Improved PSO with Disturbance Term for Solving ORPD Problem in Power Systems

Mohamed MEZAACHE [1], *Omar Fethi BENAOUDA* [1], *Hocine SEKHANE* [2,3], *Saad CHAOUCH* [1], *Badreddine BABES* [1]

[1]Research Center in Industrial Technologies "CRTI", P.O.BOX 64, Cheraga, 16014 Algiers, Algeria
[2]Department of Electrical Engineering, Faculty of Technology, University of 20th August 1955 Skikda, P.O.BOX 26, Street El-Hadaiek, 21000 Skikda, Algeria
[3]Electrical Engineering Laboratory of Constantine (LGEC), Department of Electrical Engineering, Faculty of Science and Technology, Mentouri Brothers University of Constantine 1, P.O.BOX 325, Street Ain El Bey, 25000 Constantine, Algeria

mohamedmezaache@gmail.com, benaouda.omar@gmail.com, docsekhoc@gmail.com, saad.yassin21@gmail.com, elect_babes@yahoo.fr

DOI: 10.15598/aeee.v20i4.4570

Article history: Received May 24, 2022; Revised Nov 18, 2022; Accepted Dec 24, 2022; Published Dec 31, 2022.

Abstract. *The essential purpose of an energy system is to provide electricity to its loads effectively and economically, as well as safely and reliably. Therefore, the solutions to the problems of Optimal Power Flow (OPF) and Optimal Reactive Power Dispatch (ORPD) to enable the efficient employment of various energy distributions should be found. Our work focuses on the ORPD issue; it can be formulated as a non-linear constraint and with single or multiple objectives optimization problems. Minimizing total losses is one of the main objective functions to solve the ORPD problem. This paper presents the use of an improved particle swarm optimization -with a disturbance term- (called PSO-DT) algorithm, to find the solution of ORPD in the standard IEEE 30-bus power system for reducing electrical power transmission losses. The obtained results demonstrate that the proposed method is more efficient and has a more extraordinary ability to get better solutions compared to the basic PSO method.*

Keywords

Basic PSO, Optimal Power Flow, Optimal Reactive Power Dispatch, PSO-DT.

1. Introduction

Providing a balanced and reliable source of electrical energy to consumers is the principal goal of power producers. Reactive and active powers of generators (in an interconnected electrical network) must vary within the usage limits to meet a specific load request at the lowest fuel costs. In the production station, there are two factors that must be taken into account at each variation of load, namely the load division and the economic component. Following the liberalization of the industry, Optimal Power Flow (OPF) is utilized to deal with these issues. The OPF was presented for the first time by Dommel and Tinney in 1968; it is one of the fundamental issues in the planning and operation of the energy system [1]. The main purpose of an OPF is to find the optimal settings of control variables in an electrical power system by optimizing a specific goal along with the satisfaction of certain operational constraints [2].

Solving the problem of the Optimal Reactive Power Dispatch (ORPD) is another important factor in the electrical energy management system [3]. ORPD is considered a complex, non-linear, concave, discontinuous and multi-model problem involving both discrete and continuous variables. Thus, its solution includes various objective functions such as reducing power losses, improving voltage stability and minimizing transmission costs, etc. [4] and [5]. In electrical networks, the main goal of ORPD is to find the best values of control parameters including the voltage of generators, reactive power provided by shunt compensators and tap positions of transformers, so as to optimize the objective function taking into account the constraints. Moreover, dependent variables such as the voltage of charging buses, reactive power of generators and flow of apparent power in transportation lines must be within the specified permissible range [6].

Several conventional methods such as Linear Programming (LP) [7], Quadratic Programming (QP) [8] and [9] and Interior Point (IP) [10] methods have solved the problem of ORPD in certain situations. However, they are stagnating at the local optimum level in other situations, particularly to find optimal values of reactive and active power flows for large-scale systems [11] and [12].

To avoid shortages of the above methods, many optimization algorithms were applied: Particle Swarm Optimization (PSO) [13], Comprehensive Learning PSO (CLPSO) [14], Quasi Oppositional Teaching-Learning-Based Optimization (QOTLBO) [15], Moth-Flame Optimization (MFO) [16], two-Archive Multi-Objective Grey Wolf Optimizer (2Arch-MGWO) [17], Water Wave Optimization (WWO) [18], Whale Optimization Algorithm (WOA) [19], Modified Stochastic Fractal Search Algorithm (MSFSA) [6], and PSO hybrid with Imperialist Competitive Algorithm (PSO-ICA) [20]. All of these meta-heuristic techniques have their own significance, special impact, limitations and application in solving the ORPD problem [12].

Basic PSO is a part of the various stochastic (random) search modalities. It evolved by simulating a simplified social system and has proven powerful for finding solutions to problems of nonlinear continuous optimization. This original optimization method was introduced for the first time by Eberhart and Kennedy in 1995; fundamentally grounded on the sociological behavior related to a flock of birds. Several amendments have been suggested for improving the performance of this method, such as the coordinated aggregation PSO method and parallel vector evaluated PSO method [21].

One of the best developments to improve a standard PSO performance was made by He and Han in 2007 using an improved PSO algorithm that adds a Disturbance Term (PSO-DT) to the velocity update equation by trying to avert the default value of a standard PSO [22]. For solving the problem of ORPD, the applied PSO-DT is performed on an IEEE 30-bus power system wherein the control of bus voltage of generators, tap ratio of transformers, and reactive power provided by shunt compensators are involved for reducing transmission losses in the energy system.

Simulation results have shown that the PSO-DT technique was superior to the old PSO method in order to find the best solutions in terms of algorithm diversity and durability.

2. Problem Formulation of ORPD

ORPD case is considered as a non-linear optimization problem that contains the constraints of inequality and equality in the electrical network.

Generally, ORPD determines the loss of active power in a transport network, by setting the optimum parameters for controlling the energy system while simultaneously respecting the constraints of inequality and equality [3].

2.1. Reduction of Total Real Power Losses

Minimizing active power losses is one of the main objectives for the ORPD in a transport system F which may be edited in the following form:

$$F = \min \sum_{k \in N_n} P_{\text{loss}} = \\ = \min \left[\sum_{k \in N_n} G_k \left(V_i^2 + V_j^2 - 2 V_i V_j \cos \varphi_{ij} \right) \right], \tag{1}$$

where:

- $\sum_{k \in N_n} P_{\text{loss}}$: total losses of active power in the transport network.
- $k = (i, j)$; $i \in N_b$; $j \in N_a$.
- N_b: total number of buses in a specific network.
- N_a: number of buses adjacent to bus i (including bus i) in a particular network.
- N_n: number of network branches in a system.
- G_k: conductance at the branch k.
- V_i and V_j: voltages at buses i and j respectively.
- φ_{ij}: difference in loading angle between buses i and j in a network.

2.2. System Constraints

A problem of reactive power distribution has inequality and equality constraints in processing.

