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Equilibrium Optimizer Algorithm for Optimal Reactive Power Dispatch

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Abstract
Optimal Reactive Power Dispatch (ORPD) is a significant research area in terms of maintaining the reliability and safety of the power system and operating it more economically. ORPD problem can be formed from a variety of perspectives including the minimization of the active power losses and voltage deviation, and improving the voltage stability performance. The majority of methods so as to deal with ORPD problem is meta-heuristic techniques because of the complex, non-linear and non-convex nature of the problem. In this paper, a new physic-based meta-heuristic algorithm, Equilibrium Optimizer (EO), is proposed for ORPD problem to reach the optimal settings of control variables such as voltage magnitudes in PV buses, tap positions of transformers and reactive power support of shunt devices. The introduced algorithm is evaluated on IEEE 30-bus test system by using various objectives, and a comparison of the implemented method to other optimization techniques described in the literature is utilized to assess its efficacy. Simulation results and statistical indicators demonstrate that the EO algorithm validates its computational efficacy and robustness in handling the ORPD problem.

Keywords: Equilibrium optimizer, meta-heuristics, optimal reactive power dispatch, optimization algorithms.

Optimal Reaktif Güç Dağıtımı için Equilibrium Optimizasyon Algoritması

Öz
Optimal Reaktif Güç Dağıtımı (ORPD), şebekenin güvenilirliğini ve güvenliğini sağlamak ve güç sistemini daha ekonomik bir şekilde işletmek açısından önemli bir araştırma alanıdır. ORPD problemi, aktif güç kayıplarının ve gerilim sapmasının en aza indirilmesi ve gerilim kararlılık performansının iyileştirilmesi dahil olmak üzere çeşitli açılardan oluşturulabilir. ORPD problemiyle başa çıkmak için kullanılan yöntemlerin çoğu, problemin karmaşık, doğrusal olmayan ve dışbükey olmayan doğası nedeniyle meta-sezgisel tekniklerdir. Bu çalışmada, ORPD probleminin PV baralardaki gerilim büyüklükleri, transformatörlerin kademe pozisyonları ve şönt ekiomanların reaktif güç desteği gibi kontrol değişkenlerinin optimal ayarlarına ulaşması için fizik-tabanlı yeni bir meta-sezgisel algoritma olan Equilibrium Optimizer (EO) önerilmiştir. Tanıtılan algoritma, çeşitli hedefler kullanılarak IEEE 30-baralı test sistemi üzerinde değerlendirilmiştir ve etkinliğini tespit edebilmek için uygulanan yöntemin literatürde açıklanan diğer optimizasyon teknikleri ile karşılaştırılması yapılmıştır. Simülasyon sonuçları ve istatistiksel göstergeler, EO algoritmasının ORPD problemini çözme açısından etkinliğini ve sağlamlığını doğrulamaktadır.

Anahtar Kelimeler: Equilibrium optimizasyon algoritması, meta-sezgisel, optimal reaktif güç dağıtımı, optimizasyon algoritmaları.

1. Introduction

The Optimal Reactive Power Dispatch (ORPD) can be seen as a subproblem of Optimal Power Flow (OPF) (Biswas et al., 2019; Elsayed & Elattar, 2021). Although the reactive power only circulates in the power system, it is indispensable for voltage stability and power transfer (Saddique et al., 2020). Reactive power control and management are required in the power system to keep voltages on all busbars within acceptable limits and reduce the active power losses. Reactive power flow should not be disregarded since it's used by inductive loads and some types of equipment in the power system. Hence, reactive power generation in a power system should be adequate to satisfy the related components without causing additional power loss and undesired voltage drop.

The objective of ORPD can be minimizing the active power loss based on the premise that reactive

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power flow increases the active power losses and voltage deviations of load buses in the network, and enhancing the voltage stability. Control variables such as generator bus voltages, transformer tap positions and reactive power support of the shunt compensators or reactors are modified in order to achieve the desired objective. (Li et al., 2013) has concentrated to minimize the active power losses while (Gangotri & Bhimwal, 2010) and (Robbins & Domínguez-García, 2016) have focused on improving the system security through the voltage stability index and voltage deviation equations, respectively. (Nguyen & Vo, 2020) has tackled the ORPD problem in different perspectives such as the minimization of active power loss, voltage deviation and voltage stability index. It is worth mentioning that constraints related to the power system such as power balance, the reactive power capability of generators and shunt compensators or reactors, limits of bus voltages and transmission lines should be maintained during the optimization process.

