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Optimum Tuning of Power System Stabilizers via CDCARLA Optimization Technique

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Abstract— One of the effective methods of damping low-frequency oscillations in power systems is the utilization of power systems stabilizers (PSS). This paper demonstrates the use of a novel technique knows as combinatorial discrete and continuous action reinforcement learning automata (CDCARLA), to optimally tune the parameters of a power system stabilizer. A single-machine infinite bus system is considered to demonstrate the suggested technique. Simulation results show that the proposed power system stabilizer is effective and robust.

Keywords – Power system stabilizer, PSS, Reinforcement learning automata, SMIB, Dynamic stability.

I. INTRODUCTION

Power system stabilizers are one the most effective devices for damping low frequency oscillations and for increasing the stability margin of power systems [1].

Nowadays, the conventional lead-lag power system stabilizer is widely used by power system utilities [2].

In recent years, several approaches based on modern control theory have been applied to the PSS design problem. [3-7]. Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag power system stabilizer (CPSS) structure. The reasons behind that might be the decentralized nature and the ease of on-line tuning of CPSS. Various optimization methods such as genetic algorithms and tabu search have also been proposed for PSS designing [8-10].

In this paper, a novel designing method for the tuning of conventional PSS parameters is proposed. The proposed method is based on the Reinforcement Learning Automata (RLA) approach. It includes two stages; in the first stage, the best variation limits of the PSS parameters are obtained using a *Discrete Action Reinforcement Learning Automata* (DARLA) and in the second stage the best value of these parameters within the specified limit is determined. The second stage which was initially proposed by Howell et. al. [11] for a vehicle suspension control application in 1997 is based on a *Continuous Action Reinforcement Learning Automata* (CARLA) technique. CARLA has numerous advantages such as high speed of convergence; however, it requires pre-specified decision variables variation limits. These limits can be obtained using any simple method such as local linearization. Therefore, CARLA method requires the knowledge of the system dynamics.

DARLA has similar properties to CARLA such as fast convergence, system dynamics independency, and the ability to incorporate nonlinear characteristics.

This paper proposes combining the DARLA and CARLA methods for the tuning of PSS. This proposed method is called *Combinatorial Discrete and Continuous Action Reinforcement Learning Automata* (CDCARLA); it combines the advantages of both DARLA and CARLA techniques.

For evaluating the performance of the CDCARLA tuning method, the performance of the designed PSS is compared with a PSS which is designed by analytical methods for the single machine infinite bus power system model. The simulation results shows that the proposed PSS provides better performance and is more robust compared to the analytically designed PSS, for various power system disturbances.

II. POWER SYSTEM STABILIZER

The function of the PSS is to provide appropriate supplementary stabilizing signals through the synchronous generator excitation system for damping low-frequency oscillations due to faults and disturbances in the power system [1].

A commonly and widely used conventional lead-lag PSS is shown in Fig. 1. The PSS consists of three units: phase compensation unit, washout filter, and gain unit. Rotor speed deviation (Δω) or accelerating power (ΔP) is usually chosen as input to the PSS.

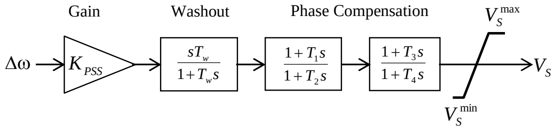

Fig. 1. Conventional PSS structure

The first term is a washout term with a time lag T_w and is usually selected between 1 to 20 seconds [12]. The second term is a lead compensation to improve the phase lag through the system.

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Therefore, the transfer function of the conventional PSS is:-

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

In this study, the PSS parameters K_s, T_1, T_2, T_3, and T_4 are assumed to be adjustable parameters and are thus considered as decision variables in the optimization problem.

In the analytical approach for the design of PSS parameters, a linear model of power system is computed and these parameters are determined so that the power system and PSS have acceptable performance in the frequency domain, therefore, such analytical design methods will require knowledge of the power system model, The proposed tuning method does not require the knowledge of the system dynamics nor any other information about the power system.

III. POWER SYSTEM MODEL

In this paper, a single machine infinite bus (SMIB) model is used to evaluate the merits of the proposed design method. The single line diagram of the model is shown in Fig. 2.