1) Equality Constraints

In this case, there are two equality constraints that can be expressed as follows:

The two equations below reveal the balance of active and reactive power needed in each normal electric grid:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{N_a} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\varphi_{ij}\right) = 0, \tag{2}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{N_a} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\varphi_{ij}\right) = 0, \tag{3}$$

where P_{G_i} and P_{D_i} are the active power injected and demanded at the bus i, respectively. G_{ij} and B_{ij} are respectively the real and fictional parts of the admittance matrix at buses i and j. Q_{G_i} and Q_{D_i} are respectively the reactive power injected and demanded at the bus i in a network [13] and [23].

2) Inequality Constraints

There are several inequality constraints that must be taken into account in the ORPD formulation, such as:

Equation (4) represents the voltage limits of buses V_i. $V_i^{\min}$ and $V_i^{\max}$ are the minimum and maximum voltage of the i-th bus, respectively. N_b is the overall number of buses:

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i = 1, \ldots, N_b. \tag{4}$$

Equation (5) and Eq. (6) give the limits of active and reactive power for generators P_{G_i} and Q_{G_i}, respectively. In this case, $P_{G_i}^{\min}$ and $P_{G_i}^{\max}$ are respectively the minimum and maximum generation of the active power of the i-th bus. $Q_{G_i}^{\min}$ and $Q_{G_i}^{\max}$ are respectively the minimum and maximum reactive power generation of the i-th bus in a system. N_g is the number of bus generators in a network:

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \quad i = 1, \ldots, N_g, \tag{5}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \quad i = 1, \ldots, N_g. \tag{6}$$

Equation (7) explains the limits of reactive power provided by capacitor banks Q_{C_i}. In this case, $Q_{C_i}^{\min}$ and $Q_{C_i}^{\max}$ are respectively a minimum and maximum injection of reactive power of the i-th parallel compensator, while N_c is the number of capacitor banks:

$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max}, \quad i = 1, \ldots, N_c. \tag{7}$$

Equation (8) describes the bounds of tap positions of transformers T_i. In this case, $T_i^{\min}$ and $T_i^{\max}$ are respectively the minimum and maximum tap setting of the i-th transport line and N_t is a number of transformer branches available for tap changing:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \ldots, N_t. \tag{8}$$

Finally, Eq. (9) indicates the limit of power flow for each line of transport S_{L_i}. $S_{L_i}^{\max}$ is the maximum flow of apparent power in the i-th line, and N_l is the number of load branches in a network [13], [20] and [23]:

$$|S_{L_i}| \le S_{L_i}^{\max}, \quad i = 1, \ldots, N_l. \tag{9}$$

The constraints of dependent variables are incorporated into the target function as terms of penalty. For that, Eq. (1) is replaced by Eq. (10) as follows:

$$F_{\text{Global}} = \min \sum_{k \in N_n} P_{\text{loss}} + F_{\text{Penalty}}, \tag{10}$$

where

$$\begin{aligned} F_{\text{Penalty}} &= K_P f\left(P_{G_1}\right) + K_V \sum_{i=1}^{N_b=30} f\left(V_i\right) + \\ &+ K_Q \sum_{i=1}^{N_g=6} f\left(Q_{G_i}\right) + K_S \sum_{i=1}^{N_l=41} f\left(S_{L_i}\right), \end{aligned} \tag{11}$$

while the three penalty factors are defined as $K_P = K_V = K_Q = K_S = 10^4$.

Calculation of the penalty value for active power violation of slack generator P_{G_1} is:

$$f\left(P_{G_1}\right) = \begin{cases} 0 & \text{if } P_{G_1}^{\min} \le P_{G_1} \le P_{G_1}^{\max}, \\ \left(P_{G_1}^{\min} - P_{G_1}\right)^2 & \text{if } P_{G_1} < P_{G_1}^{\min}, \\ \left(P_{G_1} - P_{G_1}^{\max}\right)^2 & \text{if } P_{G_1} > P_{G_1}^{\max}. \end{cases} \tag{12}$$

Penalty value calculation for bus voltage violation is:

$$f\left(V_i\right) = \begin{cases} 0 & \text{if } V_i^{\min} \le V_i \le V_i^{\max}, \\ \left(V_i^{\min} - V_i\right)^2 & \text{if } V_i < V_i^{\min}, \\ \left(V_i - V_i^{\max}\right)^2 & \text{if } V_i > V_i^{\max}. \end{cases} \tag{13}$$

Calculation of the penalty value for the reactive power violation of complete generators (the PV buses and the slack bus) is expressed by Eq. (14):

$$f\left(Q_{G_i}\right) = \begin{cases} 0 & \text{if } Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \\ \left(Q_{G_i}^{\min} - Q_{G_i}\right)^2 & \text{if } Q_{G_i} < Q_{G_i}^{\min}, \\ \left(Q_{G_i} - Q_{G_i}^{\max}\right)^2 & \text{if } Q_{G_i} > Q_{G_i}^{\max}. \end{cases} \tag{14}$$

Penalty value calculation for line flow violations is:

$$f\left(S_{L_i}\right) = \begin{cases} 0 & \text{if } S_{L_i} \le S_{L_i}^{\max}, \\ \left(S_{L_i} - S_{L_i}^{\max}\right)^2 & \text{if } S_{L_i} > S_{L_i}^{\max}. \end{cases} \tag{15}$$

Therefore, the penalty function values will be zero if the whole control settings are within their bounds. Conversely, the expressions of the penalty function will be appended to the target function to punish a violation that can happen if the control variables exceed their limits.

3. Overview of the Improved PSO-DT

For improving the ability of global optimization, particle diversity should be preserved throughout the iteration process; thus, the particles must not widely converge at a late stage.

The velocity updating formula has been improved as follows [24]:

$$V_{id}^{t+1} = wV_{id}^{t} + c_1 r_1 \left(\text{Pbest}_{id}^{t} - X_{id}^{t}\right) + \\ + c_2 r_2 \left(\text{Gbest}_{d}^{t} - X_{id}^{t}\right) + \alpha(r_3 - 0.5). \tag{16}$$

The position update equation is as follows:

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1}, \tag{17}$$

where:

- $i \in [1, 2, \ldots, N]$; N: the number of particles in a swarm (population size).
- The index t indicates the iteration counter, and d is the dimension index of the optimization search space.
- V_{id}^{t+1} and X_{id}^{t+1}: the speed (velocity) value and position of the particle at the new iteration $(t+1)$, respectively.
- V_{id}^{t} and X_{id}^{t}: the particle's speed value and position at the current iteration (t), respectively.
- w: the inertia weight that controls a particle's exploration for research purposes.
- c_1 and c_2: numbers greater than zero, called cognitive and social components, respectively.
- r_1, r_2 and r_3: distinct indiscriminate numbers divided into a group $[0, 1]$.
- Pbest_{id}^{t}: the best personal position for each particle at t iteration in a swarm.
- Gbest_{d}^{t}: the best global position for all particles at t iteration [25], [26] and [27].
- α is a small constant.