The ORPD is modeled as a nonlinear programming problem, and some conventional techniques such as Interior Point Method (Granville, 1994) and Quadratic Programming (Grudinin, 1998) have been utilized so as to solve this challenging problem. However, the majority of ORPD approaches are meta-heuristics due to the non-linear character of the problem(Saddique et al., 2020). There are many investigations implemented to solve the ORPD problem by using meta-heuristic algorithms such as Gravitational Search Algorithm (Duman et al., 2012), Grey Wolf Optimizer (Sulaiman et al., 2015), Particle Swarm Optimization (Singh et al., 2015), Coyote Optimization Algorithm (Güvenç et al., 2020), Barnacles Mating Optimizer (Sulaiman et al., 2020) and some hybrid techniques (Nasouri Gilvaei et al., 2020; Shaheen et al., 2021). The reason of this valuable attention has been given to the meta-heuristics is that they have capable of effectively solving a variety of large-scale complex problems. However, they could diverge to local optima and do not guarantee to figure out the best solution. Another drawback of the meta-heuristics is the long solution time at computationally expensive problems. Therefore, researchers maintain to investigate the most suitable meta-heuristic algorithm in terms of solving capability and robustness to deal with the ORPD problem.

This paper focuses on determining the appropriate control parameters for reducing the active power losses of the IEEE 30-bus test system and explains how to implement the novel Equilibrium Optimization strategy in order to improve voltage profiles. Comparative analyses have been conducted with well-known meta-heuristic techniques in the Literature in order to demonstrate the effectiveness of the proposed EO algorithm in solving the ORPD problem.

The rest of the paper is organized as follows. First of all, the objection functions and constraints to be used in ORPD are explained in Section 2. In Section 3, the proposed Equilibrium Optimizer algorithm is introduced to deal with the ORPD problem. Section 4 presents the results and statistical indicators for case studies. Finally, the conclusion is reported in Section 5.

2. Problem Formulation

The ORPD problem purposes to minimize the investigated objective function while meeting operational equality and inequality constraints, obtaining the best solution for independent control variables. The ORPD shows a non-linear and non-convex behaviour, and it's an NP-hard problem, which means it's tough to solve using mathematical methods. The general frame of the ORPD (Biswas et al., 2019), including equality and inequality constraints, can be written as follow:

$$\text{Minimize: } f(x,u) \tag{1}$$

$$\text{Subject to: } g(x,u) \leq 0 \text{ and } h(x,u) = 0 \tag{2}$$

where x and u represent control and state variables of the problem respectively. f symbolizes the objective function, g and h stand for inequality and equality constraints.

Independent control variables of the ORPD problem consist of voltage magnitude of the PV bus, tap position of transformers and reactive power injected into the network by the shunt devices, which all of them creates the search space of the problem. Although transformers and shunt devices tap positions need integer variables, they are considered as decimal in this study in order to achieve the optimal point more effectively. The set of independent control and dependent state variables can be created as follows:

$$x^T = \left[V_{g1}, .., V_{gN_g}, T_1, .., T_{N_t}, Q_{c1}, .., Q_{cN_c}\right] \tag{3}$$

$$u^T = \left[Q_{g1}, .., Q_{gN_g}, V_{l1}, .., V_{lN_l}, S_1, .., S_{NT_l}\right] \tag{4}$$

2.1. ORPD Functions

The objective function of the ORPD can be modelled with three different perspectives, which are the minimization of the active power losses, voltage deviations and voltage stability index. Furthermore, these objectives can be handled together by using the multi-objective optimization concept.

2.1.1. Active Power Loss

The ORPD problem's initial objective is to reduce the total active power loss in the network, which may be expressed as (Nasouri Gilvaei et al., 2020):

$$\text{Minimize: } f_1 = P_{loss}(x,u) \rightarrow \sum_{i=1}^{N_B}\sum_{j=1}^{N_B} G_{ij}\left[\left(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}\right)\right], i \neq j \tag{5}$$

where N_B represents the number of buses, V_i and V_j are the voltage magnitude of the bus i and j respectively, δ_{ij} and G_{ij} symbolize the difference of voltage angles and the conductance of the transmission line between bus i and j respectively.

2.1.2. Total Voltage Deviation

The second target to be optimized in ORPD problem can be the minimization of the total voltage deviation like given in (Abaza et al., 2021):

$$\text{Minimize: } f_2 = TVD(x,u) \rightarrow = \sum_{i=1}^{N_l} \left| V_i - V_{ref} \right| \quad (6)$$

where N_l symbolizes the number of PQ or load buses, V_i is the voltage magnitude of the i[th] PQ bus and V_{ref} represents the reference voltage magnitude considered as 1.0 pu.

2.1.3. Voltage Stability Index

Another option that can be utilized in the ORPD problem as an objective is the improvement voltage stability of the power system. The capacity of a power system to keep the voltage within its limit at each bus in the network under normal operating circumstances is referred to as voltage stability. When a system is subjected to a disturbance, such as a surge in load demand or a change in the system configuration, it might experience voltage instability, which can result in a gradual and unpredictable drop in voltage. As a result, improving a system's voltage stability is a crucial aspect of power system management and planning (Ettappan et al., 2020).

