_3	15.59
	T_4	22.72		T_4	16.23

6. Results and discussions

For performance evaluation of the proposed design method, nonlinear time domain simulations of the considered power system [19–21] were performed using Matlab® and Simulink® softwares. Moreover, the designed PSSs are compared with the IEEE Multi-band PSS [22] and conventional PSS [1,6] under different kind of disturbance conditions.

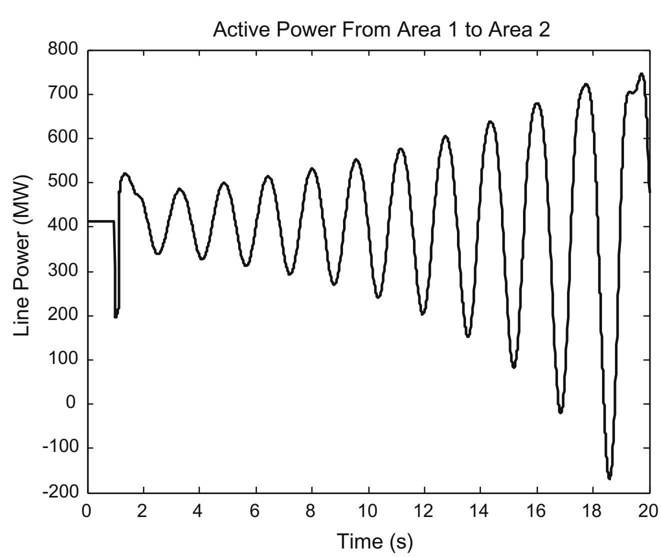

Fig. 9. Tie-line power variation due to small signal disturbance.

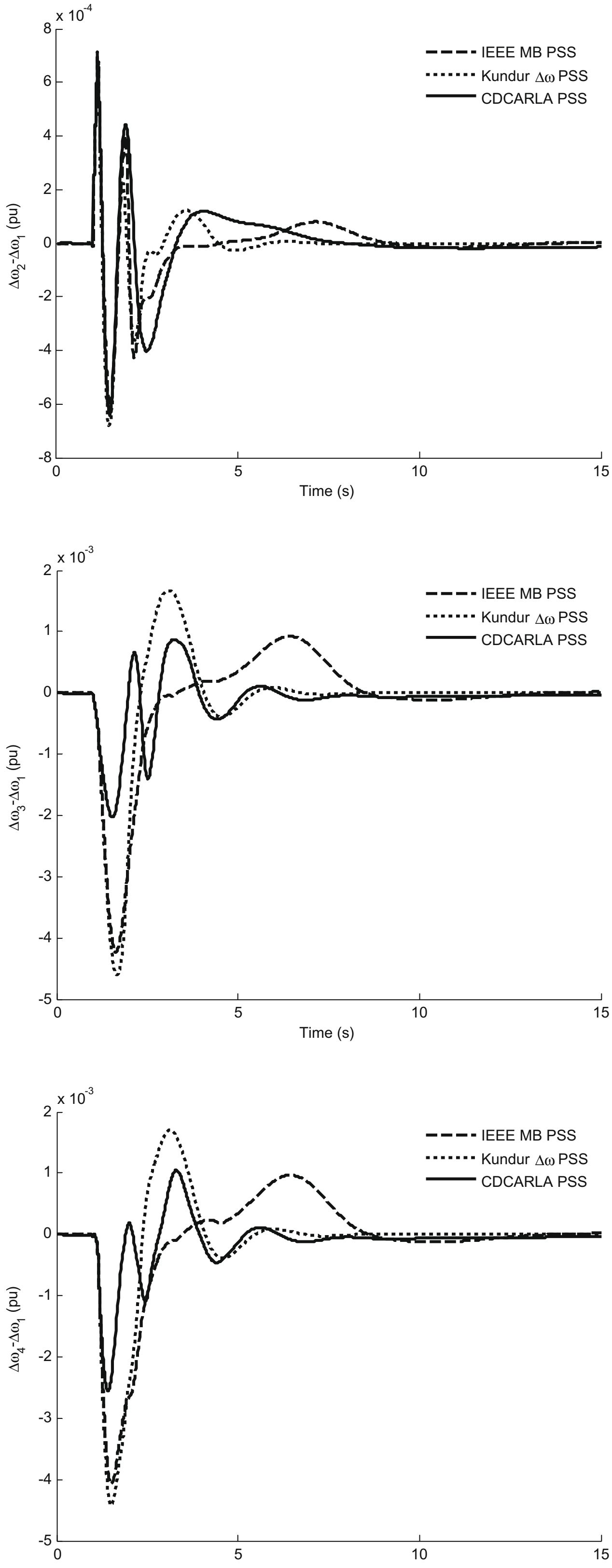

Fig. 10. The performance comparison of PSSs due to three phase earth fault on Tie-Line 2 disturbance.