We call the fourth part of Eq. (16): $\alpha(r_3 - 0.5)$ as the disturbance term. Compared to the basic PSO, this term is not added to the velocity equation.

During the first phase of the calculation, the PSO has a fairly strong global search capacity; this is due to the relatively high velocity of particles. At this moment, the disturbance term is much smaller than the previous three parts of the velocity equation and its effect on the algorithm's search ability is small enough to be neglected. During the final or intermediate phases of the search process, the convergence property of the particles will slow down their speed. This allows the fourth element of Eq. (16) to guarantee that the particle search velocity will not drop down to zero. Consequently, the whole optimization will not allow the update for continuing and overcoming faults falling facilely into the local optimum of an basic PSO; thus, obtaining precise solutions [13].

The detailed procedure for updating individuals' speed and position for the PSO-DT method is displayed in Fig. 1.

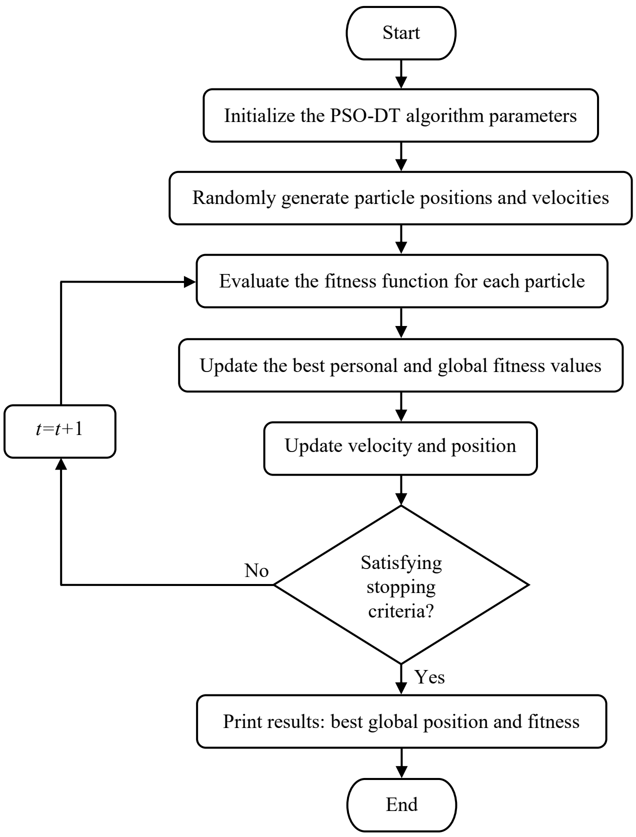

Fig. 1: Block diagram of suggested algorithm.

4. Results and Discussions

For proving the ability of the PSO and PSO-DT methods proposed in this study, an IEEE 30-bus power system is considered as a test system. This network contains 41 branches and is shown in Fig. 2. The bus load and injection data of the IEEE 30-bus system, reactive power limit of the same network and system summary are presented in Tab. 1, Tab. 2 and Tab. 3, respectively. Both methods have been implemented using the computing environment MATLAB 2014b.

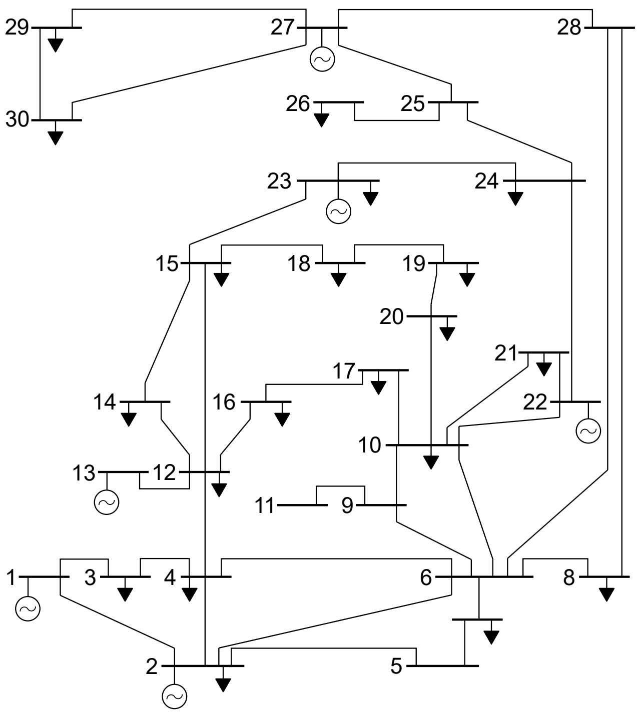

Fig. 2: IEEE 30-bus system single-line diagram [28].

Tab. 1: Bus load and injection data of the IEEE 30-bus system [28].

Bus	Load (MW)	Bus	Load (MW)
1	0.0	16	3.5
2	21.7	17	9.0
3	2.4	18	3.2
4	67.6	19	9.5
5	34.2	20	2.2
6	0.0	21	17.5
7	22.8	22	0.0
8	30.0	23	3.2
9	0.0	24	8.7
10	5.8	25	0.0
11	0.0	26	3.5
12	11.2	27	0.0
13	0.0	28	0.0
14	6.2	29	2.4
15	8.2	30	10.6

In both algorithms, the number of populations (swarm size), maximum iteration, learning factors ($C_1 = C_2$), minimum and maximum inertia weights are 40, 300, 2, 0.4 and 0.9, respectively, knowing that $\alpha = 0.04$.

Tab. 2: Reactive power limit of the IEEE 30-bus system [28].

Bus	Qmin (p.u.)	Qmax (p.u.)	Bus	Qmin (p.u.)	Qmax (p.u.)
1	−0.2	0.0	16	–	–
2	−0.2	0.2	17	−0.05	0.05
3	–	–	18	0.0	0.055
4	–	–	19	–	–
5	−0.15	0.15	20	–	–
6	–	–	21	–	–
7	–	–	22	–	–
8	−0.15	0.15	23	−0.05	0.055
9	–	–	24	–	–
10	–	–	25	–	–
11	−0.1	0.1	26	–	–
12	–	–	27	−0.055	0.055
13	−0.15	0.15	28	–	–
14	–	–	29	–	–
15	–	–	30	–	–

In this work, 10 tests are performed for solving the problem of ORPD. The best results using a suggested method and those of a PSO approach are presented in Tab. 4.

A set of solutions of the optimal control variables obtained from PSO-DT and PSO are summarized in Tab. 5.

Convergence features of an old PSO and a proposed algorithm are presented in Fig. 3.