The improvement of the voltage stability can be accomplished by minimizing the voltage stability criteria known as the L-index, a scalar value having a range of [0,1], at each PQ bus (Nasouri Gilvaei et al., 2020). A maximum value of the L-index results near 0 indicates that the system is almost stable, while a value close to 1 indicates that the system is on the verge of reaching voltage collapse (Rajan & Malakar, 2016). The L-index of the j[th] PQ bus can be calculated as follows (Kessel & Glavitsch, 1986):

$$\text{Minimize: } f_3 = VSI(x,u) = L_{max} \rightarrow \quad (7)$$

$$= L_{max} = \max(L_j), \forall j \in N_l \quad (8)$$

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ij} \frac{V_i}{V_j} \right|, \forall j \in N_l \quad (9)$$

$$F_{ij} = -[Y_1]^{-1}[Y_2] \quad (10)$$

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \quad (11)$$

2.2. Equality Constraints

Equality constraints in ORPD are commonly represented by power balance equations for both active and reactive power, which ensure that the load demand is satisfied by taking into account the power losses, and are depicted as follows:

$$P_{gi} - P_{li} = |V_i| \sum_{j=1}^{N_B} |V_j| \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}\right), \forall i \in N_B \quad (12)$$

$$Q_{gi} - Q_{li} = |V_i| \sum_{j=1}^{N_B} |V_j| \left(G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}\right), \forall i \in N_B \quad (13)$$

where N_B symbolizes the total number of buses in the power system, P_{gi}, P_{li}, Q_{gi}, Q_{li} and B_{ij} represent active and reactive power generation and demand in bus i and line susceptance between i[th] and j[th] buses, respectively. Except for the slack bus, whose output is a dependent variable since it is affected by power losses, all active power generation of PV buses is fixed. The Q_i is also a state variable because the reactive power injected varies when the control variables are changed.

2.3. Inequality Constraints

Control and state variables are the two forms of inequality constraints used in ORPD. The transformer output, generator bus voltages, and the reactive power provided by the shunt capacitors are all control variables, while active power generation at the slack bus, reactive power generation at the PV bus, voltages of the PQ bus, and power flow of transmission lines are among the state variables. The inequality constraints on control variables can be written as follows:

$$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max}, \forall i \in N_g \quad (14)$$

$$T_i^{min} \leq T_i \leq T_i^{max}, \forall i \in N_t \quad (15)$$

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max}, \forall i \in N_c \quad (16)$$

The inequality constraints on state variables can be created as follows:

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, \forall i \in N_g \quad (17)$$

$$V_{li}^{min} \leq |V_{li}| \leq V_{li}^{max}, \forall i \in N_l \quad (18)$$

$$S_i \leq S_i^{max}, \forall i \in NT_l \quad (19)$$

$$P_{gs}^{min} \leq P_{gs} \leq P_{gs}^{max}, s = slack \quad (20)$$

Voltages in PQ buses and the loading levels of the transmission lines can be considered as security constraints, while reactive power generations of units are related to the operational limitations.

2.4. Constraints Handling

A suitable solution to the ORPD problem can only be achieved by complying with the relevant constraints. The inequality constraints on independent control variables have already been satisfied through determining upper and lower limits that meta-heuristic algorithm can allocate. However, there is a need to be concerned with inequality constraints on dependent variables. Reactive power limits of generators and active power limit of the slack bus can be determined while using the Newton Raphson power flow equation so that if control variables violate these constraints, power flows will take place according to allowable limits, which means that the exact value of the control variable will not be satisfied. On the other hand, the voltage limit of PQ buses and transmission line thermal limits are constraints that need to be addressed in the solution process.

Various papers such as (Rajan & Malakar, 2016) and (Ettappan et al., 2020) have resolved the compliance problem to the constraints by using the punishment and aggregating method so that any violation in constraints reduces the solution quality of the objective function. Therefore, the objective function of ORPD can be reconstructed through binding related constraints to the function as a penalty.

$$\text{Minimize: } P = f_{obj} + \omega_v + \omega_s \tag{21}$$

where,

$$\omega_v = \lambda_v \sum_{i=1}^{N_l} \left\{\max\left(0, abs(V_i - V_i^{lim})\right)\right\}^2 \tag{22}$$

$$\omega_s = \lambda_s \sum_{i=1}^{NT_l} \{\max(0, S_i - S_i^{max})\}^2 \tag{23}$$

$$V_i^{lim} = \begin{cases} V_i^{max}, if\ V_i > V_i^{max} \\ V_i^{min}, if\ V_i < V_i^{min} \end{cases} \tag{24}$$

where ω_v and ω_s are punishments relevant to voltage violation in PQ buses and overloading in transmission lines while λ_v and λ_s represent constant penalty coefficients, f_{obj} symbolizes the main objective, which can stand for one of the objectives, including power loss, voltage deviation and voltage stability index. It is worth mentioning that f_{obj} can be also designed as a multi-objective framework by using either the aggregating method or pareto-optimality technique.