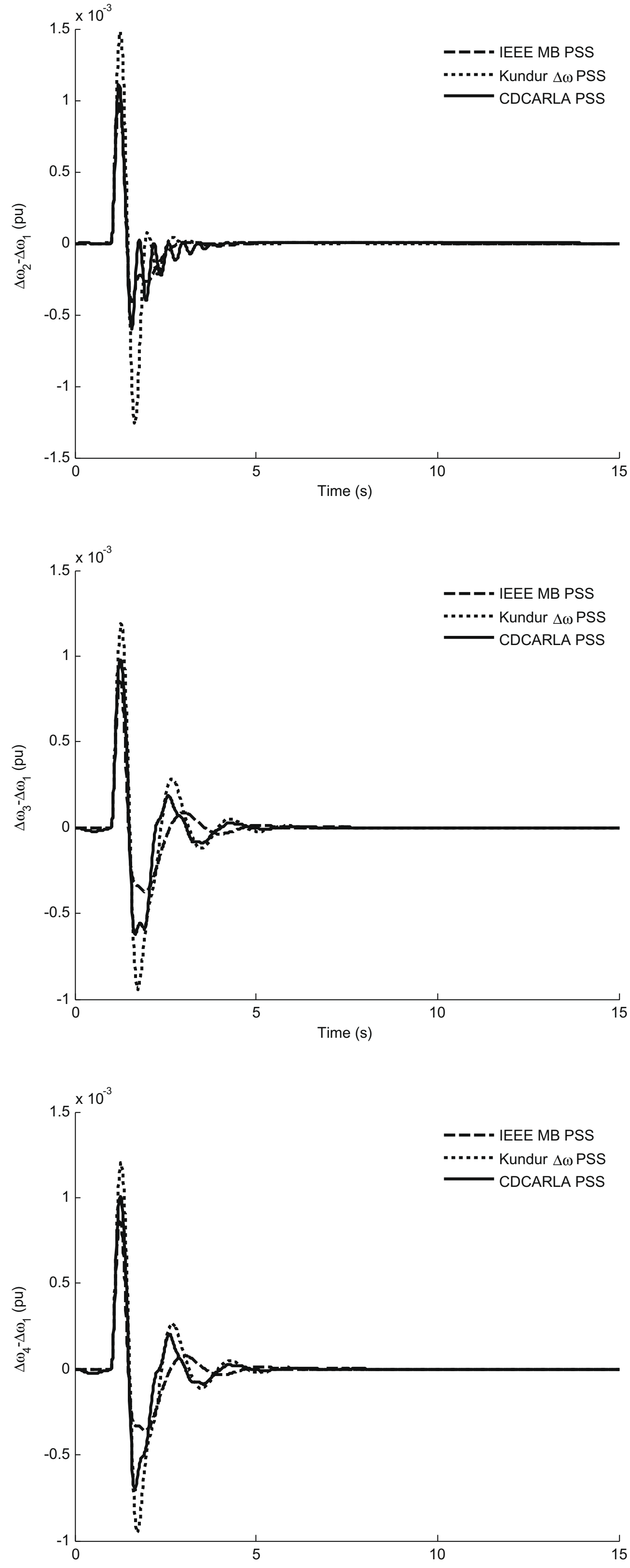

Fig. 11. The performance comparison of PSSs due to step change in Generator 1 voltage reference disturbance.

