Power efficiency improvement in reactive power dispatch under load uncertainty

Naima Agouzoul[1], Aziz Oukennou[2], Faissal Elmariami[1], Jamal Boukherouaa[1], Rabiaa Gadal[1]
[1]Energy and Electrical Systems Laboratory, National Higher School of Electricity and Mechanics, Hassan II University, Casablanca, Morocco
[2]SARS Team, ENSA, Cadi Ayyad University, Safi, Morocco

Article Info

Article history:

Received Oct 24, 2023
Revised Mar 19, 2024
Accepted Apr 2, 2024

Keywords:

Gray wolf optimizer
Improved gray wolf optimizer
Load uncertainty
Monte Carlo simulation
Optimization
Power loss
Reactive power dispatch

ABSTRACT

Nowadays, there is a significant rise in electricity demand, posing challenges for power grid operators due to inaccurate forecasting, leading to excessive power losses and voltage instability. This paper addresses these issues by focusing on solving optimal reactive power dispatch (ORPD) while considering load demand uncertainty. The main objective of solving ORPD is to reduce power losses by adjusting generator voltage ratings, transformer tap ratio, and shunt capacitors' reactive power. Monte Carlo simulation (MCS) is employed to generate load scenarios using the normal probability density function, while a reduction-based technique is implemented to decrease the number of those scenarios. The improved gray wolf optimization (I-GWO) algorithm is introduced for the first time to address the stochastic ORPD problem. Experimentation is conducted on an IEEE-30 bus system when results are contrasted with conventional gray wolf optimization (GWO) and five other algorithms as stated in the literature. The I-GWO algorithm's performance is assessed with and without considering load demand uncertainty. Through Friedman's statistical tests, a significant decrease of 20.96% in active power losses and 63.06% in the summation of expected power losses is observed. The I-GWO algorithm's results on the ORPD problem demonstrate its effectiveness and robustness.

Corresponding Author:

Naima Agouzoul
Energy and Electrical Systems Laboratory, National Higher School of Electricity and Mechanics, Hassan II University
Road El Jadida, Km 7, BP: 8118, Oasis-Casablanca, Morocco
Email: naima.agouzoul@ensem.ac.ma

1. INTRODUCTION

Optimal reactive power dispatch (ORPD) is critical in efficiently managing electrical networks, ensuring optimal and stable operation under diverse loads and conditions. ORPD ensures power system stability by maintaining adequate voltage levels despite load fluctuations. The appropriate resolution of ORPD reduces power losses in the system, improves voltage profiles, and enhances system stability. Initially, simple methods with fixed capacitors and reactors were used; however, their flexibility was limited [1]. In the mid-20th century, optimization techniques emerged, exploring mathematical methods to enhance reactive power flow in electrical grids [2]. Early studies aimed at minimizing transmission losses or maximizing system efficiency under various operating conditions [3]. Recently, there has been a focus on using load forecasting techniques to predict demand changes and adjust reactive power based on load variations [4]. In pursuit of this objective, recent optimization algorithms have been adapted to solve stochastic ORPD [5].

The conventional ORPD problem was solved by fixing the load variation. It used modern meta-heuristic optimization algorithms such as improved antlion optimization (IALO) [6], passerine swarm optimization algorithm [7], particle swarm optimization (PSO) [8], chaotic PSO (CPSO) [9], artificial bee colony and salp swarm algorithms (ABC-SSA) [10], chaotic turbulent flow of water-based optimization (CTFWO) [11], ant lion optimizer (ANT) [12], enhanced butterfly optimization algorithm (EBOA) [13], and sine cosine algorithm (SCA) [14]. Including charge uncertainty in the resolution process of the ORPD is crucial for ensuring optimal operational reliability in the face of unpredictable demand fluctuations, promoting the development of a resilient and flexible electrical network that meets the evolving needs of society [15]. Various meta-heuristic methods have been used in the field of ORPD to tackle challenges arising from load uncertainty. In [4], power loss and voltage deviation values for different load conditions were obtained using a modified JAYA. In [16], the Harris hawk-PSO (HHOPSO) is employed to minimize power losses and maintain a stable voltage level. In [17], an algorithm called fractional calculus with PSO gravitational search algorithm (FPSOGSA), which builds upon PSO, is presented. This algorithm integrates GSA and Shannon entropy to reduce power losses in both the IEEE 30-bus and 57-bus test systems. In [18], the efficiency of the marine predator algorithm (MPA) in determining the minimum power loss of the IEEE-30 bus system was demonstrated. In [19], success was achieved by employing an enhanced grey wolf optimizer (EGWO) to solve the ORPD problem, both with and without consideration of load fluctuations. In [20], an improved lightning attachment procedure optimization (ILAPO) is introduced to decrease the active losses of the system, both in deterministic and probabilistic cases. It effectively reduces active power losses, enhances voltage stability, and improves voltage profile, considering load uncertainty. Additionally, in [21], the improved marine predator algorithm (IMPA) addressed the ORPD problem by taking the load demands' and renewable energy sources (RERs) uncertainties to minimize active power losses. Similarly, in [5], a novel adaptive manta-ray foraging optimization was introduced for solving stochastic ORPD takes wind and load demand power uncertainty into account.

The review of existing literature on ORPD reveals significant research gaps. While some studies have addressed ORPD without considering load demand uncertainty, others have tackled this uncertainty using methods such as central centroid sorting with a minimal number of scenarios, typically less than 15. However, this approach fails to effectively reduce computational complexity or prioritize scenarios to achieve robust decision-making [22]. Additionally, certain studies have focused on specific test systems, such as the IEEE 57 network, while neglecting others, such as the IEEE 30 network. In references [17], [18], [21], [22], the ORPD problem was addressed by incorporating load demand uncertainty using the scenario-based approach. Nevertheless, this method, though simple to apply, remains approximate and imprecise [23]. Therefore, it is imperative to use more accurate and efficient methods for incorporating load uncertainty into ORPD.

In summary, by filling existing research gaps, it is possible to better manage load uncertainty and improve the accuracy of probabilistic operational planning in the ORPD problem. The use of techniques such as Monte Carlo simulation (MCS) and scenario-based reduction approaches (SBR) holds great promise for generating an appropriate number of scenarios. Adopting these methods can significantly enhance decision-making, even when faced with operational uncertainties [5].

The recently developed grey wolf optimizer (GWO) algorithm has proven effective in addressing the ORPD problem in electrical networks. It optimally adjusts reactive power sources while considering operational limitations and wind-integrated power systems [24]. Despite surpassing other metaheuristic algorithms like particle swarm optimizer (PSO), backtracking search algorithm (BSA), and whale optimization algorithm (WOA), the GWO demonstrates poor convergence and encounters local optima in complex problems, posing a high risk of converging to these optima and thus reducing population diversity [25].