3. Equilibrium Optimizer

The Equilibrium Optimizer has been constructed based on control volume mass balance models used to estimate both dynamic and equilibrium states (Faramarzi et al., 2020). Position (concentration) of each particle represents search agents in EO. To finally reach the equilibrium state, which means an optimal solution, the search agents update their positions at random with regard to the best-so-far solutions, termed equilibrium candidates. EO has been created in order to deal with single-objective optimization problems and position updating rule implemented can be written as follow:

$$\vec{C} = \vec{C}_{eq} + \left(\vec{C} - \vec{C}_{eq}\right)\vec{F} + \frac{\vec{G}}{\vec{\lambda}}(1 - \vec{F}) \tag{25}$$

where, $\vec{C}$ is the new position vector of each particle, $\vec{C}_{eq}$ represents equilibrium point retrieved from a pool comprising some best solutions, $\vec{F}$ is an exponential term and $\vec{G}$ is generation rate. The second term of the equation allowing to investigate a wider range in search space is related to a difference in concentration between a particle and the equilibrium state. Particles act as explorers by searching the entire search space in this way. On the other hand, the third term associated with the generation rate ensures the exploitation of obtained search areas with short steps, though it can also serve as an explorer. The extended formulations of these terms are given as follows:

$$\vec{F} = a_1 sign(\vec{r} - 0.5)[e^{-\vec{\lambda}t} - 1] \tag{26}$$

$$t = (1 - \frac{Iter}{MaxIter})^{(a_2 \frac{Iter}{MaxIter})} \tag{27}$$

$$\vec{C}_{eq} = random.choice(\vec{C}_{eq,pool}) \tag{28}$$

$$\vec{C}_{eq,pool} = (\vec{C}_{eq(1)}, .., \vec{C}_{eq(4)}, \vec{C}_{eq(avg)}) \tag{29}$$

$$\vec{C}_{eq(avg)} = \frac{\vec{C}_{eq(1)} + \vec{C}_{eq(2)} + \vec{C}_{eq(3)} + \vec{C}_{eq(4)}}{4} \tag{30}$$

$$\vec{G} = \vec{G}_0 \vec{F} \tag{31}$$

$$\vec{G}_0 = \overrightarrow{GCP}(\vec{C}_{eq} - \vec{\lambda}\vec{C}) \tag{32}$$

$$\overrightarrow{GCP} = \begin{cases} 0.5r_1, & r_2 \geq GP \\ 0, & r_2 < GP \end{cases} \tag{33}$$

where a_1 is a constant coefficient controlling step size in exploration phase, a_2 is a constant coefficient that regulate exploitation phase, $\vec{r}$ and $\vec{\lambda}$ are uniform distributed random vector between 0 and 1, r_1 and r_2 are uniform distributed random number between 0 and 1, $\overrightarrow{GCP}$ is generation rate control parameter and GP is generation probability.

The equilibrium pool $\vec{C}_{eq,pool}$ comprise best four particles obtained until related iteration and average value of these particles. These four particles improve the exploration capabilities of the algorithm, whereas the average particle strengthens the exploitation ability. The main tool in order to exploit the promising region is the generation rate $\vec{G}$. The higher the GP generation probability, the lesser particle takes advantage of the generation rate since $\overrightarrow{GCP}$ that is generation rate control parameter becomes zero. Another meaningful expression is $sign(\vec{r}-0.5)$ determining the motion direction of each particle.

A proper balance between exploration and exploitation phases should be constructed in all meta-heuristic approaches so as to acquire quality solution. In EO, exploration phase is conducted by generation probability and a_1 constant while exploitation stage is performed through memory saving (like p_{best} of particle swarm optimization) and a_2 constant. Equilibrium pool and $sign(\vec{r}-0.5)$ term are also crucial terms for establishing balance between phases.

During the first iterations, the individuals are all spatially isolated from one another. The algorithm's capacity to explore the space broadly is confirmed by updating the concentrations depending on these candidates of equilibrium pool. At first iterations, when particles are far apart, the average particle of equilibrium pool also assists in the discovery of unknown search areas. The concentration update mechanism will help in local search around the candidates since individuals of equilibrium pool are close to each other in the last iterations. Therefore, the equilibrium pool manages either exploration or exploitation phases according to iteration level.

4. Result and Discussion

The IEEE- 30 bus power system has been utilized as a test system to validate the efficacy and robustness of the proposed EO Algorithm based Reactive Power Dispatch. The EO is executed in the Python programming language with PSS/E 35.2 software package, and numerical tests are performed on a computer with an Intel® Core™ i7-8850U CPU at 2.60GHz with 16GB of RAM. To solve the ORPD problem with EO, the Mealpy software package (Thieu & Molina, 2021), a set of state-of-the-art Meta-heuristic algorithms in Python, is used.

