Asian Journal of Water, Environment and Pollution, Vol. 19, No. 6 (2022), pp. 11-18.
DOI 10.3233/AJW220083

Optimal Reactive Power Dispatch by Success History Based Adaptive Differential Evolution Salp Swarm Algorithm

Naveen Kumar* and Ramesh Kumar
Department of Electrical Engineering, National Institute of Technology, Patna – 800005, India
✉ naveen.ee18@nitp.ac.in

Received January 22, 2022; revised and accepted March 22, 2022

Abstract: In this study, a novel hybrid algorithm success history-based adaptive differential evolution salp swarm algorithm (SHADE-SSA) is proposed to solve two different cases of IEEE 30 bus reactive power dispatch problems integrated with thermal generators, wind farms and solar photovoltaic plants. Real power loss minimization and voltage deviation minimization are considered as main objectives in the present work. The performance and robustness of the proposed hybrid SHADE-SSA algorithm are compared with the results of five different metaheuristic algorithms for the same test system and consider the same control variables and constraints. The results of the simulation of the proposed algorithm conform to the effective choice for the solution of optimal reactive power dispatch problems of power systems.

Key words: Renewable energy, solar photovoltaic plant, windfarm, environment, reactive power dispatch, real power loss, total voltage deviation, SHADE-SSA.

Introduction

The main objective of the economic load dispatch (ELD) problem is to minimise the generation cost of the power plant by allocating optional power generation to fulfil the total demand of load (Kumar et al., 2020). In the economic load dispatch problem, in order to achieve the total load demand and losses both active and reactive power are changed between maximum and minimum limits. Reactive power plays a vital role in the secure operation of the generation, transmission and distribution system of a power plant (Panda et al., 2020). As real power dispatch is important for us likewise reactive power dispatch also has great importance as each generated load has a reactive power requirement (Mota-Palomino and Quintana, 1986). But in the economic load dispatch problem, the objective function is the only cost of fuel for active power generation which cannot be justified cost function (Biswas et al., 2017). Therefore, cost considering both active and reactive power as the objective function gives rise to a new section of optimal power flow known as optimal reactive power dispatch (Ahmad et al., 2021). The cost of active power generation is dependent on the generation of real power (Panda et al., 2020).

Formulation of Optimal Reactive Power Dispatch Problem

Optimal reactive power dispatch (ORPD) problems can be represented in form of objective functions and certain constraints (Afgan and Carvalho, 2002). The key purpose of the ORPD problem is to fulfil three objectives, comprising of reduction of transmission

*Corresponding Author

line real power loss (P_{LOSS}), reduction of total voltage deviation (*TVD*) and reduction of voltage stability L-index (*VSI*) while simultaneously satisfying various equality and inequality constraints such as load buses voltage boundary, upper and lower range of apparent power flow and balance of real and reactive power flowing in buses (Panda and Tripathy, 2015).

Objective Function

Minimisation of Real Power Losses

The real power loss in the transmission line is always insignificant, which causes offensiveness in power system stability and value (Kadir and Volkan, 2016). Therefore, reduction of active loss in transmission and improving stability is one of the most important goals for operators and researchers (Kumar et al., 2016). The mathematical expression of this objective is expressed as

$$\text{Minimisation of } P_{Loss} = \sum_{m \in N} P_{mloss} + P_{fun} \tag{1}$$

$$\sum_{m \in N} P_{mloss} = \sum_{m \in N} G_m = (V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij}) \tag{2}$$

$$P_{fun} = l_m \sum_{j=1}^{N_g} f(Q_j) + l_n \sum_{k=1}^{N} j(S_p) \tag{3}$$

where $\sum_{m \in N} P_{mloss}$ is total real power losses in transmission lines, P_{fun} is the penalty function defined in equation (3), V_i and V_j are voltage magnitude of buses, θ_{ij} is phase angle, G_m is conductance, l_m and l_n are penalty factors.