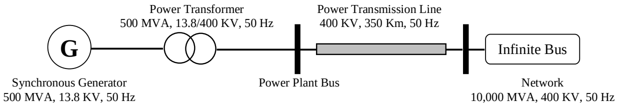


Fig. 2. Single line diagram of SMIB model

The mathematical model of each element is described below.

A. Generation Unit

The generation unit consists of the synchronous generator, the turbine and governor, the excitation system, the automatic voltage regulator (AVR) and the PSS. Fig. 3 shows the generation unit diagram.

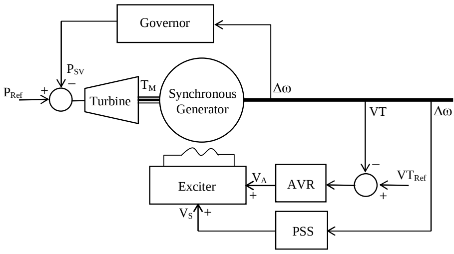


Fig. 3. Generation unit diagram

A.1. Synchronous Generator

In this paper, the transient model of synchronous machine is considered.

$$\begin{aligned} \Delta\omega(t) &= \frac{1}{2H}\int_0^t (T_M - T_E)dt - K_d\Delta\omega(t) \\ \omega(t) &= \Delta\omega(t) + \omega_0 \end{aligned} \tag{2}$$

Where, Δω is the rotor speed variation, ω is the rotor mechanical speed, H is the inertia constant, T_M and T_E are the mechanical and electrical torques respectively, and K_d is the damping factor.

The synchronous machine is described by a sixth order model [13,14]. The synchronous generator parameters are shown in the Appendix.

A.2. Turbine and Governor

A nonlinear model [15] for the hydraulic turbine and governor is used as shown in Fig. 4. The Hydraulic turbine and governor parameters are shown in the Appendix.

Where, ω_e, P_e are the rotor speed and the electrical power respectively, and ω_{Ref}, P_{Ref} are their reference values.

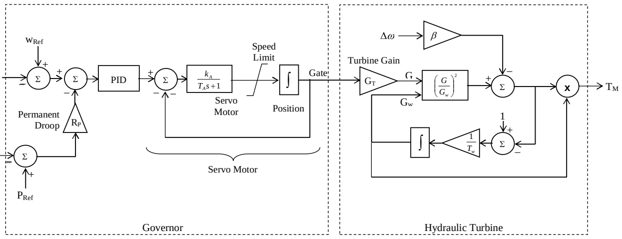


Fig. 4. Turbine and Governor model

A.3. AVR and Excitation System

Fig. 5 shows the model of the AVR and excitation system based on IEEE standard 421.5 [16].

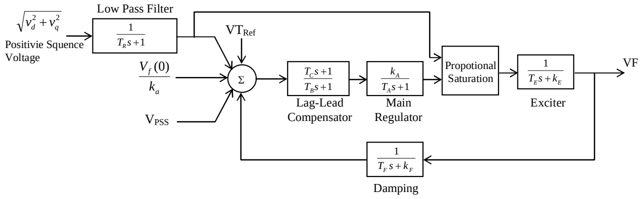


Fig. 5. AVR and excitation system model

Where v_d, v_q are the stator d and q axis voltages respectively, $V_f(0)$ is the initial excitation system voltage, VT_{Ref} is the terminal voltage reference, V_{PSS} is the PSS supplementary signal, and VF is the applied excitation voltage. The AVR and excitation system model parameters are given in the Appendix.

B. Power Transformer

Mathematical model of power transformer considers core saturation, core and winding losses and leakage flow. Equivalent circuit parameters are shown in the Appendix.

C. Transmission Line

The Mathematical model of transmission line that implements lumped losses is based on Bergeron traveling wave theorem [17]. The Transmission line parameters used in SMIB model are shown in the Appendix.

IV. DESIGN METHODOLOGY

The proposed design method is based on Reinforcement Learning Automata and has two stages: first stage is based on discrete action and determines best variation limits for each PSS parameters (DARLA), and second stage searches the best value of each parameter in specified range at previous stage (CARLA).