This paper presents an innovative adaptation of the I-GWO algorithm to address the ORPD problem in the presence of load demand uncertainty, focusing on reducing active power losses. The I-GWO algorithm is known for its adaptability, capable of adjusting to various problem types and optimization objectives, including continuous, binary, or multi-objective scenarios. The effectiveness of the I-GWO algorithm was evaluated using both four distinct engineering challenges and the suite of benchmarks for CEC 2018 [26]. Importantly, our research highlights a gap in the literature, as no prior studies have explored applying the I-GWO approach to tackling stochastic ORPD with 15 load uncertainty-generated scenarios based on the MCS and SBR techniques. The experimentation is conducted on the IEEE-30 bus system, and the results are compared with those obtained from the conventional GWO algorithm and other algorithms mentioned in the literature. Applying the I-GWO algorithm successfully meets all imposed constraints, demonstrating its robustness and efficiency in solving the ORPD problem while considering the random character of load demand.

This paper is structured as follows: section 2 outlines the mathematical formulation of the ORPD problem and the method of representing load uncertainty. Section 3 introduces the proposed solution for ORPD while considering load uncertainty. The results obtained and the statistical analysis are presented in Section 4. The conclusion is provided in the final section.

2. PROBLEM FORMULATION

The ORPD problem is generally an optimization problem. It aims to identify the optimal control variables for minimizing active power losses in a power system. This optimization objective remains the same for both deterministic and stochastic cases, where system constraints must be carefully considered.

2.1. The problem's mathematical formulation

2.1.1. Case 1: power losses minimization OF_{un} in ORPD without considering load demand uncertainty

Transmission line losses depend on particular power system parameters, such as the conductance of the transmission line g_{ij}, V_i and V_j representing the magnitudes of the voltages at buses i and j, and the associated angles δ_{ij}. The power losses is calculated using (1) [13]:

$$P_{\text{Lss}} = \sum_{i=1}^{n_L} g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\,\delta_{ij}\right) \tag{1}$$

2.1.2. Case 2: power losses minimization OF_{un} in ORPD with considering load demand uncertainty

Considering the random character of load demand in ORPD, the optimization of power losses is performed twenty times for the fifteen scenarios outlined in this paper. The expected power loss is calculated based on the probability of load demand and power losses for each scenario. The summation of expected power losses for the fifteen scenarios is then calculated using (2) [21]:

$$S_{exp}\,PL = \sum_{scig=1}^{N_{scig}} EPL_{scig} = \sum_{scig=1}^{N_{scig}} \tau_{S,scig} \times P_{\text{Lss},scig} \tag{2}$$

where $S_{exp}\,PL$ represents the summation of expected power losses, EPL_{scig} represents the expected power losses for the $scig$th scenario, and the total number of generated scenarios is denoted by N_{scig}.

2.2. Constraints

Two types of constraints can be imposed in this problem: the equality constraints [12]:

$$\begin{cases} P_{Gi} - P_{Li} = |V_i| \sum_{j=1}^{NB} |V_j| \left(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}\right) \\ Q_{Gi} - Q_{Li} = |V_i| \sum_{j=1}^{NB} |V_j| \left(G_{ij}sin\delta_{ij} - B_{ij}cos\delta_{ij}\right) \end{cases} \tag{3}$$

where NB corresponds to the total number of buses in the power network. B_{ij} denotes the susceptance between bus i and bus j. P_{Gi} and Q_{Gi} represent the active and reactive power generation, while P_{Li} and Q_{Li} refer to the active and reactive load demand. The inequality constraints [27]:

$$\begin{cases} P_{Gn}^{min} \le P_{Gn} \le P_{Gn}^{max} \;\; \text{n} = 1,2,\dots,NG \\ Q_{Gn}^{min} \le Q_{Gn} \le Q_{Gn}^{max} \;\; \text{n} = 1,2,\dots,NG \\ V_{Gn}^{min} \le V_{Gn} \le V_{Gn}^{max} \;\; \text{n} = 1,2,\dots,NG \\ T_k^{min} \le T_k \le T_k^{max} \;\; \text{k} = 1,2,\dots,NT \\ Q_{Ck}^{min} \le Q_{Ck} \le Q_{Ck}^{max} \;\; \text{k} = 1,2,\dots,NC \\ S_{Lk} \le S_{Lk}^{min} \;\; \text{k} = 1,2,\dots,NS \\ V_{Lk}^{min} \le V_{Lk} \le V_{Lk}^{max} \;\; \text{k} = 1,2,\dots,NL \end{cases} \tag{4}$$

The PV buses, transformers, compensators, branches, and PQ buses are denoted by NG, NT, NC, NS, and NL, respectively. The active and reactive power of generators, compensator reactive power, generators voltage, transformers tap position, transmission lines loading, and load bus voltage are presented by P_{Gn}, Q_{Gn}, Q_{Ck}, V_{Gn} , T_k, S_{Lk} and V_{Lk} ,respectively.

The function (5) has been designed to effectively manage these constraints and eliminate all disproportionate solutions using the weight sum approach [23]:

$$OF_{un} = OF_{un} + w_1\left(P_{G1} - P_{G1}^{lim}\right)^2 + w_2 \sum_{i=1}^{N_G} \left(Q_{Gi} - Q_{Gi}^{lim}\right)^2 + w_3 \sum_{i=1}^{N_q} \left(V_{Li} - V_{Li}^{lim}\right)^2 + w_4 \sum_{i=1}^{N_L} \left(S_{Li} - S_{Li}^{lim}\right)^2 \tag{5}$$

OF_{un} represents the fitness function, P_{G1} is the power generated at the slack bus, Q_{Gi} is the reactive power emitted by generating units, V_{Li} is the load bus voltage, and S_{Li} represents the apparent power flowing through the transmission line. Lim denotes the minimum and maximum limits of variables. Meanwhile, w_1, w_2, w_3, and w_4 are the penalty weighting factors, each assigned a value of 100, 100, 1000, and 100, respectively [21].

3. METHOD

The solution method described in this paper introduces an innovative adaptation of the improved gray wolf optimizer (I-GWO) algorithm. This adaptation aims to efficiently solve the ORPD problem in power systems. In particular, it focuses on managing load demand uncertainty.

3.1. Uncertainty modeling

The loading uncertainty was represented using a normal probability density function (PDF) of a random variable x_{LM}, characterized by a mean (μ_{LM}) and standard deviation (σ_{LM}) [28]. The equation for the normal probability density function is presented as (6):

$$f(x_{LM}) = \frac{1}{\sqrt{2\pi\sigma_{LM}}} \exp\left(-\frac{(x_{LM}-\mu_{LM})^2}{2\sigma_{LM}{}^2}\right) \quad (6)$$

In this paper, Monte Carlo simulation (MCS) is utilized to generate 800 scenarios using a normal PDF with $\mu_{LM} = 70$ and $\sigma_L = 10$ according to [14]. Figure 1 shows the probability distribution of load demand scenarios.

A scenario-based reduction approach (SBR) is utilized to decrease the scenario number generated by the MCS method to an appropriate number, aiming at simplifying the calculation process. The SBR method involves three steps: scenario generation, scenario-based formulation, scenario-based reduction, and solving the reduced formulation [29].