Minimisation of Voltage Deviation of Load Buses

Voltage and frequency are the most two important factors for maintaining supply power qualities (Kumar et al., 2017). Frequency can be controlled by balancing reactive power dispatch while voltage can be monitored by controlling generator reactive power, losses of reactive power in capacitors, load branches and also in transformers. The mathematical expression of these objectives is expressed as (Biswas et al., 2017):

$$\text{Minimisation of } V_{Devation} = \sum_{k=1}^{N_l} \left| V_{load} - V_{ref} \right| \tag{4}$$

System Constraints

Equality Constraints

Balance of Real and Reactive Power Flow

In a power system, active power flow depends mainly on three factors- alternators, lines and loads while reactive power flow depends on four factors- generators, lines, capacitors and loads (Mohamed et al., 2017). The balancing of all the factors must satisfy the following equations:

$$P_{GK} - P_{Dk} = V_k \sum_{l=1}^{N_{Bus}} V_l (G_{kl} \cos\delta_{kl} + B_{kl} \sin\delta_{kl}) \tag{5}$$

$$Q_{GK} - Q_{Dk} = V_k \sum_{l=1}^{N_{Bus}} V_l (G_{kl} \cos\delta_{kl} + B_{kl} \sin\delta_{kl}) \tag{6}$$

where N_{Bus} is number of buses, P_{Gk} and Q_{Gk} are real and reactive power dispatch at k^{th} bus, P_{Dk} and Q_{Dk} are active and reactive power demand at the k^{th} bus, G_{kl} and B_{kl} are conductance and susceptance between k^{th} and l^{th} buses, respectively (Tanabe and Fukunaga, 2013).

Inequality Constraints

Generator Constraints

The voltages of generation bus and reactive power output should lie in range of upper and lower limits as below:

$$V_{Gk}^{Min} \le V_{Gk}^{Min} \le V_{Gk}^{Min},\ k = 1, 2, 3, \ldots \ldots \ldots, Ng \tag{7}$$

$$Q_{Gk}^{Max} \le V_{Gk} \le Q_{Gk}^{Max},\ k = 1, 2, 3, \ldots \ldots \ldots, Ng \tag{8}$$

where V_{Gk}^{Min} and V_{Gk}^{Min} are minimum and maximum values of generator voltages of k^{th} unit, Q_{Gk}^{Max} and Q_{Gk}^{Max} are the minimum and maximum value of reactive power output of k^{th} unit.

Transformer Constraints

Minimum and maximum tap settings of transformers must be restricted in the range of their lower and upper limits as below:

$$T_k^{Min} \le T_k \le T_k^{Max},\ \ k = 1, 2, 2, \ldots \ldots \ldots, N_g \tag{9}$$

where T_k^{Min} and T_k^{Max} are lower and upper limits of tap setting of k^{th} transformer.

Shunt var Compensator Constraints

Minimum and maximum shunt var injection of shunt compensators must lie within lower and upper limits as below:

$$Q_{Ck}^{Min} \le Q_{Ck} \le Q_{Ck}^{Max},\ k = 1, 2, 3, \ldots \ldots \ldots \ldots, N_g \tag{10}$$

where Q_{Ck}^{Min} and Q_{Ck}^{Max} are lower and upper limits of shunt var injection of k^{th} shunt compensator.

Security Constraints

Voltages at the load buses and transmission line must lie within lower and upper limits as below:

$$V_{line}^{Min} \le V_{line} \le V_{Line}^{Max}, \quad k = 1, 2, 3, \ldots \ldots \ldots, N_{line} \quad (11)$$

$$S_{line}^{Min} \le S_{\text{line}} \le S_{line}^{Max}, \quad k = 1, 2, 3, \ldots \ldots \ldots, N_{line} \quad (12)$$

where $V_{Load\ line}^{Min}$ and $V_{Load\ line}$ are minimum and maximum limits of load voltage of k^{th} line. S_{line}^{Min} and S_{line}^{Max} are limits of minimum and maximum power flow in k^{th} line.