The key idea of DARLA and CARLA is that, if a value of decision variable (PSS parameter) results in good performance, then close values of that decision variable has have probably a relative good performance.

The criterion of fitness of selection in both DARLA and CARLA is based on a predefined cost function. In addition, both methods use probability distribution function (PDF) and through changing them for sufficient time for obtaining optimal value of decision variables. The detailed descriptions of stages are as follows:

A. Design Stage 1: Discrete Action Reinforcement Learning Automata (DARLA)

In DARLA the variation limits of decision variables are divided into usually same length sub-limits and discrete probability distribution function (DPDF) for each of those sub-limits is assigned. These DPDFs are initially set as a uniform one; this means the probability of each sub-limit to be selected as optimal sub-limit is equal. The Probability of selection of each sub-limit is performed by DPDF and after each selection of decision variables the shape of DPDFs is changed proportional to the fitness of that selection. Fig. 5 shows diagram of DARLA method.

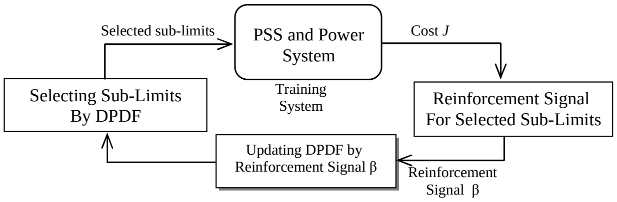
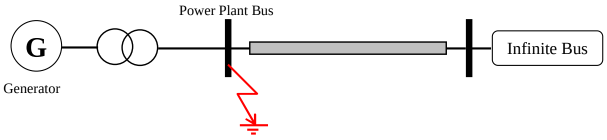


Fig. 5. DARLA workflow

The training system showed in Fig. 5 is the same as shown in Fig. 2. This training system is shown in Fig. 6, and as shown, single phase to earth fault occurs at t=0.1s on phase A and cleared at t=0.2s.



Singke Phase Earth Fault
On Phase A @ 0.1 sec
And Cleared @ 0.2 sec

Fig. 6. Training power system

It is assumed that each PSS parameter varies between 0 and 10. This limit was divided into 10 equal sub-limits. The number of divisions does not severely affect the design performance, yet, it must be selected large enough. As a result, we have 5 DPDFs with 10 elements that are initially defined as:

$$f_i^{(0)}(n)=\begin{cases}\frac{1}{10} & n=1,2,...,10\\ 0 & other\end{cases} \qquad (3)$$
$$i=1,2,...,5$$

where, $f_i^{(k)}(p)$ is the probability density of selecting the pth sub-limit of the ith PSS parameter at the kth iteration.

After selecting the sub-limits by cumulative probability of DPDFs, the center of each limit is used to construct the PSS transfer function and the cost function J is calculated as:

$$J^{(k)}=G_1\int_0^T t\left|\Delta\omega\right|dt+G_2\sup_t\Delta\omega \qquad (4)$$

where $J^{(k)}$ is the cost function at the kth iteration, T is the simulation time and must be large enough (for example T=5^{sec}), Δω is the rotor speed deviation, sup(.) denotes the supreme norm function, G_1 and G_2 are the cost function component weights. After calculating J, the reinforcement signal β is calculated as:

$$\beta^{(k)}=\min\left\{1,\max\left\{0,\frac{J_{mean}-J^{(k)}}{J_{mean}-J_{\min}}\right\}\right\} \qquad (5)$$

where $\beta^{(k)}$ is the kth reinforcement signal, and J_{mean} and $J_{\min}$ are the average and minimum values of previous cost functions, respectively. Defining the reinforcement signal as in (5) guarantees convergence of the method.

After obtaining the reinforcement signal, the DPDFs are updated as follows:

$$f_i^{(k+1)}(n)=\alpha_i^{(k)}\left(f_i^{(k)}(n)+\beta^{(k)}Q_i^{(k)}\right) \qquad (6)$$
$$i=1,2,...,5$$

where $Q_i^{(k)}$ is an exponential function centralized in selected sub-limit and defined as:

$$Q_i^{(k)}=r_q 2^{-(n-\tilde{n}_i)^2} \qquad (7)$$

where $\tilde{n}_i$ is the ith selected sub-limit and r_q is a positive constant.