4.1. IEEE 30 bus system

There are six generator units located at buses 1, 2, 5, 8, 11, and 13 – bus 1 is chosen as slack bus, twenty-four load buses with 2.834 pu and 1.262 pu for both active and reactive power demand, four regulating tap-changing transformers at branches 4-12, 6-9, 6-10 and 28-27, and nine shunt VAR capacitors at the buses 10, 12, 15, 17, 20, 21, 23, 24, and 29 in the IEEE 30-bus system. The limit of voltage magnitude is considered between 0.95 and 1.1 pu for generator buses and 0.90 and 1.1 pu for load buses. The maximum output of the shunt capacitors is determined as 5 MVar while the transformer tap settings have been configured to vary between 0.9 and 1.1 pu. The test system data is available in (*Pg_tca30bus*, n.d.).

4.2. Experimental Case Studies

On the IEEE 30-bus test system, the EO approach is performed to minimize the penalty function, including the active power loss, total voltage deviation or voltage stability index as a single objective function with the penalty terms related to mentioned constraints. Six different cases have been evaluated in the test system in order to compare the effectiveness of EO according to the other meta-heuristics in the Literature. Table-1 shows the generation amounts adjusted to implement the first and second three cases. Every three cases consist of the objectives of the minimization of the active power loss and voltage deviation, and the improvement of the voltage stability. It is worth mentioning that λ_v and λ_s penalty coefficients (equation 22 and 23) are 500 and 700 as in (Rajan & Malakar, 2016). It should also be emphasized that each objective function is subjected to 30 trial runs with determining the population size and iteration as 50 and 1000, respectively. The results have been compared to those obtained using numerous meta-heuristics, including GSA (Duman et al., 2012), COA (Güvenç et al., 2020), ABC (Ettappan et al., 2020) and SMA (Elsayed & Elattar, 2021), implemented for addressing the same ORPD problem to demonstrate the advantage of EO.

Table 1. Generator data for IEEE 30-bus test system

Bus No	P_g (MW) Case 1,2,3	P_g (MW) Case 4,5,6	$Q_{g,min}$ (MVar)	$Q_{g,max}$ (MVar)
1	Slack	Slack	-20	150
2	75	80	-20	60
5	40	50	-15	62.5
8	30	20	-15	48.7
11	25	20	-15	40
13	30	20	-15	46.5

Table 2 presents the optimal values for all control variable ranges in case studies in order to minimize the relevant objective functions. It can be recognized in Table 2 that the EO is capable of reducing the power loss to 4.108 MW in case-1 and 4.54 MW in case-4. The percentages of reduction in power loss are 23.61% in case -1 and 21.99% in case-4 according to the base case values. There are a total of 24 load buses in the system under investigation and the highest conceivable cumulative total of TVD would theoretically be 2.4 pu (i.e. 24x((1.1-1.0) or (1.0-0.9))) if all of these buses run at their limits. Therefore, the total voltage deviation value for the 30-bus system should never exceed 2.4 pu in order to keep the load bus voltages between 0.9 and 1.1 pu and the achieved TVD values because of the minimizing the power losses are 1.87, which means that there will be no violation for both case-1 and case-4. On the other hand, if we turn the objective function into the total voltage deviation perspective, the optimal values of TVD in case-2 and case-5 are 0.14 and 0.115 pu, resulting in higher active power losses according to the base cases. However, if the voltage stability index is chosen as the objective, the L indexes in case-3 and case-6 are obtained as 0.09762 and 0.09758, which do not significantly increase the active power losses.

from EO have been achieved in the voltage stability index objective. The L-index results of EO for cases 3 and 6 are superior in comparison with other meta-heuristics. Nonetheless, the best results for TVD are provided by Green Lourie Swarm Optimization (Kanagasabai, 2020) for case 2 and Exchange Market Algorithm (Rajan & Malakar, 2016) for case 5. It should be noted that comparing the performance of two methods solely on the basis of numerical values of outcomes may be inappropriate for a constrained optimization problem due to using coefficients.