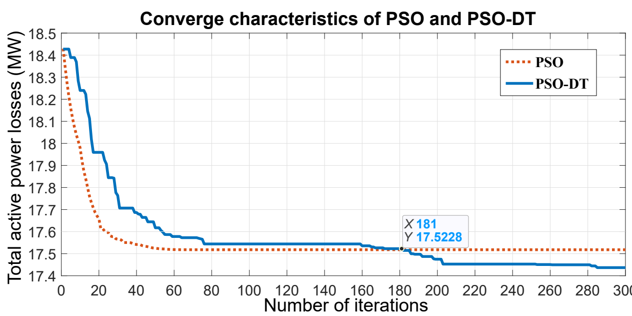

Fig. 3: The real power losses curve of PSO and PSO-DT.

According to Fig. 3 and Tab. 4, a minimum loss of active power acquired by a suggested technique was set at 17.44 MW at the 282nd iteration.

The bus data obtained by PSO is shown in Tab. 6 in App. B.

The bus data obtained by PSO-DT is shown in Tab. 7 in App. B.

The branch data obtained by PSO is shown in Tab. 8 in App. B.

The branch data obtained by PSO-DT is shown in Tab. 9 in App. B.

This value of power loss resulting from PSO-DT is less than 0.08 MW, compared with the results of basic PSO which is 17.52 MW at the 50th iteration or more (in lower simulation implementation time than the

Tab. 3: Summary of the IEEE 30-bus system.

	How many? How much?		P (MW)	Q (Mvar)
Buses	30	Total gen capacity	900.2	−125.6 to 251.1
Generators	6	On-line capacity	900.2	−125.6 to 251.1
Committed gens	6	Generation (actual)	300.9	108.6
Loads	21	Load	283.4	126.2
Fixed	21	Fixed	283.4	126.2
Dispatchable	0	Dispatchable	−0.0 of −0.0	−0.0
Shunts	3	Shunt (inj)	−0.0	50.9
Branches	41	Losses (I^2Z)	17.51	67.98
Transformers	4	Branch charging (inj)	–	34.7
Inter-ties	0	Total inter-tie flow	0.0	0.0
Areas	1			
	Minimum		**Maximum**	
Voltage magnitude	0.962 p.u. at bus 30		1.061 p.u. at bus 1	
Voltage angle	−18.37 deg at bus 30		0.00 deg at bus 1	
P losses (I^2R)	–		5.11 MW at line 1–2	
Q losses (I^2X)	–		15.31 Mvar at line 1–2	

Tab. 4: Power losses obtained before and after optimization.

Parameters	Losses before optimization	Losses after optimization by PSO	Losses after optimization by PSO-DT
Active power losses	18.430 MW 6.124 %	17.518 MW 5.821 %	17.436 MW 5.790 %
Reactive power losses	68.350 Mvar 62.937 %	67.980 Mvar 62.596 %	66.780 Mvar 61.491 %

Tab. 5: Control variables obtained before and after optimization.

Bus	Control variables	Initial values	Optimized values by PSO	Optimized values by PSO-DT
3	Q_{C_3} (Mvar)	0.000	19.9918	19.9035
10	$Q_{C_{10}}$ (Mvar)	0.000	19.9666	19.9472
24	$Q_{C_{24}}$ (Mvar)	0.000	15.0408	15.1290
1	V_1 (p.u.)	1.050	1.0613	1.0619
2	V_2 (p.u.)	1.040	1.0417	1.0465
5	V_5 (p.u.)	1.010	1.0086	1.0104
8	V_8 (p.u.)	1.010	1.0082	1.0205
11	V_{11} (p.u.)	1.050	1.0069	0.9936
13	V_{13} (p.u.)	1.050	1.0012	1.0216
6-9 (branch 11)	T_1 (p.u.)	1.078	1.0315	1.0344
6-10 (branch 12)	T_2 (p.u.)	1.069	0.9827	0.9843
4-12 (branch 15)	T_3 (p.u.)	1.032	1.0134	1.0030
28-27 (branch 36)	T_4 (p.u.)	1.068	0.9912	0.9911
Total			65.1459	65.1470

proposed algorithm). The point of intersection of the two curves of the real power losses between the two methods is 17.52 at iteration 181, which corresponds to the lower value obtained by PSO.

In order to validate the results obtained, we have compared our data with other articles already published. Authors in [33] proposed a MAS-based Reinforcement Learning (MASRL) algorithm and other algorithms such as Discrete Particle Swarm Optimization (DPSO) and Interior Point (IP) to solve the Optimal Reactive Power Dispatch (ORPD) problem for the purpose to minimize transmission active power losses in power systems. These methods were applied in the Ward-Hale 6-bus, IEEE 30-bus, and IEEE 162-bus systems. Comparing our simulation results and those obtained in the IEEE 30-bus, it was observed that our optimal value (17.436 MW) was better than their best active power values (17.94 MW, 17.93 MW and 18.15 MW), respectively. For another comparison, authors in [34] used the Hierarchically Distributed approach using a Mixed-Integer extension of the Augmented Lagrangian-based Alternating Direction Inexact Newton (ALADIN) algorithm for solving the line loss minimization problem. Their proposed method was tested on the IEEE 14-bus and 30-bus systems. The best real power value obtained was 17.999 MW on the last network used. Our value (17.436 MW) was also better than theirs.

This quick comparison between the different results allowed us to demonstrate the applicability and efficiency of our proposed algorithm.

From Tab. 3, it may also be noticed that the proposed method achieves the least reactive power loss of 66.78 Mvar, compared to the result of PSO (67.98 Mvar).

Consequently, the PSO-DT algorithm clearly appears to have a big capacity to identify optimal or near-ideal solutions and to respond efficaciously to constraints imposed by optimization issues. Including a disturbance term founded on actual structure strongly corrects faults [29].

5. Conclusion

An ORPD is a sub-group of an OPF, that has been defined as a nonlinear problem of optimization by a combination of continuous and/or discrete variables in an electrical network.

In this paper, PSO and PSO-DT methods are employed to properly resolve this issue. Obtained results from simulation clearly demonstrate that a chosen method PSO-DT yields better quality of the optimal global or near-global solutions compared to other standard PSO results. It was found that PSO-DT can be more sensitive in response to changing environments and maintain greater particle diversity than basic PSO.

The optimization results confirm the effectiveness of this method in providing near-optimal solutions and explain the superiority and robustness of a selected algorithm to correctly solve an ORPD issue regarding power losses. Consequently, the PSO-DT technique can be advised as a highly promising algorithm to solve several complex optimizations of engineering issues for researchers in future.

Acknowledgment

This research has been supported by our Research Center in Industrial Technologies "CRTI" in Algeria.

Author Contributions

M.M. performed the measurements, developed the theoretical formalism, performed the analytic calculations, and performed the numerical simulations. O.F.B., H.S., S.C. and B.B. contributed to the analysis of the results and to the proofreading of this manuscript. All the authors provided critical feedback, helped to shape the research and conduct the analysis and thus contributed to the final version of the manuscript.