Result and Discussion

In order to satisfy the potential, efficiency and functioning of the hybrid SHADE-SSA algorithm for solving optimal reactive power dispatch problems, the algorithm has been tested on a standard IEEE 30-bus test system for the minimisation of deviation of voltage and real power loss. All the algorithms were executed in MATLAB 2021b and run-on PC incorporated with i7 7200U CPU @ 2.7 GHz with 8GM RAM. The size of population (N) and iterations number are set as 60 and 24000, respectively, for IEEE 30-bus test system. For simulation and results, a total 30 number of test trial runs were performed for both cases.

The IEEE 30-bus test system consists of six generators of which three are thermal generators, two wind farms and one solar photovoltaic, connected to bus number 1, 2, 8, 5, 11 and 13, respectively as shown in Figure 1. Total number of branches is 41. The considered test system consists of 11 control variables, in which there are 5 generators, 3 tap changing transformers and 2 shunt capacitors. Total active power and reactive power demands are 283.4 MW and 126.2 MVAr, respectively. Minimum and maximum generation limits of generators and limits of control variables are mentioned in Table 1.

SHADE-SSA Optimiser

In order to achieve a globally optimal solution, with the finest convergence output, an algorithm should be equipped with manipulation and searching properties. The proposed SHADE-SSA algorithm aims to keep balancing these properties. A SHADE-SSA algorithm is developed to the best capability of exploitation and exploration in them (as shown in Figure 2). In the SSA algorithm, the position of the leader is updated by following the proposed equation (Mirjalili et al., 2017):