$\alpha_i^{(k)}$ in (6) is a normalization factor calculated as:

$$\alpha_i^{(k)}=\frac{1}{\sum_{n=1}^{10}f_i^{(k)}(n)+\beta^{(k)}Q_i^{(k)}} \qquad (8)$$

After sufficient number of iterations, the selection probability of the optimal limit for each DPDF is maximized. Fig. 7 shows discrete convergence surface of one of the PSS parameters for 300 iterations, G_1=10, G_2=50 and r_q=0.05.

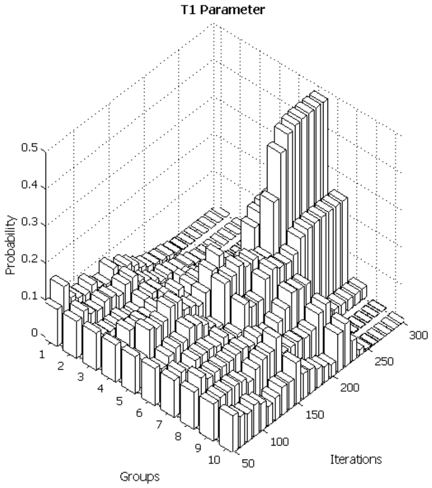


Fig 7. Convergence surface for PSS parameter #2 (T_1)

Fig. 8 shows the cost function variation versus the algorithm number of iterations. As expected it has a decreasing behavior.

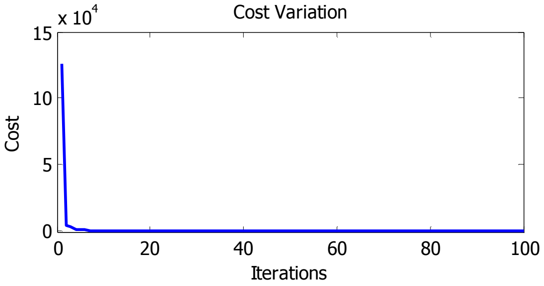


Fig. 8. Cost variation of DARLA design stage

The limit with highest probability of selection at the end of the iterations for each PSS parameter is the optimum sub-limit for that parameter. Table I summarizes the optimal sub-limits.

TABLE I
PSS PARAMETERS OPTIMAL SUB-LIMITS

PSS parameter	Optimal sub-limit
K_{PSS}	[9,10]
T_1	[5,6]
T_2	[4,5]
T_3	[0,1]
T_4	[1,2]

B. Design Stage 2: Continuous Action Reinforcement Learning Automata (CARLA)

The structure of CARLA is the same as DARLA with slight differences. In this stage, the selection is performed in a continuous space and therefore a continuous probability distribution function (CPDF) is used. The CARLA method searches continuously in optimal sub-limits obtained from previous stage. The workflow of CARLA is the same as DARLA in Fig. 5 except that DPDF must be replaced by CPDF. CPDFs are initially defined uniformly as

$$f_i^{(0)}(x) = \begin{cases} 1 & x \in X_i \\ 0 & other \end{cases} \qquad (9)$$
$$i = 1,2,...,5$$

where, X_i is the ith optimal sub-limit. The calculation of the cost function is the same as DARLA, and is given

$$J^{(k)} = G_1 \int_0^T t\,|\Delta\omega|\,dt + G_2 \sup_t |\Delta\omega| + G_3 E_{SS}^{\Delta\omega} \qquad (9)$$

where $E_{SS}^{\Delta\omega}$ is the steady state value of rotor speed deviation.