Table 2. The results of EO at different cases

Control Variables	Base Case (1-2-3)	Base Case (4-5-6)	Case-1 (P_{loss})	Case-2 (TVD)	Case-3 (L_{index})	Case-4 (P_{loss})	Case-5 (TVD)	Case-6 (L_{index})
V_{g1}	1.05	1.05	1.1	0.9835	1.0953	1.1	0.9814	1.0997
V_{g2}	1.04	1.04	1.0945	1.0746	1.1	1.0942	0.9607	1.1
V_{g3}	1.01	1.01	1.0733	1.0129	1.0993	1.074	1.0566	1.1
V_{g4}	1.01	1.01	1.0809	1.0862	1.0899	1.0764	1.0135	1.0939
V_{g5}	1.05	1.05	1.1	1.0735	0.9625	1.1	1.0530	0.9642
V_{g6}	1.05	1.05	1.1	1.0407	0.9504	1.1	1.0598	0.9970
T_{4-12}	1.032	1.032	0.9856	0.9948	0.9012	0.98	1.0961	0.9
T_{6-9}	1.078	1.078	1.0433	1.0429	0.9260	1.0489	1.0680	0.9222
T_{6-10}	1.069	1.069	0.9034	0.9	0.9	0.9	0.9	0.9
T_{27-28}	1.068	1.068	0.9638	0.9461	0.9287	0.9748	0.9478	0.9261
Q_{10}	0	0	0	0	3.86	2.97	5.0	0
Q_{12}	0	0	0	0	0	0.06	2.9	0
Q_{11}	0	0	4.98	0	0	3.26	3.28	0
Q_{17}	0	0	4.96	0	0	4.87	3.17	3.6567
Q_{20}	0	0	4.56	4.5	0	4.99	5.0	0
Q_{21}	0	0	4.86	0	0	4.93	3.70	0
Q_{23}	0	0	0	0.7	0	4.94	4.35	0
Q_{24}	0	0	5	4.3	0	2.97	4.78	0
Q_{29}	0	0	0	0	0	1.1	6.98	0
$\boldsymbol{P_{loss}}$	5.38	5.82	**4.108**	6.25	5.19	**4.54**	6.9464	5.58
$\boldsymbol{TVD}$	1.19	1.19	1.87	**0.14**	1.89	1.87	**0.115**	1.87
$\boldsymbol{L_{index}}$	0.24897	0.24548	0.105	0.12	**0.09762**	0.17	0.1241	**0.09758**
% $\boldsymbol{Reduction}$	-	-	23.61	88.24	60.79	21.99	90.34	60.24

Table 3. The comparison of EO with other meta-heuristics

Algorithms	Case-1 (P_{loss})	Case-2 (TVD)	Case-3 (L_{index})	Case-4 (P_{loss})	Case-5 (TVD)	Case-6 (L_{index})
EO	**4.108**	0.1349	**0.09762**	4.54	0.115	**0.09758**
SHADE-EC (Biswas et al., 2019)	4.4126	0.08886	-	4.8612	0.08724	-
COA (Güvenç et al., 2020)	4.41238	0.08837	-	4.861183	0.08724	-
GWO-PSO (Shaheen et al., 2021)	-	-	-	5.09037	0.27800	-
EMA (Rajan & Malakar, 2016)	-	-	-	**4.4978**	**0.061311**	0.09797
SMA (Elsayed & Elattar, 2021)	-	-	-	4.5181	-	-
SCA (Saddique et al., 2020)	-	-	-	4.7086	-	-
ABC (Ettappan et al., 2020)	-	-	-	4.5804	-	-
ECOA (Abaza et al., 2021)	-	-	-	4.547	-	-
GLS (Kanagasabai, 2020)	4.216	**0.064**	0.1160	-	-	-
FA-APTFPSO (Nasouri Gilvaei et al., 2020)	-	-	-	4.8664	0.0841	0.1186
PSOGSA (DUMAN, 2018)	-	-	-	4.5950	0.1234	0.1242
BMO (Sulaiman et al., 2020)	-	-	-	4.5862	-	-
GSA (Duman et al., 2012)	-	-	-	4.51431	0.067633	0.11607

Table 3 compares the solutions of EO with the results obtained from different methods in the IEEE 30-bus system. As can be seen in Table 3 that the active power loss value obtained from EO in case-1 is the best one among the published results. It should be stated at this point that the range of the voltage limit for the load buses is determined within 0.9 pu and 1.1 pu in this study. The other effective solutions acquired

When it comes to meta-heuristics, not only their efficacy but also their robustness is critical. Therefore, a more extensive and in-depth examination is required. In this direction, Table 4 compares the min, max, mean and standard deviation outcomes received with EO to those

Table 4. The comparison the statistical indicators of EO with other published solutions

Algorithms	Indicator	Case-1 (P_{loss})	Case-2 (TVD)	Case-3 (L_{index})	Case-4 (P_{loss})	Case-5 (TVD)	Case-6 (L_{index})
EO	Min	**4.108**	**0.1349**	**0.0976**	4.543	0.115	**0.0975**
	Max	**4.198**	**0.1788**	**0.0991**	4.653	0.175	**0.0987**
	Mean	**4.156**	**0.1572**	**0.0982**	4.588	0.154	**0.0981**
	Std	**0.0223**	**0.0134**	**0.00038**	0.02475	0.013	**0.00027**
SMA (Elsayed & Elattar, 2021)	Min	-	-	-	4.5181	-	-
	Max	-	-	-	4.7814	-	-
	Mean	-	-	-	4.63	-	-
	Std	-	-	-	0.0979	-	-
FA-APTFPSO (Nasouri Gilvaei et al., 2020)	Min	-	-	-	4.8664	0.0841	0.1186
	Max	-	-	-	4.8853	0.0984	0.1198
	Mean	-	-	-	4.8689	0.0894	0.1191
	Std	-	-	-	0.00504	0.00427	0.00039
SCA (Saddique et al., 2020)	Min	-	-	-	4.708	-	-
	Max	-	-	-	5.286	-	-
	Mean	-	-	-	5.030	-	-
	Std	-	-	-	0.133	-	-
EMA (Rajan & Malakar, 2016)	Min	-	-	-	**4.4978**	**0.061311**	0.09797
	Max	-	-	-	**4.50**	**0.0725**	0.1011
	Mean	-	-	-	**4.4999**	**0.06558**	0.098744
	Std	-	-	-	**0.0003716**	**0.0008328**	0.000458