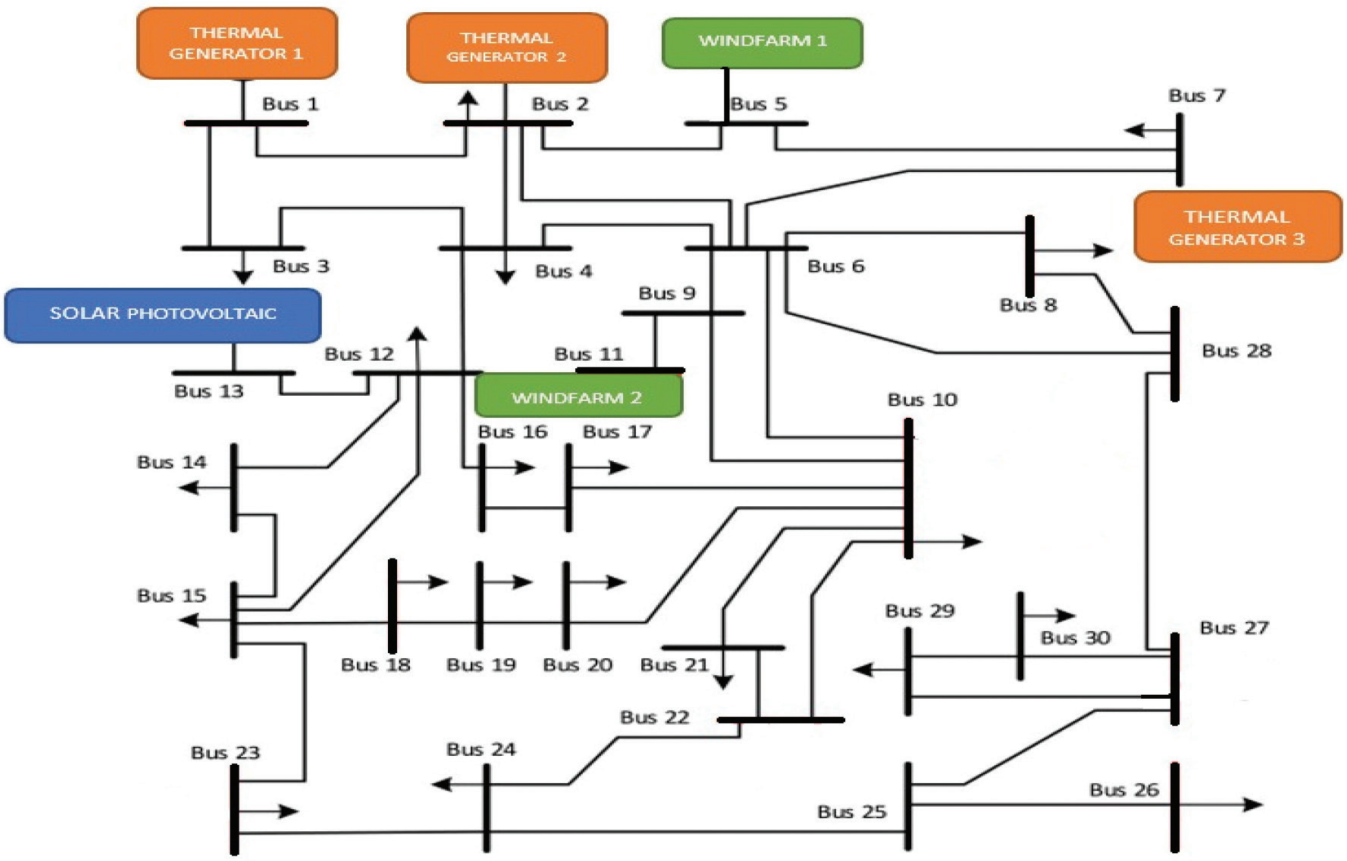

Figure 1: IEEE 30-bus test system under consideration.

$$x_k^1 = \begin{cases} F_k + c_1\left((ub_k - lb_k)c_2 + lb_k\right)c_3 \geq 0 \\ F_k - c_1\left((ub_k - lb_k)c_2 + lb_k\right)c_3 < 0 \end{cases}$$

where x_k^1 represent position of leader salp in the k^{th} dimension, F_k is the position of food source in k^{th} dimension, ub_k and lb_k represent upper and lower bound of k^{th} dimension, respectively. c_1, c_2 and c_3 are random numbers. Coefficient c_1 is a very significant parameter in SSA, as it establishes equilibriums between exploration and exploitation and can be defined as (Mirjalili et al., 2017):

$$2e^{-\left(\frac{4it}{mt}\right)^2}$$

where it represents the current iteration and mt represents the maximum number of iterations.

The position of the follower's salp in the kth dimension can be updated by the following equations:

$$x_j^i = 1/2\,(x_k^i + x_k^{i-1})$$

Where $i \geq 2$ and x_k^i represent position of ith follower salp in the kth dimenson.

In the SHADE-SSA algorithm, the current position to the best position is updated by following the proposed equation (Tanabe and Fukunaga, 2013):

$$v_j^t = x_j^t + f_j^t \cdot (x_{P_{best}}^t - x_j^t) + f_j^t \cdot (x_{r_1}^t - x_{r_2}^t)$$

where r_1 and r_2 are randomly chosen integer from the considered population, $x_{P_{best}}^t$ is the best generation and f_j^t is the position control parameter.

Case 1: Minimisation of Active Power Loss

The novel hybrid SHADE-SSA algorithm is tested and implemented on the IEEE 30-bus test system for achieving the goal i.e. reduction of real power loss considering the penalty factor, which is mathematically represented in equations (1) & (2).

Table 1 shows the performance and novel results generated by the hybrid SHADE-SSA algorithm and those generated from other metaheuristic algorithms such as SHADE-SF, PSO, CSO, MCSO and SSA. From the simulation result, the best minimum real power loss is 2.0525, which is better than the results obtained from other algorithms. Figure 3 shows power loss minimisation via a 2D line chart.