The CPDF updating rule is a little different and is given by

$$f_i^{(k+1)}(x) = \alpha_i^{(k)}\left(f_i^{(k)}(x) + \beta^{(k)} H_i^{(k)}\right) \qquad (9)$$
$$i = 1,2,...,5;\ x \in X_i$$

where H is an exponential function centralized on selected PSS parameter value $\tilde{x}_i$,

$$H_i^{(k)} = g_h \exp\left(-\frac{(x-\tilde{x}_i)^2}{2g_w}\right) \qquad (10)$$

where g_h and g_w are the height and width of the exponential function, respectively. $\alpha_i^{(k)}$ in (9) is a normalization factor given by

$$\alpha_i^{(k)} = \frac{1}{\int_{x\in X_i} f_i^{(k)}(x) + \beta^{(k)} H_i^{(k)} dx} \qquad (11)$$

By doing enough iteration of the above steps, the CARLA method will converge to an optimum value for each PSS parameter. Fig. 9 shows the continuous convergence surface of PSS gain for 300 iterations using the following constants: G_1=10, G_2=50, G_3=500, g_w=0.003 and, g_h=0.9.

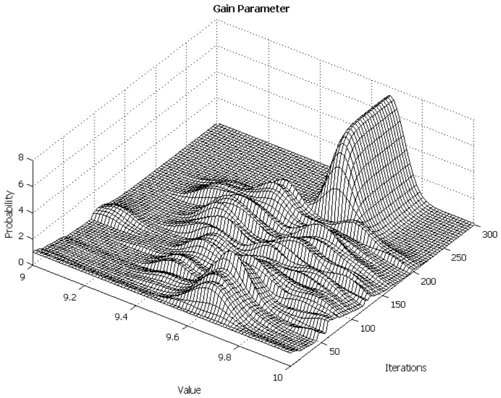


Fig 9. Convergence surface for PSS parameter #1 (K_{PSS})

The variation of the cost function versus the number of iterations is shown in Fig. 10.

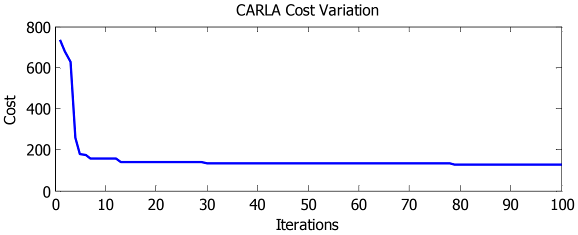


Fig 10. Variation of the CARLA cost function

Table II summarizes the PSS parameters optimal value.

TABLE II
PSS PARAMETERS OPTIMAL VALUE

PSS parameter	Optimal Value
K_{PSS}	9.6693
T_1	5.988
T_2	4.0541
T_3	0.0561
T_4	1.0902

In practical applications a real time power system simulator can be used as a training system, thus all nonlinear features of power system will be taken into account when tuning the PSS.

The other noticeable advantage of the proposed tuning method is its high speed of convergence. Fig 8 and 10 show that the algorithm converges in early iterations which is very fast in comparison with similar algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO).

V. SIMULATION RESULTS

In this section, the performance of the designed PSS is evaluated and compared with analytically designed PSS [12]. The simulations were carried out using MATLAB® and SIMULINK® environments. For evaluating the robustness of

CDCARLA design method, different types of disturbances were considered.

A. Design Performance Evaluation

Fig. 11 shows the rotor speed deviation following a single phase to earth fault on the generator bus as depicted in Fig. 6 for three situations: without PSS, CDCARLA designed PSS, and analytically designed conventional PSS. Fig. 12 also shows line power variation of different PSS.

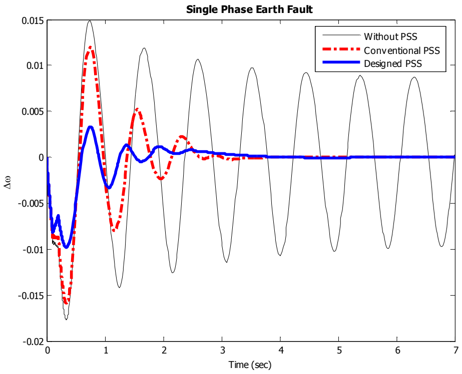


Fig 11. Rotor speed deviation for single phase to earth fault

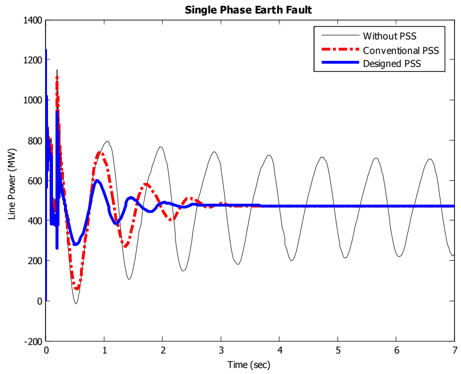


Fig. 12. Line power variation for single earth fault

As shown, the PSS designed by the proposed method has better performance than that of other PSSs in damping low frequency oscillations. In addition, in case without PSS the oscillation will persist.