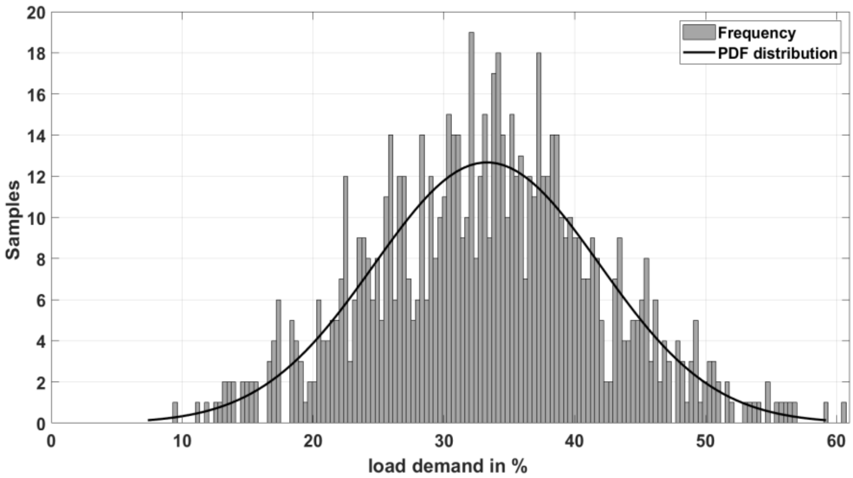

Figure 1. The probability distribution of load demand scenarios

3.2. The improved gray wolf optimization algorithm

The conventional GWO algorithm [30] is straightforward but faces population diversity issues linked to exploitation and exploration. Although its position update equation is effective for exploitation, its overall performance is limited according to [26]. To tackle this problem, an I-GWO was introduced in [26].

The initialization phase involves randomly distributing N wolves within a specified range $[l_n, u_q]$ in the search region. Their positions are shown as a real value vector, and their fitness is calculated using $f(X_{q(t)})$.

$$X_{qn} = l_n + \text{rand}_n[0,1] \times (u_n - l_n), q \in [1, N], n \in [1, D] \quad (7)$$

At each iteration (L), the position of the i^{th} wolf is represented as a vector of values denoted by $\{x_{q1}, x_{q2} \dots . x_{qD}\}$ where D represents the dimensionality of the problem.

The pop matrix stores the population of all wolves with *N* rows (representing the number of wolves) and *D* columns (representing the dimension). The I-GWO incorporates a hunting strategy based on dimensional learning (DLH), where multi-neighbor learning occurs in the neighborhood of $x_q(j)$. The calculation of the dth dimension $X_{q-DLH,d}(j+1)$ involves a neighbor $X_{n,d}$ (j) and a random wolf, $X_{r,d}$ (j) chosen from $N_q(j)$. The specific equation for these positions is given (8):

$$X_{q-DLH,d}(j+1) = X_{q,d}(j) + \text{rand} \times \left(X_{q,d}(j) - X_{r,d}(j)\right) \quad (8)$$

$N_q(j)$ corresponds to the neighbors of $x_q(j)$ and is created using (9) based on the radius $R_q(j)$, calculated by (10), where D_q represents the Euclidean distance between $x_q(j)$ and $X_n(j)$.

$$N_q(j) = \{X_n(j) \mid D_q\left(X_q(j), X_q(j)\right) \leq R_q(t), X_q(j) \in Pop\} \quad (9)$$

$$R_q(j) = \|X_q(j) - X_{q-GWO}(j+1)\| \quad (10)$$

The selection and updating phases involve comparing the fitness values of two candidates, $X_{q-GWO}\,(j+1)$ and $X_{q-DLH}(j+1)$, using (11).

$$X_q(j+1) = \begin{cases} X_{q-GWO}(j+1), & \text{if } f\left(X_{q-GWO}\right) < f\left(X_{q-DLH}\right) \\ X_{q-DLH}(j+1) & \text{otherwise} \end{cases} \quad (11)$$

The selected candidate updates $x_q(j)$ if its value is lower than $x_q(j)$; otherwise, $x_q(j)$ remains unchanged in the pop. The I-GWO algorithm repeats this process for all individuals, incrementing the iteration counter until the maximum iteration is reached.

3.3. The proposed solution for ORPD taking into account the random character of load demand

In this paper, the I-GWO algorithm adjusts the reactive power outputs of controllable devices, such as transformer tap configurations, generator voltages, and compensator-supplied reactive power. This adjustment is made while adhering to operational constraints and accommodating variations in load demand. A visual representation of the proposed solution for the ORPD problem is presented in Figure 2.

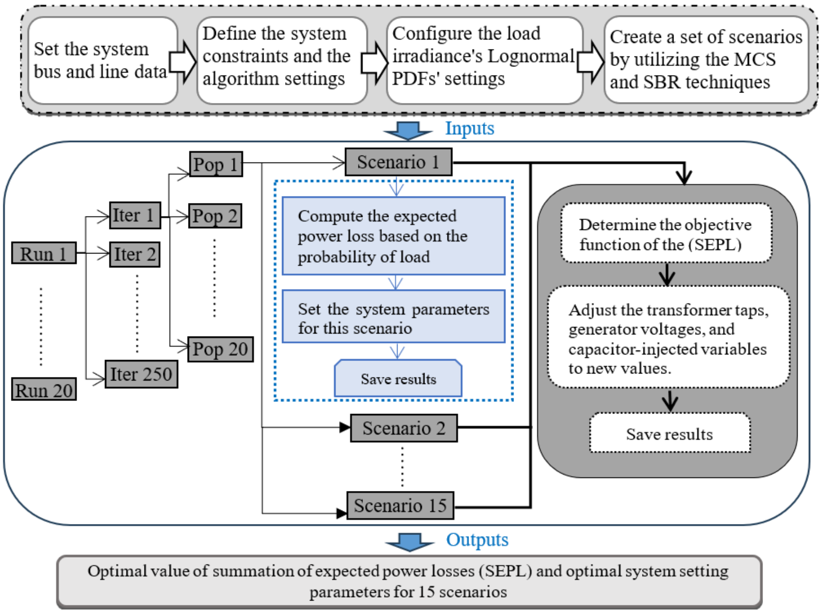

Figure 2. The proposed solution of the ORPD accounts for the load's uncertainty

The following is a summary of the steps involved in addressing the ORPD problem:

- Step 1: Establish the system's bus and line data.
- Step 2: Define system constraints and configure algorithm settings.
- Step 3: Adjust settings for the normal probability density function (PDF) of load demand.
- Step 4: Generate scenarios using MCS and SBR techniques.
- Step 5: Assess each particle's fitness by calculating expected power losses for each scenario based on load probability. Sum up losses from each scenario to calculate the total expected power losses. This step is repeated 20 times because the population contains 20 particles.

– Step 6: Choose the best solution from the current population.
– Step 7: Repeat steps 5 and 6 for a maximum of 250 iterations and update the population by selecting solutions with improved fitness values.
– Step 8: Execute I-GWO over 10 runs to enhance result reliability, minimize initial condition impact, and consider algorithm randomness.
– Step 9: Analyze the final set of solutions to identify the optimal solution and return it.
– The entire process of the I-GWO algorithm, which considers the random character of load demand across 15 generated scenarios, is illustrated in the flowchart in Figure 3.