Table 1: Simulation results of case 1 for minimisation of power loss

	Parameter	*Min value*	*Max value*	*SHADE-SF*	*PSO*	*CSO*	*MCSO*	*SSA*	*SHADE-SSA*
Control Variables	P_{Tg1}	50	140	50.000	50.000	50.000	50.000	50.000	50.000
	P_{Tg1}	20	80	25.059	25.081	25.054	25.057	25.083	25.063
	P_{Tg1}	10	35	35.000	35.000	35.000	35.000	35.000	35.000
	P_{Wg1}	0	75	75.000	75.000	75.000	75.000	75.000	75.000
	P_{Wg2}	0	60	59.999	60.000	59.878	59.999	59.997	60.000
	P_{sv}	0	50	40.414	40.392	40.785	40.875	40.235	40.836
	V_{bus1}	0.95	1.1	1.0584	1.0527	1.0537	1.0542	1.0764	1.0541
	V_{bus2}	0.95	1.1	1.0530	1.0435	1.0653	1.0834	1.0654	1.0856
	V_{bus5}	0.95	1.1	1.0437	1.0516	1.0453	1.0896	1.0325	1.0679
	V_{bus8}	0.95	1.1	1.0500	1.0966	1.0867	1.0439	1.0674	1.0875
	V_{bus11}	0.95	1.1	1.0998	1.0798	1.0865	1.0421	1.0963	1.0583
	V_{bus13}	0.95	1.1	1.0588	1.0678	1.0321	1.0943	1.0478	1.0784
Reactive Power of Generator	Q_{Tg1}	-20	150	-5.0653	-5.2752	-5.2653	-5.0864	-5.2547	-5.3421
	Q_{Tg2}	-20	60	7.9370	6.4670	6.4670	7.9674	6.4670	6.4670
	Q_{Tg3}	-15	40	40.000	40.000	40.000	40.000	40.000	40.000
	Q_{wg1}	-30	35	20.820	20.485	20.485	20.820	20.485	20.485
	Q_{wg2}	-25	30	20.820	30.000	28.654	25.675	27.876	20.654
	Q_{sv}	-20	25	18.518	17.653	19.654	16.876	18.986	16.886
Objective Function	Power loss (MW)			2.0712	2.0753	2.0741	2.0695	2.0745	**2.0525**