References

[1] ROY, P. K. and S. DUTTA. *Optimal Power Flow Using Evolutionary Algorithms.* 1st ed. Hershey: IGI Global, 2019. ISBN 978-1-5225-6971-8.

[2] BOUCHEKARA, H. R. E. H., M. A. ABIDO and M. BOUCHERMA. Optimal power flow using Teaching-Learning-Based Optimization technique. *Electric Power Systems Research.* 2014, vol. 114, iss. 1, pp. 49–59. ISSN 1873-2046. DOI: 10.1016/j.epsr.2014.03.032.

[3] GHASEMI, M., M. TAGHIZADEH, S. GHAVIDEL, J. AGHAEI and A. ABBASIAN. Solving optimal reactive power dispatch problem using a novel teaching–learning-based optimization algorithm. *Engineering Applications of Artificial Intelligence.* 2015, vol. 39, iss. 1, pp. 100–108. ISSN 1873-6769. DOI: 10.1016/j.engappai.2014.12.001.

[4] MOUASSA, S., T. BOUKTIR and A. SALHI. Ant lion optimizer for solving optimal reactive power dispatch problem in power systems. *Engineering Science and Technology, an International Journal.* 2017, vol. 20, iss. 3, pp. 885–895. ISSN 2215-0986. DOI: 10.1016/j.jestch.2017.03.006.

[5] SADDIQUE, M. S., A. R. BHATTI, S. S. HAROON, M. K. SATTAR, S. AMIN, I. A. SAJJAD, S. S. UL HAQ, A. B. AWAN and N. RASHEED. Solution to optimal reactive power dispatch in transmission system using metaheuristic techniques—Status and technological review. *Electric Power Systems Research.* 2020, vol. 178, iss. 1, pp. 1–16. ISSN 1873-2046. DOI: 10.1016/j.epsr.2019.106031.

[6] NGUYEN, T. T., D. N. VO, H. V. TRAN and L. V. DAI. Optimal Dispatch of Reactive Power Using Modified Stochastic Fractal Search Algorithm. *Complexity.* 2019, vol. 2019, iss. 1, pp. 1–28. ISSN 1099-0526. DOI: 10.1155/2019/4670820.

[7] DEEB, N. I. and S. M. SHAHIDEHPOUR. An Efficient Technique for Reactive Power Dispatch Using a Revised Linear Programming Approach. *Electric Power Systems Research.* 1988,

vol. 15, iss. 2, pp. 121–134. ISSN 1873-2046. DOI: 10.1016/0378-7796(88)90016-8.

[8] QUINTANA, V. H. and M. SANTOS-NIETO. Reactive-power dispatch by successive quadratic programming. *IEEE Transactions on Energy Conversion*. 1989, vol. 4, iss. 3, pp. 425–435. ISSN 1558-0059. DOI: 10.1109/60.43245.

[9] LO, K. L. and S. P. ZHU. A decoupled quadratic programming approach for optimal power dispatch. *Electric Power Systems Research*. 1991, vol. 22, iss. 1, pp. 47–60. ISSN 1873-2046. DOI: 10.1016/0378-7796(91)90079-3.

[10] GRANVILLE, S. Optimal reactive dispatch through interior point methods. *IEEE Transactions on Power Systems*. 1994, vol. 9, iss. 1, pp. 136–146. ISSN 1558-0679. DOI: 10.1109/59.317548.

[11] EBEED, M., A. ALHEJJI, S. KAMEL and F. JURADO. Solving the Optimal Reactive Power Dispatch Using Marine Predators Algorithm Considering the Uncertainties in Load and Wind-Solar Generation Systems. *Energies*. 2020, vol. 13, iss. 17, pp. 1–19. ISSN 1996-1073. DOI: 10.3390/en13174316.

[12] MUHAMMAD, Y., R. KHAN, F. ULLAH, A. UR REHMAN, M. S. ASLAM, and M. A. Z. RAJA. Design of fractional swarming strategy for solution of optimal reactive power dispatch. *Neural Computing and Applications*. 2020, vol. 32, iss. 14, pp. 10501–10518. ISSN 1433-3058. DOI: 10.1007/s00521-019-04589-9.

[13] ZHAO, B., C. X. GUO and Y. J. CAO. A multiagent-based particle swarm optimization approach for optimal reactive power dispatch. *IEEE Transactions on Power Systems*. 2005, vol. 20, iss. 2, pp. 1070–1078. ISSN 1558-0679. DOI: 10.1109/TPWRS.2005.846064.

[14] MAHADEVAN, K. and P. S. KANNAN. Comprehensive learning particle swarm optimization for reactive power dispatch. *Applied Soft Computing*. 2010, vol. 10, iss. 2, pp. 641–652. ISSN 1872-9681. DOI: 10.1016/j.asoc.2009.08.038.

[15] MANDAL, B. and P. K. ROY. Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization. *International Journal of Electrical Power & Energy Systems*. 2013, vol. 53, iss. 1, pp. 123–134. ISSN 1879-3517. DOI: 10.1016/j.ijepes.2013.04.011.

[16] MEI, R. N. S., M. H. SULAIMAN, Z. MUSTAFFA and H. DANIYAL. Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique. *Applied Soft Computing*. 2017, vol. 59, iss. 1, pp. 210–222. ISSN 1872-9681. DOI: 10.1016/j.asoc.2017.05.057.

[17] NUAEKAEW, K., P. ARTRIT, N. PHOLDEE and S. BUREERAT. Optimal reactive power dispatch problem using a two-archive multi-objective grey wolf optimizer. *Expert Systems with Applications*. 2017, vol. 87, iss. 1, pp. 79–89. ISSN 1873-6793. DOI: 10.1016/j.eswa.2017.06.009.

[18] ZHOU, Y., J. ZHANG, X. YANG and Y. LING. Optimal reactive power dispatch using water wave optimization algorithm. *Operational Research*. 2020, vol. 20, iss. 4, pp. 2537–2553. ISSN 1866-1505. DOI: 10.1007/s12351-018-0420-3.

[19] BEN OUALID MEDANI, K., S. SAYAH and A. BEKRAR. Whale optimization algorithm based optimal reactive power dispatch: A case study of the Algerian power system. *Electric Power Systems Research*. 2018, vol. 163, pp. 696–705. ISSN 1873-2046. DOI: 10.1016/j.epsr.2017.09.001.

[20] MEHDINEJAD, M., B. MOHAMMADI-IVATLOO, R. DADASHZADEH-BONAB and K. ZARE. Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms. *International Journal of Electrical Power & Energy Systems*. 2016, vol. 83, iss. 1, pp. 104–116. ISSN 1879-3517. DOI: 10.1016/j.ijepes.2016.03.039.