obtained from other recently published approaches. Table 4 illustrates that the EO algorithm testifies its robustness with low statistical indicators, including standard deviation.

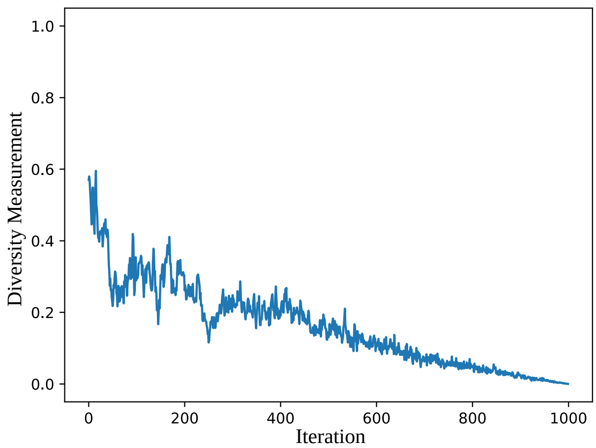

Figure 1. Diversity measurement chart of EO

In order to clarify the efficacy of the EO, performance indicators are presented in Figures 1-6. Figures 1 and 2 illustrate clear information of exploration, exploitation, and particle variety in the population of the EO. It's important to keep in mind that the reader wondering how to be visualized the diversity, exploration and exploitation abilities of a meta-heuristic algorithm should refer to the valuable paper written by (Hussain et al., 2019). it can be said from these figures that the EO algorithm prioritized exploitation above exploration for the majority of the search process. In the first iterations, a balance between exploitation and exploration is constructed (i.e. nearly 50%-50%), however, after a few iterations, the algorithm's behaviour is converted to the exploitative. This can also be seen in Figure 1, where the diversity was initially about 0.5 but steadily decreased over the iterations.

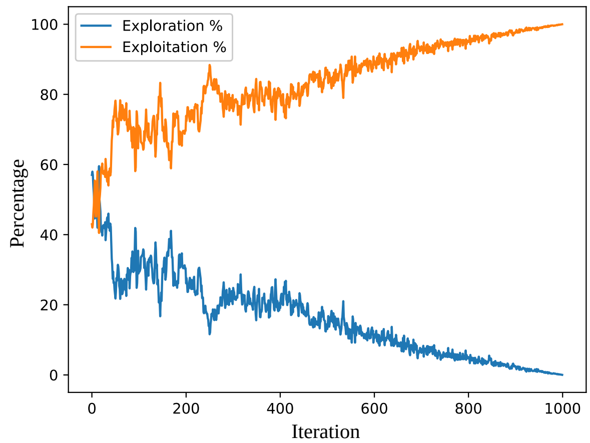

Figure 2. Exploration and Exploitation of EO

The EO convergence curve is shown in Fig. 3, and it has strong convergence properties in terms of power loss optimization. Fig. 4 presents the trajectory of two individuals of the population in two dimensions. It can be observed from this figure that nearly the entire search space is investigated. Nevertheless, in order to further clarify the behaviour of the individuals during the iterations, the trajectory of the first dimension of the first agent is demonstrated in Fig. 5. It can be concluded from this figure that frequently transitions from upper to lower bound occur in most of the search process, and the alteration in the dimension slows down at the end of the iterations. Ultimately, the runtime chart of the EO algorithm throughout the iterations can be examined in Fig. 6. Although some function evaluations exceed one second, the general solution time is roughly 0.8 seconds per iteration (each with 50 function evaluations). Direct comparisons have not been implemented with other methods based on CPU time due to particular hardware properties and different numbers of function evaluations.