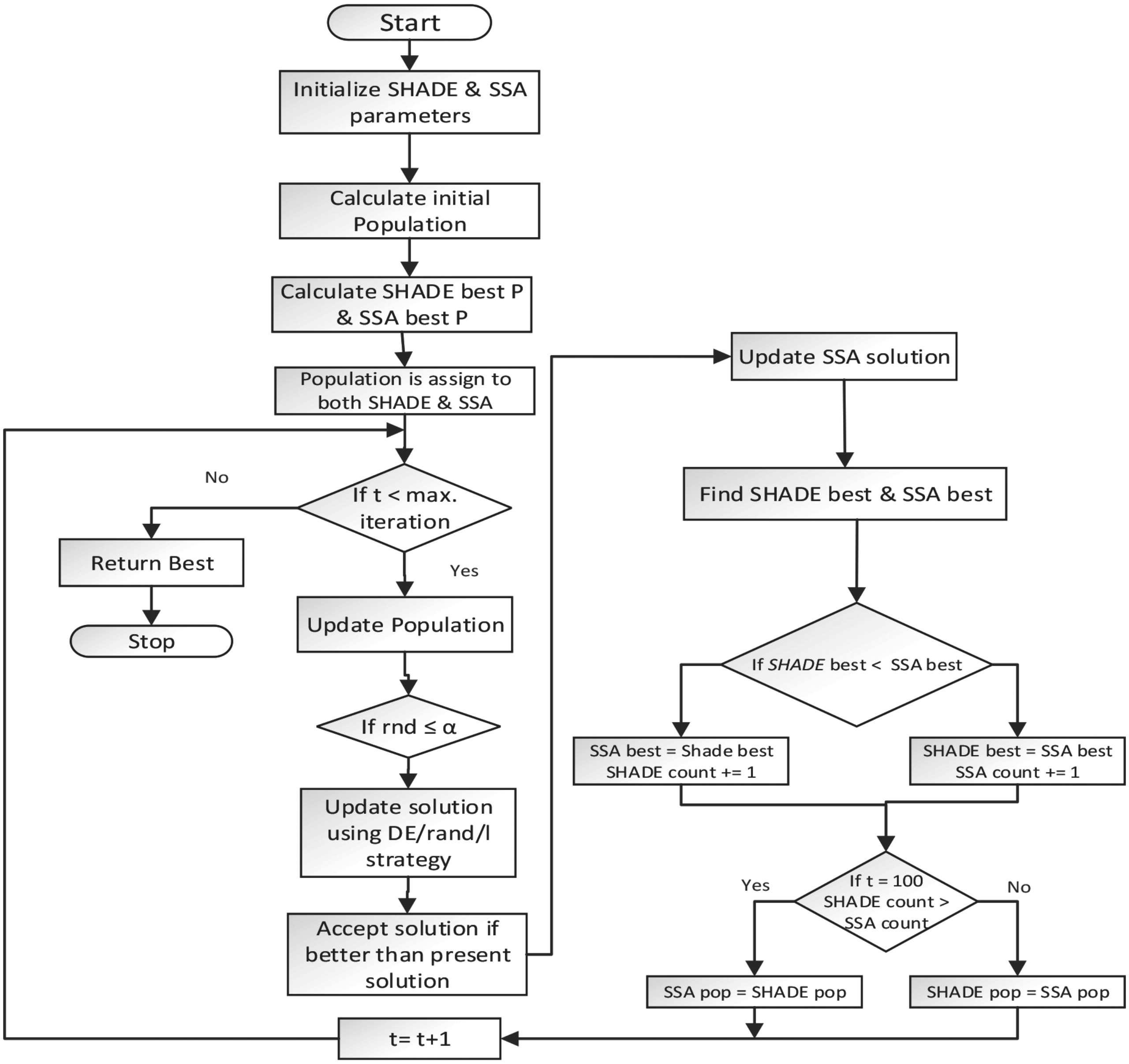

Figure 2: Flow chart of proposed SHADE-SSA algorithm.

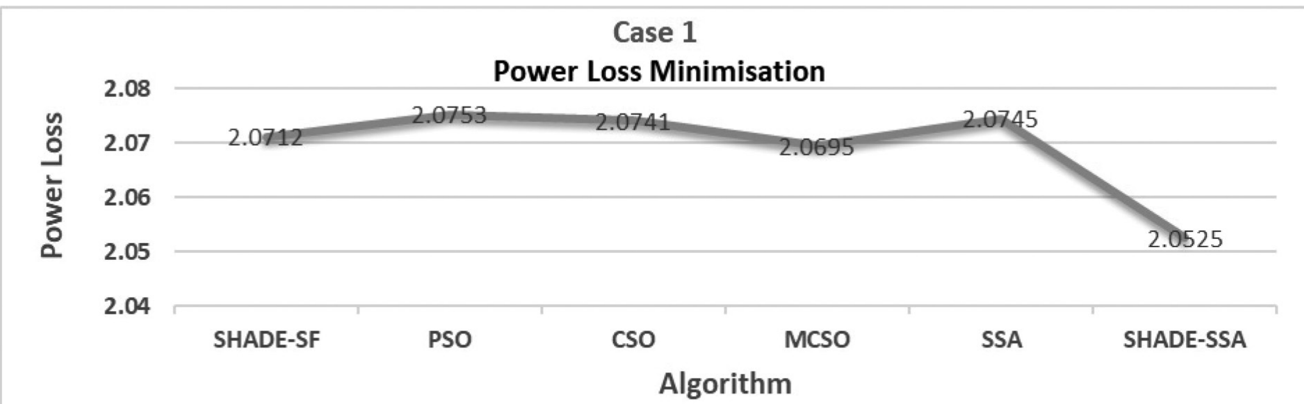

Figure 3: Power loss minimisation comparison for Case 1.

Table 2 represents best, worst, mean and standard deviation of simulation results, which also conform the performance of proposed algorithm.

Case 2: Minimisation of Voltage Deviation

For the present case, the standard novel hybrid SHADE-SSA algorithm is implemented on the IEEE 30-bus test system for the minimisation of voltage deviation, which is mathematically represented in equation 4. Table 3 represents the best novel results yielded by the standard hybrid SHADE-SSA algorithm and also those generated from other metaheuristic algorithms such as SHADE-SF, PSO, CSO, MCSO and SSA. Figure 4 shows voltage deviation minimisation via a 3D line chart. Table 4 represents best, worst, mean and standard deviation of simulation results, which also conform to the performance of the proposed algorithm.