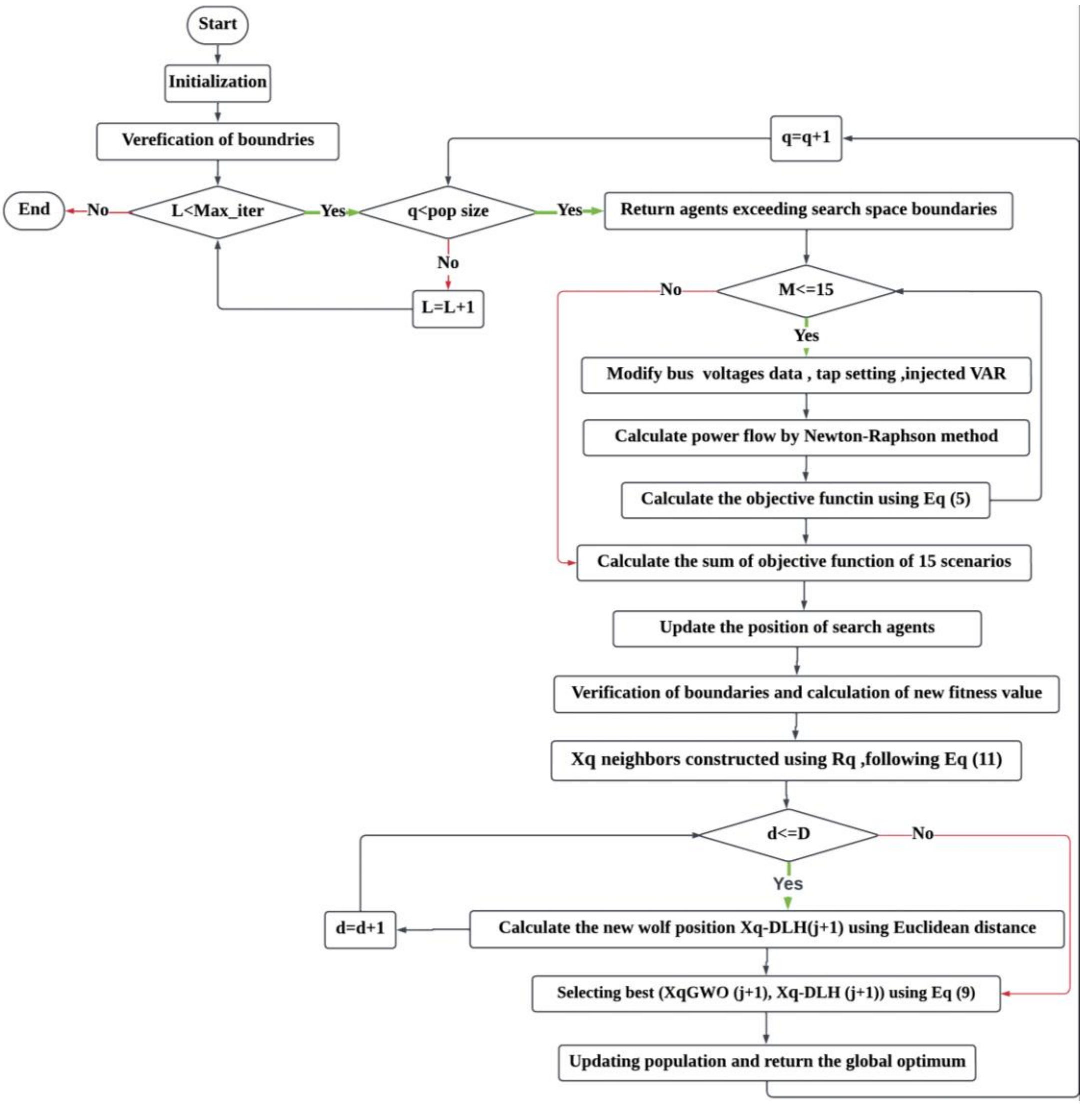

Figure 3. Global solution flowchart

4. RESULTS AND DISCUSSION

To assess the effectiveness of the I-GWO algorithm in the ORPD problem, simulations were conducted for two cases of studies using the IEEE 30-bus system, both with and without consideration of load uncertainty. The iterations were carried out on a computer with an Intel Core i7 CPU running at 1.80 GHz and 8 GB RAM, using MATLAB version R2019b. The IEEE 30-bus system includes thirty buses, forty-one branches, six thermal generators, nine shunt VAR compensators, and four transformer tap changers. To address load demand uncertainty, 15 scenarios were analyzed. 126.2 MVAr and 283.2 MW, respectively, are the reactive and active power load demands for the IEEE 30-bus system [31]. Additionally, the magnitude range for generator buses and transformer tap configurations fluctuates between 0.9 and 1.1 per unit (p.u.), and the shunt VAR compensators range from 0 to 5 MVAR [32]. The I-GWO and GWO algorithms have been optimized for the ORPD problem with a maximum iteration of 250 and 20 search agents. The “a” parameter was reduced linearly from 2 to 0, while the “C” parameter was assigned values from two ranges (0, 1) for efficient optimization.

4.1. Power losses minimization OF_{un}

4.1.1. Case 1: ORPD without consideration of load demand uncertainty

The function's goal is to reduce active power losses without considering load uncertainty, using the I-GWO and GWO algorithms. Shunt capacitor reactive power, generator voltage magnitudes, and tap-changing transformers were set as discrete variables. Figure 4 illustrates the convergence characteristics of both algorithms in minimizing power losses, showing a progressive reduction during 250 iterations.

At first, the power loss values were 6.4 MW for I-GWO and 6.05 MW for GWO. They gradually decreased to 4.58 MW for I-GWO and 4.59 MW for GWO by iterations 249 and 250, respectively. Table 1 highlights the effectiveness of I-GWO by demonstrating the lowest power loss, which equals 4.58 MW (highlighted in bold in Table 1). In comparison, the ABC, PSO, ALO, SCA, WOA, and GWO algorithms recorded power loss values of 5.79, 4.61, 4.70, 4.59, and 4.59 MW, respectively. As a result, reducing active power losses prevents over-utilization of power grid equipment, improves grid stability, and ensures safety and reliability. It also reduces production and distribution costs, as well as greenhouse gas emissions, thus improving the energy efficiency of the power grid [30].