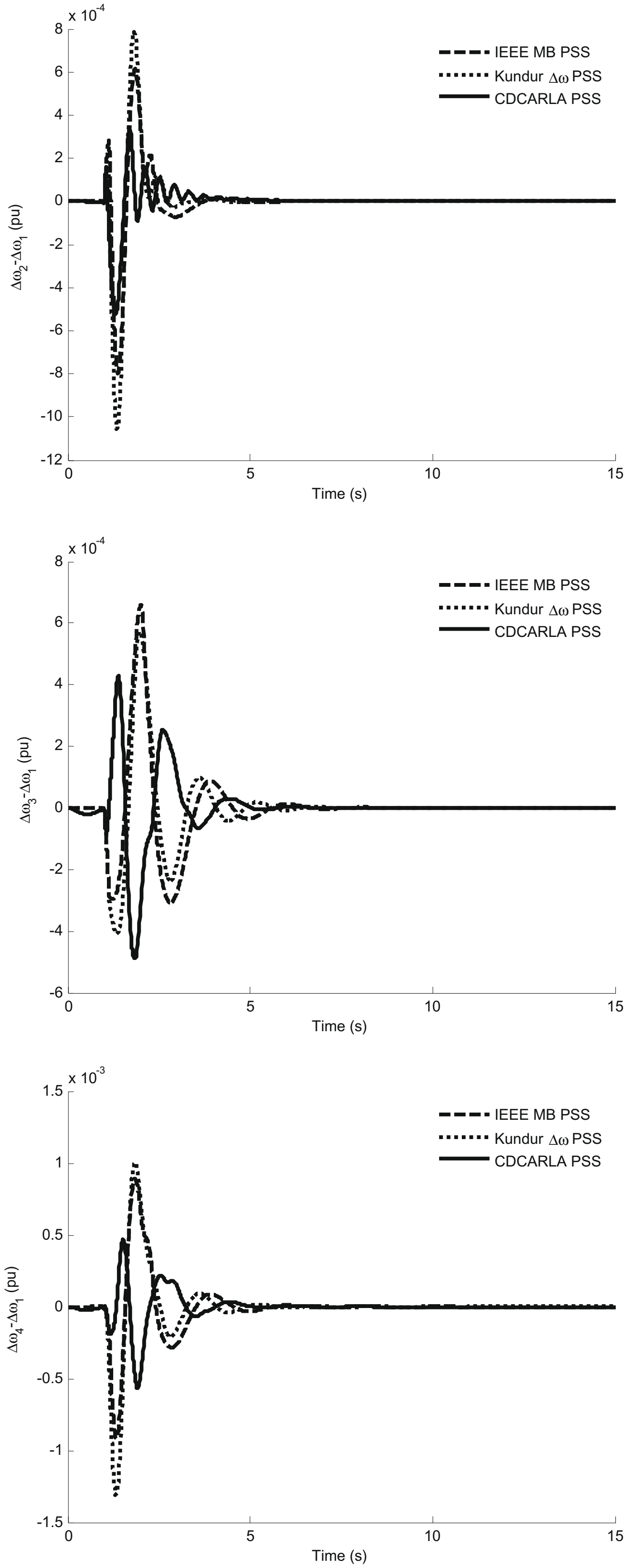

Fig. 12. The performance comparison of PSSs due to single phase earth fault on Area 2 busbar disturbance.