Table 2: Statistical results of case 1 for minimisation of power loss

Algorithm	*Best result*	*Worst result*	*Mean result*	*Standard deviation*
SHADE-SF	2.0712	2.1037	2.08782	0.01350872311
PSO	2.0753	2.1054	2.08898	0.0129854380
CSO	2.0741	2.1076	2.08946	0.01388100861
MCSO	2.0695	2.1032	2.08766	0.01392416604
SSA	2.0745	2.1065	2.08932	0.01350916726
SHADE-SSA	2.0525	2.1012	2.07422	0.01618065512

Table 3: Simulation results of case 2 for minimisation of voltage deviation

	Parameter	*Min value*	*Max value*	*SHADE-SF*	*PSO*	*CSO*	*MCSO*	*SSA*	*SHADE-SSA*
Control Variables	P_{Tg1}	50	140	76.14283	72.14456	89.34583	84.13783	89.142	73.13483
	P_{Tg1}	20	80	80.0000	78.8965	79.5643	79.9865	78.564	79.9869
	P_{Tg1}	10	35	35.0000	35.0000	35.0000	35.0000	35.000	35.0000
	P_{wg1}	0	75	75.0000	75.0000	75.0000	75.0000	75.000	75.0000
	P_{wg1}	0	60	19.0153	22.8753	25.8765	27.0342	28.015	26.9874
	P_{sv}	0	50	20.6544	19.5432	26.7653	18.6543	17.786	16.8345
	V_{bus1}	0.95	1.1	1.04538	1.02139	1.08717	1.07639	1.0941	1.02857
	V_{bus2}	0.95	1.1	1.07579	1.05768	1.09859	1.05479	1.0689	1.03859
	V_{bus5}	0.95	1.1	0.99348	0.98998	0.98537	0.99456	0.9978	0.99819
	V_{bus8}	0.95	1.1	1.0986	1.0986	1.0934	1.0979	1.0753	1.08956
	V_{bus11}	0.95	1.1	1.0924	1.0967	1.0939	1.0876	1.0935	1.08975
	V_{bus13}	0.95	1.1	1.0967	1.0897	1.0977	1.0954	1.0978	1.09457
Reactive Power of Generator	Q_{Tg1}	-20	150	-20.0000	-20.0000	-20.000	-20.000	-20.000	-20.000
	Q_{Tg2}	-20	60	58.98765	59.89765	59.8769	59.9865	59.547	59.9876
	Q_{Tg3}	-15	40	39.78657	39.89765	39.9654	39.7659	39.875	39.9876
	Q_{wg1}	-30	35	-19.6340	-17.6754	-23.5433	-26.8745	-21.654	-20.834
	Q_{Tg2}	-25	30	28.98765	29.8976	28.98765	29.7658	29.897	29.8976
	Q_{sv}	-20	25	23.89765	24.65432	24.89765	23.78654	24.654	24.8976
Objective Function	Voltage deviation (p. u.)			0.37520	0.37888	0.37450	0.37295	0.3752	**0.36920**

Table 4: Statistical results of case 2 for minimisation of voltage deviation

Algorithm	*Best result*	*Worst result*	*Mean result*	*Standard deviation*
SHADE-SF	0.37520	0.38950	0.37768	0.006435339929
PSO	0.37888	0.39670	0.383396	0.007719330541
CSO	0.37450	0.38764	0.378548	0.004651410109
MCSO	0.37295	0.37995	0.37670	0.002251888097
SSA	0.37523	0.37756	0.376678	0.0008518309691
SHADE-SSA	0.36920	0.37520	0.37340	0.002171635329