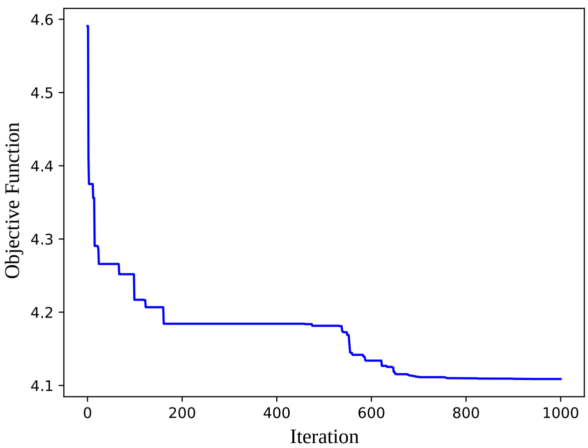

Figure 3. Convergence curve

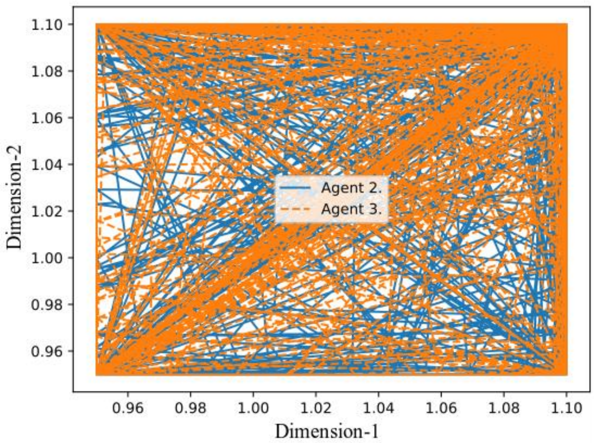

Figure 4. Trajectory of the first and second dimension of the second and third individual after generations in EO

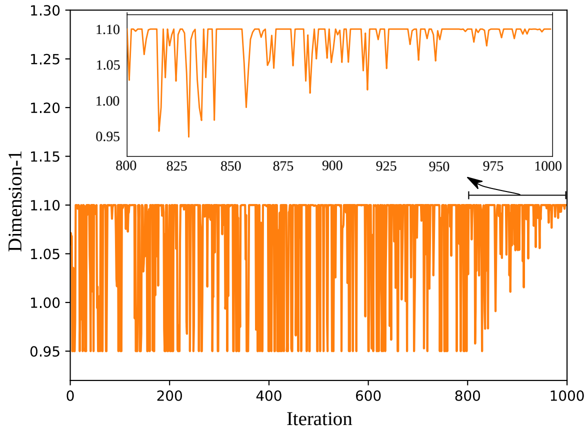

Figure 5. Trajectory of the first dimension of the first individual in EO

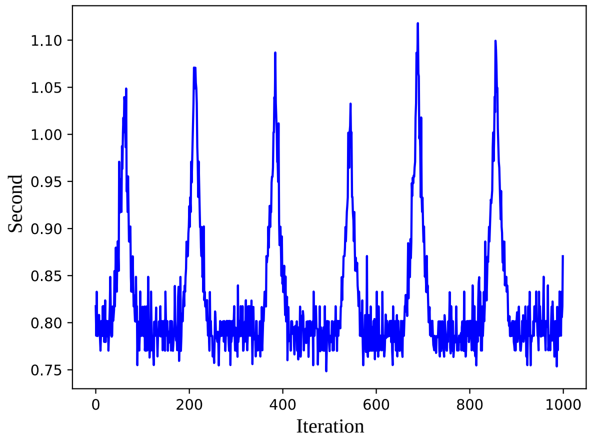

Figure 6. Runtime chart of the EO

5. Conclusions

In this paper, the Equilibrium Optimizer, a recently developed physic-based meta-heuristic algorithm, is performed to overcome the nonlinear, non-convex ORPD problem in the power system. The ORPD problem is implemented on a standard IEEE 30-bus test system in order to validate EO's search ability. Active power loss, voltage deviation and voltage stability index are calculated with optimization of network parameters, including the voltage of the PV buses, tap ratio of transformers and reactive support of shunt capacitors, under six scenarios. For the systems under investigation in case-1 and case-4, using the EO to deal with the ORPD problem resulted in a decrease in power losses of 23.61% and 21.99% with respect to the base cases, respectively. The reduction in total voltage deviation for case-2 and case-5 reached 88.24% and 90.34% while the improvements of the voltage stability for case-3 and case-6 were 60.79% and 60.24% according to the base cases.

This paper also includes comparisons of the EO with other well-known optimization techniques under different perspectives. The EO is superior among others in terms of case-1, case-3 and case-6 with the best solution obtained. Furthermore, the statistical indicators such as mean and standard deviation of independent 30 runs show that the EO is not only an efficient but also a robust meta-heuristic algorithm in solving the ORPD problem. The measurement of diversity, exploration and exploitation allows for more in-depth analysis of the causes for successful or ineffective outcomes. The analyses conducted demonstrate that the EO algorithm has better exploitation ability as compared to the exploration.

In future, this research can be expanded with the incorporation of active power loss, voltage deviation and voltage stability as an objective in a multi-objective optimization framework based on Pareto-optimality. Moreover, a better trade-off between exploitation and exploration abilities and a more consistent diversity in the population can be constructed with the modification of the EO algorithm so as to solve the ORPD problem.

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