B. Robustness Evaluation

For evaluating the robustness of the proposed PSS, various types of disturbances were used while maintaining the PSS parameters at their tuned values. These disturbances are as follows:

1) Phase to Phase fault between phases B and C at the generator bus at t=0.1 sec and cleared at t=0.3 sec.
2) 10% increase in mechanical power (P_{ref}) for 1 second and then return to 1 p.u.
3) 20% decrease in voltage reference (V_{ref}) for 2 seconds and then return to 1 p.u.
4) Outage of phase B in the middle of transmission line at t=1 sec for 15 cycles.
5) Three phase earth fault on infinite-bus at t=1 sec for 15 cycles.

The rotor speed and the line power deviations without PSS, with conventional PSS, and with CDCARLA PSS are shown the three cases cons in Fig. 13 to Fig. 22 for the disturbances mentioned.

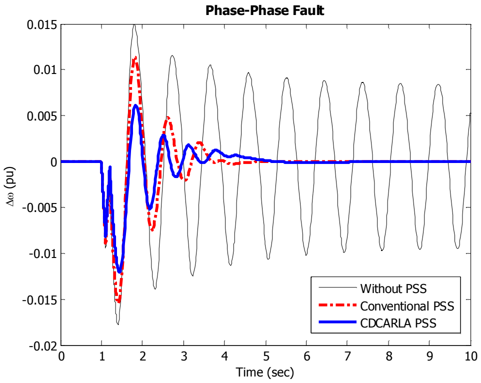


Fig. 13. Rotor speed deviation for phase to phase fault

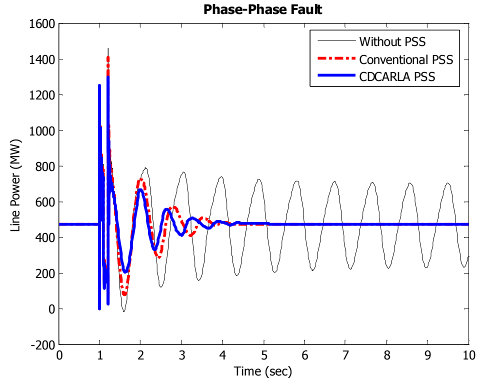


Fig. 14. Line power deviation for phase to phase fault

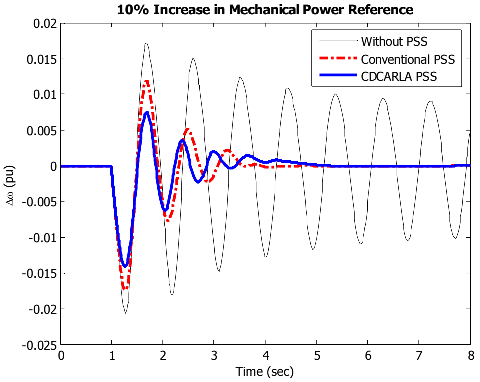


Fig. 15. Rotor speed deviation for step increase in mechanical power