[21] VILLA-ACEVEDO, W. M., J. M. LOPEZ-LEZAMA and J. A. VALENCIA-VELASQUEZ. A Novel Constraint Handling Approach for the Optimal Reactive Power Dispatch Problem. *Energies*. 2018, vol. 11, iss. 9, pp. 1–23. ISSN 1996-1073. DOI: 10.3390/en11092352.

[22] ESLAMI, M., H. SHAREEF, A. MOHAMED and M. KHAJEHZADEH. Improved Particle Swarm Optimization with Disturbance Term for Multi-machine Power System Stabilizer Design. *Australian Journal of Basic and Applied Sciences*. 2010, vol. 4, iss. 12, pp. 5768–5779. ISSN 2309-8414.

[23] LONDONO, D. C., W. M. VILLA-ACEVEDO and J. M. LOPEZ-LEZAMA. Assessment of Metaheuristic Techniques Applied to the Optimal Reactive Power Dispatch. In: *6th Workshop on Engineering Applications: Applied Computer Sciences in Engineering*. Santa Marta: Springer, 2019, pp. 250–262. ISBN 978-3-030-31019-6. DOI: 10.1007/978-3-030-31019-6_22.

[24] ZHANG, H., M. GAO and X. ZHANG. Improved hybrid particle swarm optimization algorithm. In: *2010 Sixth International Conference on Natural Computation*. Yantai: IEEE, 2010, pp. 2642–2646. ISBN 978-1-4244-5961-2. DOI: 10.1109/ICNC.2010.5583000.

[25] ALRASHIDI, M. R. and M. E. EL-HAWARY. A Survey of Particle Swarm Optimization Applications in Electric Power Systems. *IEEE Transactions on Evolutionary Computation*. 2009, vol. 13, iss. 4, pp. 913–918. ISSN 1941-0026. DOI: 10.1109/TEVC.2006.880326.

[26] SHARAF, A. M. and A. A. A. EL-GAMMAL. Particle Swarm Optimization PSO: A New Search Tool in Power System and Electro Technology. In: *Computational Intelligence in Power Engineering*. 1st ed. Heidelberg: Springer, 2010, pp. 235–294. ISBN 978-3-642-14013-6.

[27] PARSOPOULOS, K. E. and M. N. VRAHATIS. *Particle Swarm Optimization and Intelligence: Advances and Applications*. 1st ed. Hershey: IGI Global, 2010. ISBN 978-1-61520-666-7.

[28] 30-Bus System (IEEE Test Case). In: *al-roomi.org* [online]. 2015. Available at: `https://al-roomi.org/power-flow/30-bus-system`.

[29] HE, Q. and C. HAN. An Improved Particle Swarm Optimization Algorithm with Disturbance Term. In: *International Conference on Intelligent Computing ICIC 2006: Computational Intelligence and Bioinformatics*. Kunming: Springer, 2006, pp. 100–108. ISBN 978-3-540-37282-0. DOI: 10.1007/11816102_11.

[30] XU, Y., W. ZHANG, W. LIU and F. FERRESE. Multiagent-Based Reinforcement Learning for Optimal Reactive Power Dispatch. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*. 2012, vol. 42, iss. 6, pp. 1742–1751. ISSN 1558-2442. DOI: 10.1109/TSMCC.2012.2218596.

[31] MURRAY, A., A. ENGELMANN, V. HAGENMEYER and T. FAULWASSER. Hierarchical Distributed Mixed-Integer Optimization for Reactive Power Dispatch. *IFAC-PapersOnLine*. 2018, vol. 51, iss. 28, pp. 368–373. ISSN 2405-8963. DOI: 10.1016/j.ifacol.2018.11.730.

[32] XUE, H., Y. BAI, H. HU, T. XU and H. LIANG. A Novel Hybrid Model Based on TVIW-PSO-GSA Algorithm and Support Vector Machine for Classification Problems. *IEEE Access*. 2019, vol. 7, iss. 1, pp. 27789–27801. ISSN 2169-3536. DOI: 10.1109/ACCESS.2019.2897644.

[33] YANG, Z. and A. WU. A non-revisiting quantum-behaved particle swarm optimization based multilevel thresholding for image segmentation. *Neural Computing and Applications*. 2020, vol. 32, iss. 16, pp. 12011–12031. ISSN 1433-3058. DOI: 10.1007/s00521-019-04210-z.

[34] SHAMI, T. M., A. A. EL-SALEH, M. ALSWAITTI, Q. AL-TASHI, M. A. SUMMAKIEH and S. MIRJALILI. Particle Swarm Optimization: A Comprehensive Survey. *IEEE Access*. 2022, vol. 10, iss. 1, pp. 10031–10061. ISSN 2169-3536. DOI: 10.1109/ACCESS.2022.3142859.

About Authors

Mohamed MEZAACHE (corresponding author) was born in 1985. His nationality is Algerian. He obtained the degrees of B.E., M.E. and Ph.D. in Electrical Engineering (with specialization in electrical networks) from the University of Batna, Algeria, in 2008, 2011 and 2016, respectively. He is currently a senior researcher at the Research Center in Industrial Technologies "CRTI", Algiers, Algeria. His research interests include electrical networks, power electronics, artificial intelligence techniques, welding and related techniques.

Omar Fethi BENAOUDA was born on November 5th, 1984 in Tiaret, Algeria. He received a B.E. degree in electrical engineering from the University of Djelfa, Algeria in 2009, and his M.E. and Ph.D. from the University of Sciences and Technology of Oran (USTO-MB), Algeria in 2013 and 2017, respectively. He is currently a senior researcher "A" at the Research Center in Industrial Technologies "CRTI", Algiers, Algeria. He is working with the Diagnostic Group, LDEE laboratory at the University of Sciences and Technology of Oran since 2010. His research interests include electrical machines and drive control with the application of artificial Intelligence: fuzzy logic and neuron network as well as multi-level inverters and fault tolerance.

Hocine SEKHANE was born in 1985 in Algeria. He received B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from Mentouri Brothers University of Constantine, Algeria, in 2010, 2013 and 2019 respectively. He is currently a lecturer "B" at the Electrical Engineering Department of Skikda University and a researcher member in the laboratory "LGEC" at Constantine, Algeria. His research interests are Optimal Power Flow, modeling and control of FACTS systems, and system stability and protection systems.

Saad CHAOUCH received the B.E. in Electromechanical Engineering in 2007 from the University of Skikda and a M.E. degree in Electrical Engineering in 2011 from the University of Batna. Currently, he is a Ph.D. student in the Electrical Engineering Department at Houari Boumediene University of Sciences and Technology (USTHB, Algiers, Algeria) and a research fellow at the Research Center in Industrial Technologies "CRTI", Cheraga (Algeria). His research interests are in power electronics, arc welding processes and electrical machine modeling and control.