Table 1. The results comparison of simulation obtained by different algorithms in case 1

Control variables	min	max	Initial [33]	ABC [12]	PSO [8]	BOA [13]	SCA [14]	CTFWO [11]	GWO	I-GWO
V1 (P.U)	0.95	1.1	1.0500	1.1000	1.1	1.1	1.1000	1.0713	1.1000	1.0576
V2 (P.U)	0.95	1.1	1.0400	1.0971	1.1	1.0986	1.1000	1.0621	1.0956	0.9902
V5 (P.U)	0.95	1.1	1.0100	1.0866	1.0867	1.0800	1.0869	1.0397	1.0753	0.9661
V8 (P.U)	0.95	1.1	1.0100	1.0800	1.1	1.0848	1.0870	1.0399	1.0775	1.0719
V11 (P.U)	0.95	1.1	1.0500	1.0850	1.1	1.0352	1.1000	1.0318	1.0915	1.0399
V13 (P.U)	0.95	1.1	1.0500	1.1000	1.1	1.1	1.0800	1.0623	1.1000	1.0463
T11 (P.U)	0.9	1.1	1.0780	1.0700	0.9587	0.9458	1.0500	1.0134	0.9866	0.9010
T12 (P.U)	0.9	1.1	1.0690	0.9500	1.0543	1.0175	1.0500	0.9003	0.9705	1.0564
T15 (P.U)	0.9	1.1	1.0320	1.0200	1.0024	0.9698	1.0500	0.9836	1.0120	0.9455
T36 (P.U)	0.9	1.1	1.0680	1.1000	0.9755	0.9871	1.0500	0.9871	0.9737	0.0305
Q10(MVAR)	0	5	0.0000	5.0000	4.2803	2.7469	4.6310	0.0051	0.1944	0.0930
Q12(MVAR)	0	5	0.0000	0.0000	5	0	3.0890	0	0.2853	0.2980
Q15(MVAR)	0	5	0.0000	2.0000	3.0288	5	5.0000	1.8709	0.2927	0.3190
Q17(MVAR)	0	5	0.0000	5.0000	4.0365	5	4.6970	0.7921	0.3149	0.3090
Q20(MVAR)	0	5	0.0000	4.0000	2.6697	2.2745	2.1290	4.9785	0.3081	0.2170
Q21(MVAR)	0	5	0.0000	5.0000	3.8894	4.2378	3.1910	2.3600	0.0796	4.8200
Q23(MVAR)	0	5	0.0000	4.0000	0.0	0	5.0000	0.0028	0.0364	0.1680
Q24(MVAR)	0	5	0.0000	5.0000	3.5879	4.6361	4.3880	3.7161	0.3637	0.3000
Q29(MVAR)	0	5	0.0000	4.0000	2.8415	4.4570	3.5750	0	0.0769	0.0580
Ploss (MW)	-	-	5.7960	4.6110	4.6282	4.6460	4.7086	4.9448	4.5900	4.5809
Reduction %	-	-	-	20.45	20.15	19.85	18.76	14.69	20.81	20.96

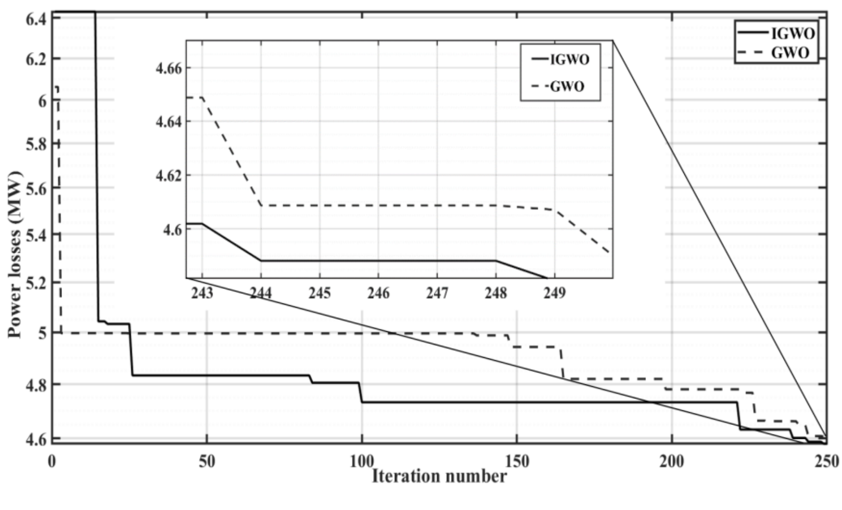

Figure 4. The convergence characteristics of I-GWO and GWO for case 1

4.1.2. Case 2: ORPD with consideration of load demand uncertainty

In the second case, we assessed the objective function to minimize the sum of expected power losses (SexpPL) considering load uncertainty. To achieve this, we employed two optimization algorithms, each run 20 times across 15 scenarios. Figure 5 displays the convergence curves of the objective function plotted over 250 iterations. As seen in Figure 5, I-GWO obtains the optimal result with lower SexpPL compared to GWO. Table 2 presents the simulation results for this case, illustrating the results produced by the two algorithms. It presents 15 scenarios, each with its probability and expected power losses. In cases where load demand is minimal, power losses remain reduced to 1.53 MW, as shown by scenario 10. Scenario 13, conversely, stands out with a significant power loss of 6.3251 MW, attributed to high load demand. Notably, scenario 14 records the highest expected power losses due to its high probability. In addition, In the study, the GWO algorithm effectively reduced the Sexp PL from 5.811 MW in the basic case [34] to 2.39 MW. Conversely, the I-GWO algorithm showed an even more impressive reduction of 2.18 MW, surpassing the Sexp PL found by the manta-ray foraging algorithm [5], the literature-reported gray wolf optimization [24], and the marine predator algorithm [18], which are equal to 4.5201, 4.1781, and 7.1223 MW respectively. The performance of the I-GWO algorithm represents a substantial 62.49% improvement over the base case.

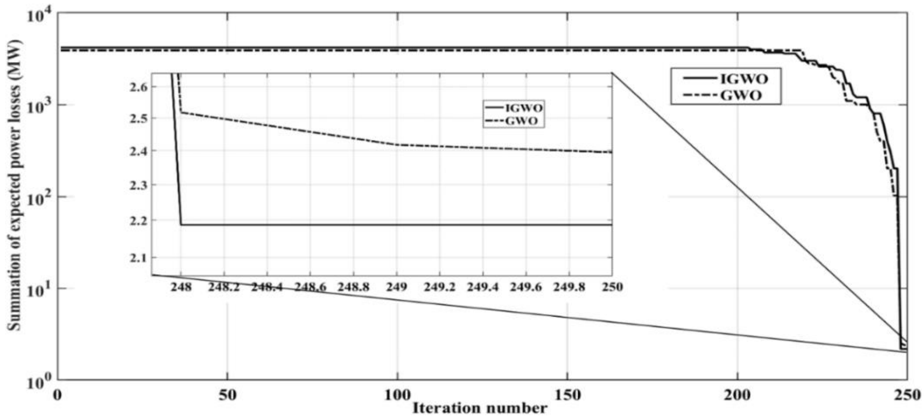

Figure 5. The convergence characteristics of I-GWO and GWO algorithms for case 2

Table 2. Simulation results of ORPD with I-GWO and GWO in case 2 for minimization of OF_{un}