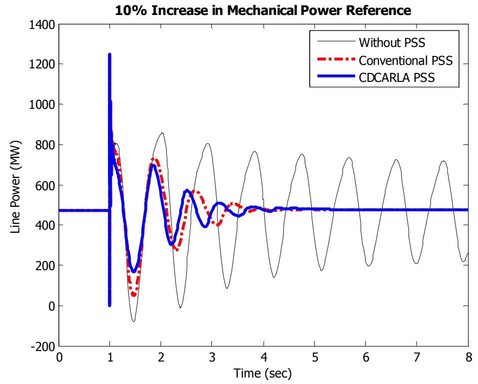


Fig. 16. Line power deviation for step increase in mechanical power

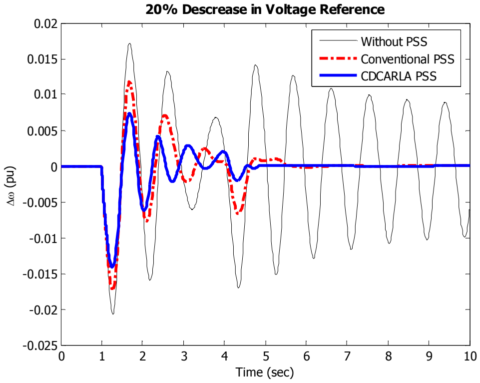


Fig. 17. Rotor speed deviation for step decrease in voltage reference

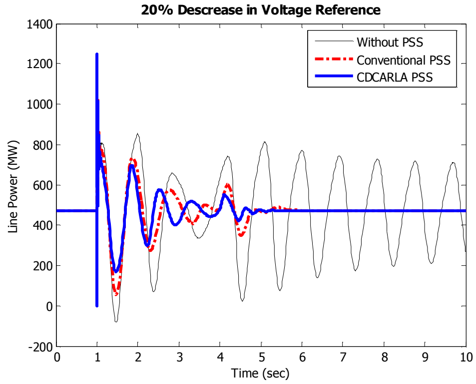


Fig. 18. Line power deviation for step decrease in voltage reference

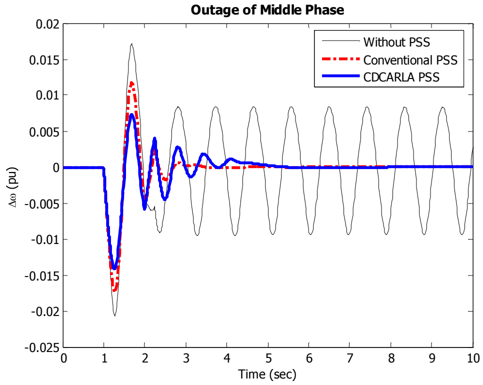


Fig. 19. Rotor speed deviation outage of phase B in the middle of line

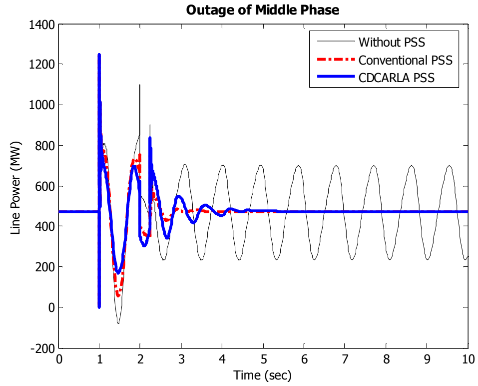


Fig. 20. Line power deviation for outage of phase B in the middle of line

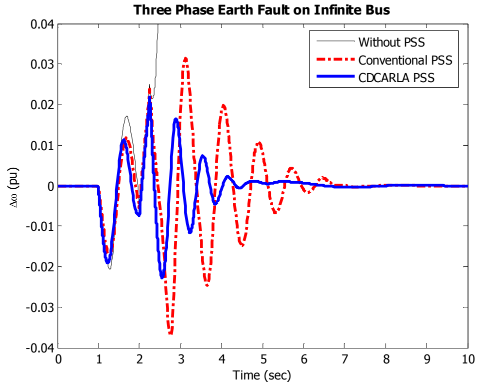


Fig. 21. Rotor speed deviation for three phase earth fault on infinite bus

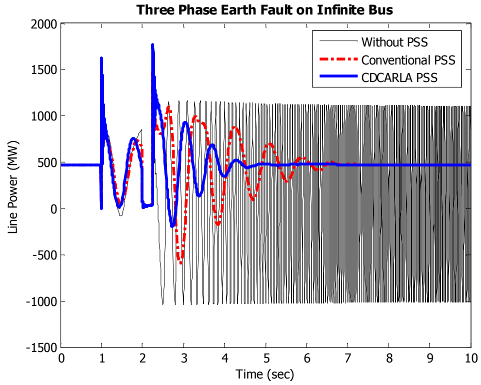


Fig. 22. Line power deviation for three phase earth fault on infinite bus

It is clear that the CDCARLA PSS is relatively more robust and effective than the conventional PSS for the disturbances considered. For a quantitative comparison of performance of different PSSs, two characteristics of the rotor speed response are considered as benchmark:

1) The settling time of the response
2) The maximum value of the response

Both of these properties are measured after the transient period of synchronous machine. These two properties can be selected as stabilization performance indexes. Table III summarizes these performance indexes for different types of PSSs due to various power system disturbances.

TABLE III
RESPONSE PERFORMANCE INDICES

System Disturbance	Performance Index	CDCARLA PSS	Analytic Designed PSS
Single Phase Earth Fault	Time of stabilization	1.27	3.93
	Max of variation	0.61%	1.23%
Phase-Phase Fault	Time of stabilization	4.00	4.02
	Max of variation	0.23%	0.17%
Change in Mech. Torque	Time of stabilization	2.93	3.95
	Max of variation	0.72%	1.26%
Change in Voltage Ref.	Time of stabilization	4.8	6.0
	Max of variation	0.75%	1.25%
Outage of Phase B	Time of stabilization	5.5	3.8
	Max of variation	0.75%	1.25%
3Ph Fault on Infinite-Bus	Time of stabilization	6.9	6.9
	Max of variation	2.1%	3.1%

VI. CONCLUSION

In this paper, a novel heuristic method for tuning power system stabilizers was proposed. This method is based on *Combinatorial Discrete and Continuous Action Reinforcement Learning Automata* (CDCARLA). In comparison to other heuristic search method CDCARLA converges faster. In addition, the proposed design method takes into account the nonlinear features of power systems. Simulation results demonstrated the effectiveness and the robustness of the proposed algorithm. In summary, CDCARLA can be used as useful design method for wide range of applications.

VII. APPENDIX

TABLE IV
SYNCHRONOUS MACHINE PARAMETER

Parameter	**Value**
Rotor Type	Salient-pole
Number of Poles	64
Nominal Power	500 MVA
Line to Line Voltage (RMS)	13.8 kV
Frequency	50 Hz
Reactances (pu)	
X_d	1.305
X'_d	0.296
X''_d	0.252
X_q	0.474
X''_q	0.283
X_I	0.18
Time Constants (s)	
T'_d	1.01
T''_d	0.053
T''_{q0}	0.1
Stator Resistance (pu)	0.0028544
Inertia Factor	3.7
Friction Factor	0

TABLE V
HYDRAULIC TURBINE AND GOVERNOR PARAMETERS

Parameter	**Value**
Governor	
Permanent Droop	0.05
Servo Motor	
K_A	3.33
T_A (s)	0.07
Speed Limit (pu)	[-0.1,0.1]
PID Regulator	
K_P	1.163
K_I	0.105
K_D	0.01
Hydraulic Turbine	
β	0
T_W (s)	2.67
G_T	1

TABLE VI
AVR AND EXCITATION SYSTEM PARAMETERS

Parameter	**Value**
Low pass Filter Time Constant (T_R)	0.002
Regulator	
Gain (K_A)	200
Time Constant (T_A)	0.001
Exciter	
Gain (K_E)	1
Time Constant (T_E)	0
Lag-Lead Compensator	
T_B	0
T_C	0
Damping Filter	
Gain (K_F)	0.001
Time Constant (T_F)	0.1

TABLE VII
POWER TRANSFORMER PARAMETERS

Parameter	**Value**
Nominal Power	500 MVA
Frequency	50 Hz
Winding 1	
Connection	Δ
Phase-Phase Voltage (RMS)	13.8 kV
Resistance (pu)	0.002
Inductance (pu)	0
Winding 2	
Connection	Y
Phase-Phase Voltage (RMS)	400 kV
Resistance (pu)	0.002
Inductance (pu)	0.12
Magnetizing Resistance (pu)	500
Magnetizing Reactance (pu)	500

VIII. REFERENCES

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