Badreddine BABES received the B.E. and M.Sc. degrees in electrical engineering and the Doctorate degree in electrical engineering (with specialization in electric drive applications and controls) from the University of Setif 1, Setif, Algeria, in 2004, 2010, and 2018, respectively. He was with Research Center in Industrial Technologies "CRTI", Algiers, Algeria, in 2017 as assistant researcher and he is currently with the CRTI as senior researcher "A". His research interests include power electronic converters, active power filters, and renewable energy.

Appendix A
Some Basic Concepts of PSO

- Fitness function:

The inertia mass of each particle is calculated according to its fitness (appropriate) value. Its updated formula is as follows:

$$\begin{cases} m_i(t) = \dfrac{\mathrm{fit}_i(t) - \mathrm{worst}(t)}{\mathrm{best}(t) - \mathrm{worst}(t)}, \\ M_i(t) = \dfrac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \end{cases} \tag{18}$$

where $\mathrm{fit}_i(t)$ is the fitness function value of particle i at t iteration, $\mathrm{best}(t)$ and $\mathrm{worst}(t)$ represent respectively the optimal and worst fitness function value of all particles at t iteration, and $M_i(t)$ is the mass of the i-th particle at iteration t.

For the minimization problem, $\mathrm{best}(t)$ and $\mathrm{worst}(t)$ are defined as follows:

$$\mathrm{best}(t) = \min_{i \in 1,\ldots,N} \mathrm{fit}_i(t), \tag{19}$$

$$\mathrm{worst}(t) = \max_{i \in 1,\ldots,N} \mathrm{fit}_i(t). \tag{20}$$

And vice versa for the maximization problem, so $\mathrm{best}(t)$ and $\mathrm{worst}(t)$ are defined as follows [32]:

$$\mathrm{best}(t) = \max_{i \in 1,\ldots,N} \mathrm{fit}_i(t), \tag{21}$$

$$\mathrm{worst}(t) = \min_{i \in 1,\ldots,N} \mathrm{fit}_i(t). \tag{22}$$

In this paper, we have minimized the function objective to reduce electrical power transmission losses.

- Stopping criteria:

Typically, there are two types of stopping criteria that are used to terminate the PSO run. In the first stopping criterion, the execution of PSO stops when a predetermined number of iterations is reached (Max iterations). The second stopping criterion is the maximum number of function evaluations (MaxFEs) and is called automatic stopping, which is calculated as follows:

$$\mathrm{MaxFEs} = S \cdot T, \tag{23}$$

where S is the swarm size and T is the maximum number of iterations.

The algorithm is terminated when the global optimal solution $\mathrm{best}(t)$ reaches the predefined accuracy or the maximum number of iterations has been reached [33] and [34]. In our case, we resorted to the first criterion to reduce the computation time.

Appendix B
Bus and Branch Data

Tab. 6: Bus data obtained by PSO.

Bus	Voltage		Generation		Load	
	Magnitude (p.u.)	Angle (deg)	P (MW)	Q (Mvar)	P (MW)	Q (Mvar)
1	1.061	0.000	260.91	−17.14	–	–
2	1.042	−5.286	40.00	40.47	21.70	12.70
3	1.030	−7.623	–	–	2.40	1.20
4	1.017	−9.279	–	–	7.60	1.60
5	1.009	−14.120	0.00	36.44	94.20	19.00
6	1.010	−11.026	–	–	–	–
7	1.001	−12.824	–	–	22.80	10.90
8	1.008	−11.765	0.00	34.04	30.00	30.00
9	0.993	−14.473	–	–	–	–
10	0.994	−16.267	–	–	5.80	2.00
11	1.007	−14.473	0.00	6.80	–	–
12	0.990	−15.380	–	–	11.20	7.50
13	1.001	−15.380	0.00	7.94	–	–
14	0.978	−16.395	–	–	6.20	1.60
15	0.977	−16.583	–	–	8.20	2.50
16	0.984	−16.089	–	–	3.50	1.80
17	0.986	−16.440	–	–	9.00	5.80
18	0.970	−17.251	–	–	3.20	0.90
19	0.969	−17.432	–	–	9.50	3.40
20	0.975	−17.205	–	–	2.20	0.70
21	0.984	−16.814	–	–	17.50	11.20
22	0.985	−16.819	–	–	–	–
23	0.976	−17.172	–	–	3.20	1.60
24	0.985	−17.562	–	–	8.70	6.70
25	0.985	−16.847	–	–	–	–
26	0.967	−17.295	–	–	3.50	2.30
27	0.994	−16.125	–	–	–	–
28	1.005	−11.684	–	–	–	–
29	0.973	−17.431	–	–	2.40	0.90
30	0.962	−18.369	–	–	10.60	1.90
Total			300.91	108.55	283.40	126.20

Tab. 7: Bus data obtained by PSO-DT.

Bus	Voltage		Generation		Load	
	Magnitude (p.u.)	Angle (deg)	P (MW)	Q (Mvar)	P (MW)	Q (Mvar)
1	1.069	0.000	260.60	−12.34	–	–
2	1.047	−5.152	40.00	27.63	21.70	12.70
3	1.039	−7.523	–	–	2.40	1.20
4	1.026	−9.154	–	–	7.60	1.60
5	1.019	−13.906	0.00	38.70	94.20	19.00
6	1.020	−10.863	–	–	–	–
7	1.001	−12.631	–	–	22.80	10.90
8	1.020	−11.621	0.00	39.96	30.00	30.00
9	0.994	−14.192	–	–	–	–
10	1.001	−15.921	–	–	5.80	2.00
11	0.993	−14.192	0.00	−0.49	–	–
12	1.007	−15.187	–	–	11.20	7.50
13	1.024	−15.187	0.00	12.42	–	–
14	0.994	−16.169	–	–	6.20	1.60
15	0.992	−16.326	–	–	8.20	2.50
16	0.997	−15.799	–	–	3.50	1.80
17	0.995	−16.115	–	–	9.00	5.80
18	0.982	−16.943	–	–	3.20	0.90
19	0.980	−17.100	–	–	9.50	3.40
20	0.985	−16.868	–	–	2.20	0.70
21	0.992	−16.467	–	–	17.50	11.20
22	0.993	−16.474	–	–	–	–
23	0.990	−15.889	–	–	3.20	1.60
24	0.996	−17.258	–	–	8.70	6.70
25	0.998	−16.571	–	–	–	–
26	0.980	−17.007	–	–	3.50	2.30
27	1.008	−15.872	–	–	–	–
28	1.015	−11.518	–	–	–	–
29	0.988	−17.140	–	–	2.40	0.90
30	0.976	−18.051	–	–	10.60	1.90
Total			300.60	105.88	283.40	126.20

Tab. 8: Branch data obtained by PSO.