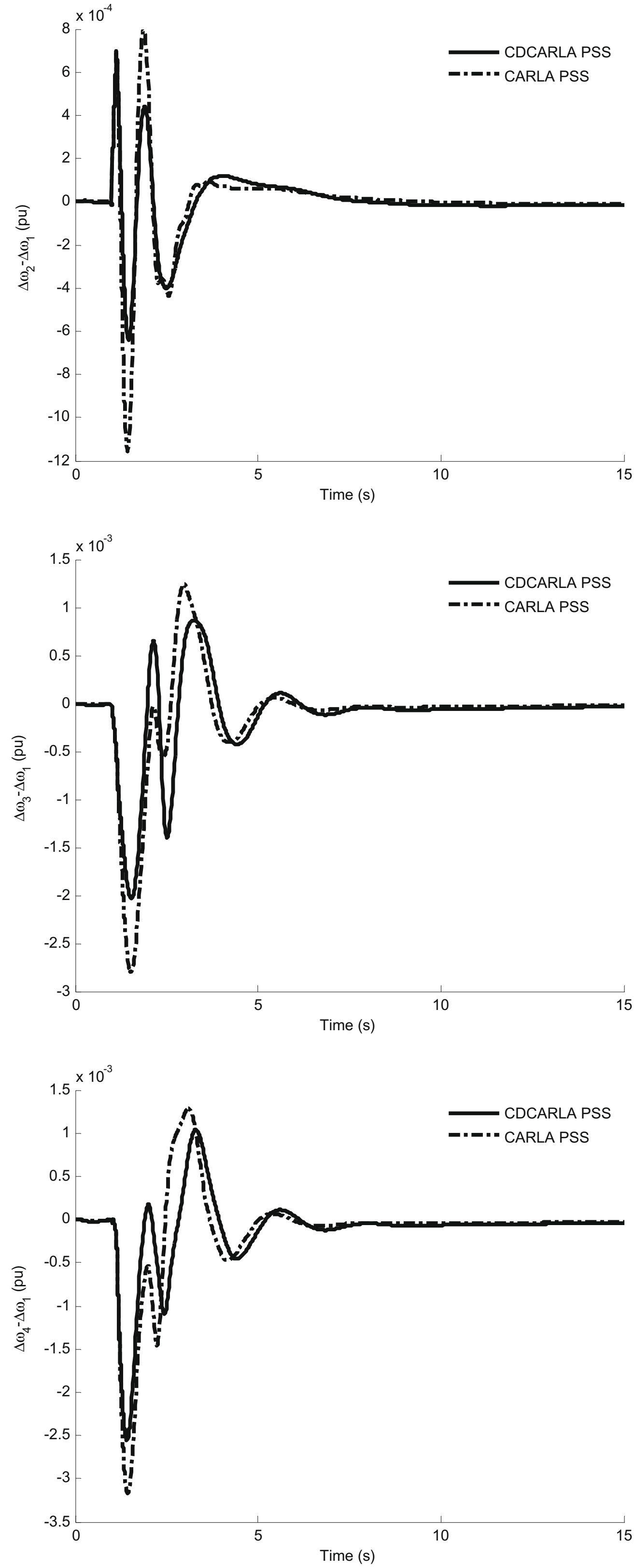

Fig. 13. The performance comparison between CDCARLA and CARLA based PSSs for 6-cycle three-phase fault disturbance.

6.1. Small signal disturbance

The stability of the power system considered without PSSs is examined by applying a three-phase fault on the middle of Tie-Line 2 at $t = 1$ s. Fig. 9 shows the variation of the active power from Area 1 to Area 2 due to this disturbance.

It can be seen that the open-loop power system response is unstable and the need for PSSs is quite obvious.

6.2. Optimal PSS performance evaluation and comparison

For performance comparison of the optimal designed CDCARLA based PSSs with the other PSS types, the response of the system with a three-phase fault in the middle of Tie-Line 2, is evaluated. Fig. 10 shows the system response with different PSSs. It is clear that the proposed CDCARLA PSSs have better performance in terms of overshoots and settling time compared to multi-band PSS and conventional PSS.

6.3. Robustness investigation

To assess the robustness of the proposed CDCARLA PSSs, different disturbances have been applied and the system performance has been examined.

A 20% pulse disturbance in the reference voltage of Generator 1 for 200 ms has been applied. Fig. 11 shows the system response with different PSSs. As a large signal disturbance, a single phase earth fault on Area 2 busbar has been applied for 6 cycles. The system response under this fault is shown in Fig. 12. Form Figs. 11 and 12, the superiority of the proposed CDCARLA PSSs is clear. It can be also concluded that the proposed PSSs are robust and have satisfactory response with small as well as large signal disturbances.

In addition, the system performance with CDCARLA based PSSs is compared to that with CARLA based PSSs under 6-cycle three phase to ground fault disturbance. The simulation results are shown in Fig. 13. It can be seen that CDCARLA based PSSs enhances greatly the first swing stability. This confirms the superiority of CDCARLA design approach over CARLA design approach.

7. Conclusion

In this paper a novel computational optimization method based on reinforcement learning automata have been proposed for optimum tuning of conventional power system stabilizer parameters. The proposed design approach has been implemented on a multimachine power system with local and interarea modes of oscillations. The performance and efficiency of designed PSSs with proposed optimization method have been investigated and compared with analytically designed PSSs and Multi-band PSSs through computer simulations of a nonlinear model. The results show that the system response with the designed PSSs is superior in terms of overshoots and settling time. The results also demonstrate the robustness of the proposed PSSs and their effectiveness under different system disturbances. However, implementation of the proposed approach on a real-life system with a wide range of the operating conditions is worth to be examined.

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