			I-GWO		GWO	
Scenario	Loading %	Probability	P_{LSS} (MW)	EPL_{scig}(MW)	P_{LSS} (MW)	EPL_{scig} (MW)
1	74.2976	0.104	2.1560	0.2242	2.5808	0.2684
2	84.7650	0.001	3.3876	0.0034	3.5718	0.0036
3	72.5892	0.002	1.7077	0.0034	2.6235	0.0052
4	66.9694	0.008	1.9924	0.0159	2.1743	0.0174
5	75.2356	0.033	2.3291	0.0769	3.5588	0.1174
6	67.9742	0.010	1.7854	0.0179	1.4504	0.0145
7	71.5085	0.085	1.8782	0.1596	1.9020	0.1617
8	80.1222	0.172	2.7661	0.4758	2.4348	0.4188
9	71.6003	0.053	1.9954	0.1058	2.6714	0.1416
10	59.6486	0.011	1.5389	0.0169	1.3068	0.0144
11	75.18362	0.018	2.1765	0.0392	1.9841	0.0357
12	74.2644	0.002	2.3790	0.0048	1.9831	0.0040
13	101.9608	0.002	6.3251	0.0127	8.4296	0.0169
14	75.9757	0.497	2.0684	1.0280	2.3590	1.1724
15	65.8654	0.002	1.4414	0.0029	1.6264	0.0033
The summation of expected power losses in (MW):				2.1872		2.3951

In this study we used MATLAB to create a box plot, visually representing our statistical technique with two algorithms for analyzing experimental data. Figure 6 shows the I-GWO and GWO box plot algorithms for the power losses minimization function for case 1 in Figure 6(a) and case 2 in Figure 6(b). Observing Figure 6(a), the minimum value in the I-GWO boxplot is smaller than that in GWO, indicating that the data in the former box tends to be lower and scattered downwards compared with that in the GWO box. According to Figure 6(b), the median line for the I-GWO and GWO algorithms is 202.3894 and 302.3703 respectively. Positioned higher, GWO's median line shows a more spread-out distribution of the data compared to I-GWO. In addition, the I-GWO box plot shows that the median is nearly identical to the lower quartile, which indicates that most of the data points are concentrated towards the lower values, while the higher values are relatively less in number. Hence, the experimental analysis showed that the I-GWO algorithm performs better than the original GWO algorithm. It consistently produces lower power losses in both case 1 and case 2.

The optimal control variables obtained with I-GWO for the 15 scenarios, including generator voltages, compensator reactive power injection, and transformer settings, are illustrated in Figures 7 to 9, respectively. Table 3 displays the results of the standardized Friedman test [35] for the statistical disparity between the data distributions obtained by simulating the two algorithms, I-GWO and GWO, on two separate objectives. In the first case, the I-GWO algorithm stands out with very low minimum, average, and maximum power losses, corresponding respectively to 4.5809, 4.6359, and 4.6359 MW. Meanwhile, the GWO algorithm achieves slightly higher values at 4.5913, 4.6491, and 4.7207 MW. This same observation is presented for the SexpPL optimization objective where I-GWO achieves the best solution of 2.1872 MW compared to GWO. Consequently, I-GWO outperforms the GWO algorithm in both study cases, demonstrating low minimum, average, and maximum power losses as shown in bolded in Table 3.

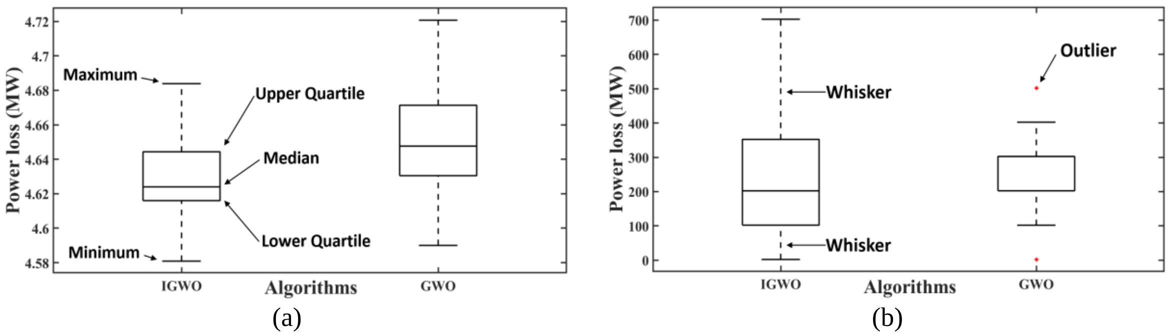

Figure 6. Classification of power losses using box plots in (a) case 1 and (b) case 2

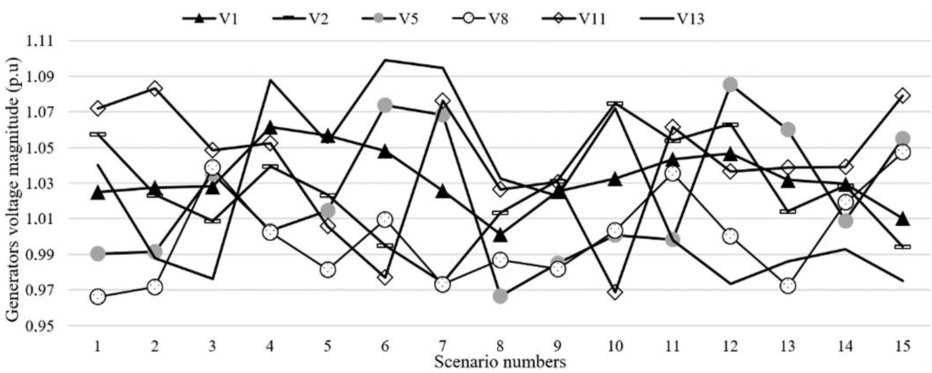

Figure 7. The I-GWO optimal voltage magnitude at each generator bus

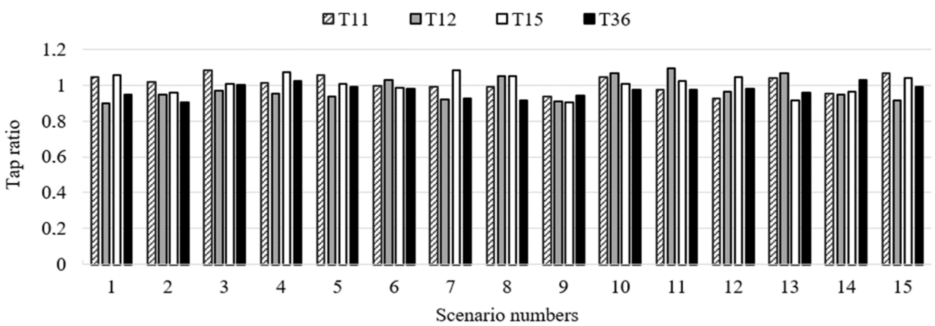

Figure 8. The I-GWO optimal transformer tap parameters

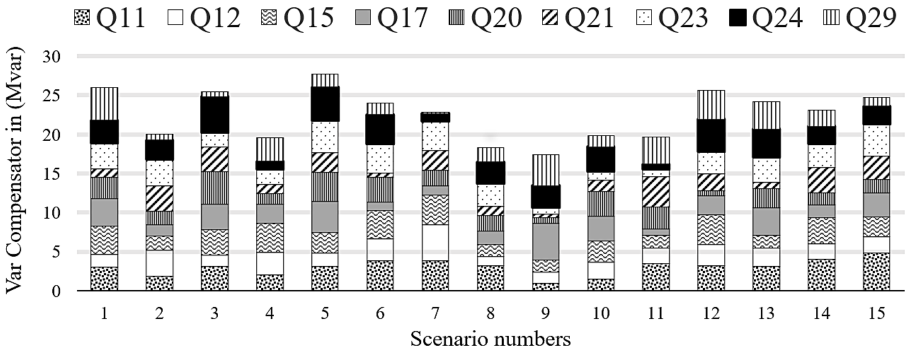

Figure 9. The I-GWO optimal VAR compensator parameters

Table 3. I-GWO and GWO statistical comparison in the two cases

			Average	Best	Run N	Worst	Run N	SD	Time (s)
Power losses	Case 1	I-GWO	4.63	4.58	20	4.63	2	0.0332	146.21
		GWO	4.64	4.59	13	4.72	12	0.0334	36.7473
	Case 2	I-GWO	242.34	2.18	4	702.71	16	126.08	1.37×10^3
		GWO	272.39	2.39	9	502.27	12	198.44	0.53×10^3