Branch#	From bus	To bus	From bus P (MW)	Injection Q (Mvar)	To bus P (MW)	Injection Q (Mvar)	Loss (I^2Z) P (MW)	Loss (I^2Z) Q (Mvar)
1	1	2	172.67	−16.38	−167.55	25.85	5.112	15.31
2	1	3	88.24	−0.76	−85.12	7.72	3.126	11.42
3	2	4	43.14	0.01	−42.16	−0.93	0.980	2.99
4	3	4	82.72	7.69	−81.86	−6.11	0.859	2.47
5	2	5	82.35	1.86	−79.40	6.17	2.957	12.42
6	2	6	60.36	0.05	−58.40	1.94	1.953	5.92
7	4	6	75.16	−2.16	−74.51	3.50	0.650	2.26
8	5	7	−14.80	11.27	14.97	−12.91	0.168	0.42
9	6	7	38.15	−2.55	−37.77	2.01	0.382	1.17
10	6	8	29.89	−5.23	−29.78	4.69	0.108	0.38
11	6	9	28.09	−5.74	−28.09	7.53	0.000	1.78
12	6	10	16.78	6.90	−16.78	−5.16	0.000	1.73
13	9	11	0.00	−6.71	−0.00	6.80	0.000	0.09
14	9	10	28.09	−0.82	−28.09	1.70	0.000	0.88
15	4	12	41.26	7.60	−41.26	−3.13	0.000	4.47
16	12	13	−0.00	−7.85	0.00	7.94	0.000	0.09
17	12	14	7.31	1.26	−7.24	−1.11	0.069	0.14
18	12	15	16.59	2.01	−16.40	−1.64	0.189	0.37
19	12	16	6.17	0.21	−6.13	−0.14	0.037	0.08
20	14	15	1.04	−0.49	−1.03	0.49	0.003	0.00
21	16	17	2.63	−1.66	−2.63	1.68	0.005	0.02
22	15	18	5.26	0.42	−5.23	−0.36	0.031	0.06
23	18	19	2.03	−0.54	−2.03	0.55	0.003	0.01
24	19	20	−7.47	−3.95	7.50	4.00	0.026	0.05
25	10	20	9.81	4.96	−9.70	−4.70	0.114	0.26
26	10	17	6.40	7.57	−6.37	−7.48	0.032	0.08
27	10	21	15.46	6.42	−15.37	−6.21	0.099	0.21
28	10	22	7.39	2.25	−7.35	−2.16	0.044	0.09
29	21	22	−2.13	−4.99	2.14	5.00	0.004	0.01
30	15	23	3.97	−1.77	−3.95	1.81	0.020	0.04
31	22	24	5.21	−2.84	−5.17	2.90	0.042	0.06
32	23	24	0.75	−3.41	−0.74	3.44	0.017	0.03
33	24	25	−2.80	1.54	2.82	−1.50	0.020	0.03
34	25	26	3.55	2.37	−3.50	−2.30	0.048	0.07
35	25	27	−6.36	−0.87	6.41	0.96	0.046	0.09
36	28	27	19.71	5.96	−19.71	−4.33	0.000	1.63
37	27	29	6.20	1.68	−6.11	−1.51	0.092	0.17
38	27	30	7.10	1.68	−6.93	−1.36	0.173	0.33
39	29	30	3.71	0.61	−3.67	−0.54	0.036	0.07
40	8	28	−0.22	−0.64	0.22	−3.69	0.001	0.00
41	6	28	20.00	1.19	−19.93	−2.27	0.067	0.24
Total							17.51	67.98

Tab. 9: Branch data obtained by PSO-DT.

Branch#	From bus	To bus	From bus P (MW)	Injection Q (Mvar)	To bus P (MW)	Injection Q (Mvar)	Loss (I^2Z) P (MW)	Loss (I^2Z) Q (Mvar)
1	1	2	172.21	−11.09	−167.22	20.11	4.989	14.94
2	1	3	88.39	−1.25	−85.30	8.00	3.088	11.29
3	2	4	43.13	−2.13	−42.17	1.12	0.967	2.95
4	3	4	82.90	7.63	−82.05	−6.09	0.848	2.43
5	2	5	82.27	−0.58	−79.35	8.36	2.915	12.25
6	2	6	60.12	−2.47	−58.20	4.29	1.915	5.81
7	4	6	74.42	−3.90	−73.79	5.14	0.627	2.18
8	5	7	−14.85	11.34	15.01	−13.02	0.166	0.42
9	6	7	38.19	−2.72	−37.81	2.12	0.376	1.15
10	6	8	29.96	−10.29	−29.84	9.76	0.115	0.40
11	6	9	27.30	−3.96	−27.30	5.59	0.000	1.63
12	6	10	16.42	6.89	−16.42	−5.24	0.000	1.65
13	9	11	0.00	0.49	−0.00	−0.49	0.000	0.00
14	9	10	27.30	−6.08	−27.30	6.96	0.000	0.87
15	4	12	42.20	7.27	−42.20	−2.76	0.000	4.51
16	12	13	−0.00	−12.21	0.00	12.42	0.000	0.21
17	12	14	7.48	1.62	−7.41	−1.47	0.071	0.15
18	12	15	17.02	3.53	−16.82	−3.14	0.197	0.39
19	12	16	6.50	2.32	−6.46	−2.23	0.044	0.09
20	14	15	1.21	−0.13	−1.21	0.13	0.003	0.00
21	16	17	2.96	0.43	−2.95	−0.41	0.005	0.02
22	15	18	5.59	1.59	−5.55	−1.52	0.037	0.07
23	18	19	2.35	0.62	−2.35	−0.61	0.004	0.01
24	19	20	−7.15	−2.79	7.17	2.83	0.021	0.04
25	10	20	9.47	3.75	−9.37	−3.53	0.097	0.22
26	10	17	6.07	5.45	−6.05	−5.39	0.022	0.06
27	10	21	15.18	5.46	−15.09	−5.26	0.090	0.19
28	10	22	7.20	1.63	−7.16	−1.55	0.039	0.08
29	21	22	−2.41	−5.94	2.42	5.95	0.005	0.01
30	15	23	4.24	−1.08	−4.22	1.12	0.019	0.04
31	22	24	4.74	−4.40	−4.69	4.47	0.049	0.08
32	23	24	1.02	−2.72	−1.01	2.74	0.011	0.02
33	24	25	−3.00	1.09	3.02	−1.05	0.019	0.03
34	25	26	3.55	2.37	−3.50	−2.30	0.046	0.07
35	25	27	−6.57	−1.32	6.61	1.41	0.049	0.09
36	28	27	19.91	6.39	−19.91	−4.76	0.000	1.63
37	27	29	6.19	1.68	−6.10	−1.51	0.089	0.17
38	27	30	7.10	1.67	−6.93	−1.36	0.167	0.32
39	29	30	3.70	0.61	−3.67	−0.54	0.035	0.07
40	8	28	−0.16	0.20	0.16	−4.63	0.004	0.01
41	6	28	20.13	0.65	−20.07	−1.77	0.066	0.23
Total							17.195	66.78