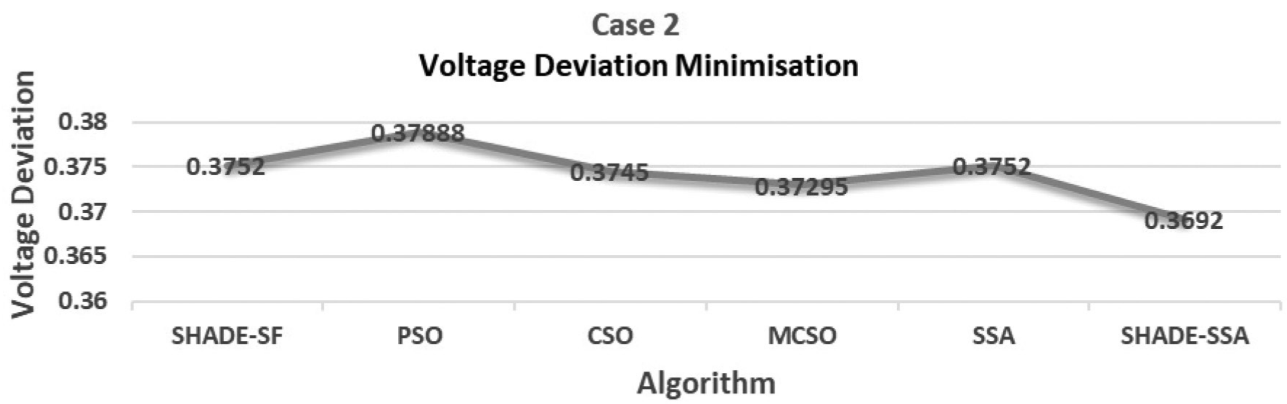

Figure 4: Voltage deviation minimisation comparison for Case 2.

Conclusion

In this study, a novel hybrid metaheuristic SHADE-SSA algorithm is proposed to solve the optimal reactive dispatch problem of the power system. The proposed algorithm is tested on a standard IEEE 30-bus system with five other metaheuristic algorithm – SHADE-SF, PSO, CSO, MCSO and SSA under the same control variables and constraints. A rigorous analysis has been performed for both cases. The simulation results conform to the outstanding and robust performance of the hybrid SHADE-SSA algorithm for solving optimal reactive dispatch problems of power systems.

References

Afgan, N.H. and M.G. Carvalho (2002). Multicriteria assessment of new and renewable energy power plants. *Energy,* **27:** 739-755.

Biswas, P.P., Suganthan, P.N. and G.A.J. Amaratunga (2017). Optimal power flow solutions incorporating stochastic wind and solar power. *Energy Convers Manage.*, **148:** 1194-1207.

Ahmad, M., Javaid, N., Niaz, I.A., Almogren, A. and A. Radwan (2021). A bio-inspired heuristic algorithm for solving optimal power flow problem in hybrid power system. *IEEE Access*, **9:** 159809-159826.

Kumar, N., Kumar, R., Mohapatra, P. and R. Kumar (2020). Modified competitive swarm technique for solving the economic load dispatch problem. *Journal of Information and Optimization Sciences*, **41:** 173-184.

Kadir, A. and Y. Volkan (2016). Differential search algorithm for solving multiobjective optimal power flow problem. *Int J Electr Power Energy Syst*, **79:** 1-10.

Kumar, R., Rajan, A., Talukdar, F., Dey, N., Santhi, V. and V.E. Balas (2017). Optimization of 5.5-GHz CMOS LNA parameters using firefly algorithm. *Neural Comput. Appl*, **28(12):** 3765-3779.

Kumar, R., Talukdar, F., Dey, N. and V. Balas (2016). Quality factor optimization of spiral inductor using firefly algorithm and its application in amplifier. *International*

Journal of Advanced Intelligence Paradigms, **11(3-4):** 299-314.

Mohamed, A.A.A., Mohamed, Y.S., El-Gaafary, A.A. and A.M. Hemeida (2017). Optimal power flow using moth swarm algorithm. *Electric Power Sys Res*, **142:** 190-206.

Mota-Palomino, R. and V.H. Quintana (1986). Sparse Reactive Power Scheduling by a Penalty Function—Linear Programming Technique. *IEEE Trans, Power Syst*. pp. 31-39.

Panda, A., Mishra, U., Tseng, M.L. and M. Ali (2020). Hybrid power systems with emission minimization: Multi-objective optimal operation. *J. Cleaner Prod*, **268:** 121418.

Panda, A. and M. Tripathy (2015). Security constrained optimal power flow solution of wind-thermal generation system using modified bacteria foraging algorithm. *Energy*, **93:** 816-827.

Tanabe, R. and A. Fukunaga (2013). Success-History Based Parameter Adaptation for Differential Evolution. *In:* IEEE CEC. pp. 71-78.