5. CONCLUSION

This paper focuses on the problem of ORPD. The paper presents the first application of the I-GWO approach to minimize power losses while considering the uncertainty of the load demand modeled by the normal probability density function. Initially, a deterministic optimal solution for the ORPD is presented using the standard IEEE 30 bus test system, without taking load uncertainty into account. Then, the paper introduces the stochastic formulation of the ORPD, taking into account the uncertain load demand, by using Monte Carlo simulation and a scenario reduction technique. The I-GWO method is thoroughly tested in comparison with the conventional GWO method and recently published algorithms. The results demonstrate that the I-GWO method achieved the best reduction in power losses. It was observed that the I-GWO method reduced power losses by 20.96% and 63.06% in the first and second cases, respectively. The application of the I-GWO algorithm meets all imposed constraints, demonstrating its robustness and efficiency in solving the ORPD problem, even in the presence of load demand uncertainty. Future research should consider the incorporation of other objective functions related to improving voltage stability, for example. Additionally, the inclusion of other sources of uncertainty in the optimization process, such as the uncertainty of power generated by renewable energy sources, should be considered.

REFERENCES

[1] M. S. Saddique *et al.*, "Solution to optimal reactive power dispatch in transmission system using meta-heuristic techniques—status and technological review," *Electric Power Systems Research*, vol. 178, Jan. 2020, doi: 10.1016/j.epsr.2019.106031.

[2] C. R. N. Estevam, M. J. Rider, E. Amorim, and J. R. S. Mantovani, "Reactive power dispatch and planning using a non-linear branch-and-bound algorithm," *IET Generation, Transmission and Distribution*, vol. 4, no. 8, pp. 963–973, 2010, doi: 10.1049/iet-gtd.2009.0422.

[3] A. S. Al Mamari, S. F. Toha, S. Ahmad, and A. S. Al Mamari, "Particle swarm optimisation for reactive power compensation on oman 6 bus electrical grid," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 12, no. 3, pp. 1912–1918, Sep. 2021, doi: 10.11591/ijpeds.v12.i3.pp1912-1918.

[4] T. Das, R. Roy, and K. K. Mandal, "Solving optimal reactive power dispatch problem with the consideration of load uncertainty using modified JAYA algorithm," in *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, Feb. 2021, pp. 1–6, doi: 10.1109/ICAECT49130.2021.9392508.

[5] S. Z. Almutairi, E. A. Mohamed, and F. F. M. El-Sousy, "A novel adaptive manta-ray foraging optimization for stochastic ORPD considering uncertainties of wind power and load demand," *Mathematics*, vol. 11, no. 11, Jun. 2023, doi: 10.3390/math11112591.

[6] Z. Li, Y. Cao, L. Van Dai, X. Yang, and T. T. Nguyen, "Finding solutions for optimal reactive power dispatch problem by a novel improved antlion optimization algorithm," *Energies*, vol. 12, no. 15, Aug. 2019, doi: 10.3390/en12152968.

[7] L. Kanagasabai, "Passerine swarm optimization algorithm for solving optimal reactive power dispatch problem," *International Journal of Advances in Applied Sciences (IJAAS)*, vol. 9, no. 2, pp. 101–109, Jun. 2020, doi: 10.11591/ijaas.v9.i2.pp101-109.

[8] Y. Muhammad, 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*, vol. 32, no. 14, pp. 10501–10518, Nov. 2020, doi: 10.1007/s00521-019-04589-9.

[9] S. H. Shri and A. F. Mijbas, "Chaotic theory incorporated with PSO algorithm for solving optimal reactive power dispatch problem of power system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 22, no. 3, pp. 1739–1747, Jun. 2021, doi: 10.11591/ijeecs.v22.i3.pp1739-1747.

[10] S. Salhi, D. Naimi, A. Salhi, S. Abujarad, and A. Necira, "A novel hybrid approach based artificial bee colony and salp swarm algorithms for solving ORPD problem," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 23, no. 3, pp. 1825–1837, Sep. 2021, doi: 10.11591/ijeecs.v23.i3.pp1825-1837.

[11] A. M. Abd-El Wahab, S. Kamel, M. H. Hassan, M. I. Mosaad, and T. A. Abdulfattah, "Optimal reactive power dispatch using a chaotic turbulent flow of water-based optimization algorithm," *Mathematics*, vol. 10, no. 3, Jan. 2022, doi: 10.3390/math10030346.

[12] S. Mouassa, 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*, vol. 20, no. 3, pp. 885–895, Jun. 2017, doi: 10.1016/j.jestch.2017.03.006.

[13] B. K. Dora, A. Rajan, S. Mallick, and S. Halder, "Optimal reactive power dispatch problem using exchange market based butterfly optimization algorithm," *Applied Soft Computing*, vol. 147, Nov. 2023, doi: 10.1016/j.asoc.2023.110833.

[14] M. S. Saddique *et al.*, "Solution to optimal reactive power dispatch in transmission system using meta-heuristic techniques―Status and technological review," *Electric Power Systems Research*, vol. 178, Jan. 2020, doi: 10.1016/j.epsr.2019.106031.

[15] M. Mokari, M. Hasan, and M. Mohammad, "Risk-cost minimization in optimal reactive power dispatch problem in the DFIG integrated system," *International Journal of Industrial Electronics Control and Optimization*, 2023.

[16] S. Shekarappa G, S. Mahapatra, and S. Raj, "Voltage constrained reactive power planning problem for reactive loading variation using hybrid Harris hawk particle swarm optimizer," *Electric Power Components and Systems*, vol. 49, no. 4–5, pp. 421–435, Mar. 2021, doi: 10.1080/15325008.2021.1970060.

[17] N. H. Khan, Y. Wang, D. Tian, R. Jamal, M. Ebeed, and Q. Deng, "Fractional PSOGSA algorithm approach to solve optimal reactive power dispatch problems with uncertainty of renewable energy resources," *IEEE Access*, vol. 8, pp. 215399–215413, 2020, doi: 10.1109/ACCESS.2020.3039571.

[18] M. Ebeed, 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*, vol. 13, no. 17, Aug. 2020, doi: 10.3390/en13174316.

[19] S. Kamel, S. Abdel-Fatah, M. Ebeed, J. Yu, K. Xie, and C. Zhao, "Solving optimal reactive power dispatch problem considering load uncertainty," in *2019 IEEE PES Innovative Smart Grid Technologies Asia*, May 2019, pp. 1335–1340, doi: 10.1109/ISGT-Asia.2019.8881322.

[20] M. Ebeed, A. Ali, M. I. Mosaad, and S. Kamel, "An improved lightning attachment procedure optimizer for optimal reactive power dispatch with uncertainty in renewable energy resources," *IEEE Access*, vol. 8, pp. 168721–168731, 2020, doi: 10.1109/ACCESS.2020.3022846.

[21] N. Habib Khan, R. Jamal, M. Ebeed, S. Kamel, H. Zeinoddini-Meymand, and H. M. Zawbaa, "Adopting scenario-based approach to solve optimal reactive power dispatch problem with integration of wind and solar energy using improved marine predator algorithm," *Ain Shams Engineering Journal*, vol. 13, no. 5, Sep. 2022, doi: 10.1016/j.asej.2022.101726.

[22] E. Kaiser *et al.*, "Cluster-based reduced-order modelling of a mixing layer," *Journal of Fluid Mechanics*, vol. 754, pp. 365–414, Aug. 2014, doi: 10.1017/jfm.2014.355.

[23] R. Jamal, J. Zhang, B. Men, N. H. Khan, M. Ebeed, and S. Kamel, "Solution to the deterministic and stochastic optimal reactive power dispatch by integration of solar, wind-hydro powers using modified artificial hummingbird algorithm," *Energy Reports*, vol. 9, pp. 4157–4173, Dec. 2023, doi: 10.1016/j.egyr.2023.03.036.

[24] M. Varan, A. Erduman, and F. Menevşeoğlu, "A grey wolf optimization algorithm-based optimal reactive power dispatch with wind-integrated power systems," *Energies*, vol. 16, no. 13, Jun. 2023, doi: 10.3390/en16135021.

[25] M. A. M. Shaheen, H. M. Hasanien, and A. Alkuhayli, "A novel hybrid GWO-PSO optimization technique for optimal reactive power dispatch problem solution," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 621–630, Mar. 2021, doi: 10.1016/j.asej.2020.07.011.

[26] M. H. Nadimi-Shahraki, S. Taghian, and S. Mirjalili, "An improved grey wolf optimizer for solving engineering problems," *Expert Systems with Applications*, vol. 166, Mar. 2021, doi: 10.1016/j.eswa.2020.113917.

[27] S. R. Salkuti, P. Sravanthi, and S. C. Kim, "Social welfare maximization based optimal energy and reactive power dispatch using ant lion optimization algorithm," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 4, pp. 1379–1387, Aug. 2021, doi: 10.12928/TELKOMNIKA.v19i4.18351.

[28] A. Ali *et al.*, "A bi-level techno-economic optimal reactive power dispatch considering wind and solar power integration," *IEEE Access*, vol. 11, pp. 62799–62819, 2023, doi: 10.1109/ACCESS.2023.3286930.

[29] M. Ebeed, S. Abdel-Fatah, S. Kamel, L. Nasrat, F. Jurado, and A. Harrison, "Incorporating photovoltaic inverter capability into stochastic optimal reactive power dispatch through an enhanced artificial gorilla troops optimizer," *IET Renewable Power Generation*, vol. 17, no. 13, pp. 3267–3288, Sep. 2023, doi: 10.1049/rpg2.12841.

[30] N. Agouzoul, F. Elmariami, A. Oukennou, A. Tarraq, and R. Gadal, "A hybrid HGWO-PSO approach for combined economic emission dispatch problem optimization," in *Lecture Notes in Electrical Engineering*, vol. 954, Springer Nature Singapore, 2023, pp. 989–998.

[31] S. N. V. S. K. Chaitanya, R. A. Bakkiyaraj, and B. V. Rao, "Multi objective optimal reactive power dispatch for enrichment of power system behavior using modified ant lion optimizer," *International Journal of System Assurance Engineering and Management*, vol. 14, no. S1, pp. 133–142, Dec. 2023, doi: 10.1007/s13198-022-01828-6.

[32] A. A. Eladl, M. I. Basha, and A. A. ElDesouky, "Techno-economic multi-objective reactive power planning in integrated wind power system with improving voltage stability," *Electric Power Systems Research*, vol. 214, Jan. 2023, doi: 10.1016/j.epsr.2022.108917.

[33] S. Sarhan, A. Shaheen, R. El-Sehiemy, and M. Gafar, "An augmented social network search algorithm for optimal reactive power dispatch problem," *Mathematics*, vol. 11, no. 5, Mar. 2023, doi: 10.3390/math11051236.

[34] N. H. Khan, Y. Wang, D. Tian, M. A. Z. Raja, R. Jamal, and Y. Muhammad, "Design of fractional particle swarm optimization gravitational search algorithm for optimal reactive power dispatch problems," *IEEE Access*, vol. 8, pp. 146785–146806, 2020, doi: 10.1109/access.2020.3014211.

[35] J. Ma *et al.*, "Metaheuristic-based support vector regression for landslide displacement prediction: a comparative study," *Landslides*, vol. 19, no. 10, pp. 2489–2511, Jun. 2022, doi: 10.1007/s10346-022-01923-6.

BIOGRAPHIES OF AUTHORS

Naima Agouzoul is a Ph.D. student at the National Higher School of Electricity and Mechanics (ENSEM), Hassan II University of Casablanca. She holds a master's degree in electronics, electrical engineering, automation, and industrial computing from Hassan II University. Her research focuses on renewable energies integrated into the transmission electrical network, optimization techniques, and stochastic and deterministic optimal reactive power dispatch. She can be contacted at email: naima.agouzoul@ensem.ac.ma.

Aziz Oukennou is an engineer, researcher, and professor at ENSA Safi, Morocco. Additionally, he is a member of the Random Signals, Networks, and Systems (SARS) Team at the same school. His research interests span various topics in electrical engineering and power electronics, with a specific emphasis on power systems, their stability, renewable energy integration, optimization, and artificial intelligence. He can be contacted at email: aziz.oukennou@gmail.com.

Faissal Elmariami is an engineer, researcher, and professor at ENSEM Casablanca. Additionally, he is a member of the RECS team and holds the qualification to direct research at the National School of Electricity and Mechanics. His primary research topics include protection coordination, the impact of the integration of DGs in the network on short-circuit current, and electrical network stability. He can be contacted at email: f-elmariami@yahoo.fr.

Jamal Boukherouaa is an engineer with a Ph.D. and holds university HDR accreditation. As a professor qualified to direct research and a member of the RECS research team at the National School of Electricity and Mechanics (ENSEM, Hassan II University), his primary focus lies in high-frequency static converters. He can be contacted at email: j.boukherouaa@yahoo.fr.

Rabiaa Gadal is a Ph.D. student at the National Higher School of Electricity and Mechanics (ENSEM), Hassan II University of Casablanca. She is an engineer who graduated from the National School of Arts and Crafts (ENSAM) holding an electrical engineering degree. Her research centers on power system stability, renewable energy integration, optimization, and smart grids. She can be contacted at email: rabiaa.gadal@ensem.ac.ma.