A comparative analysis of bio-inspired optimization algorithms for Optimal Reactive Power Dispatch

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***Abstract*—In this paper, it is developed an analysis of the usage of meta-heuristic models inspired by nature to obtain the Optimal Reactive Power Dispatch of a 30 bus system. Firstly, the objective function is presented, considering its power flow parameters. Afterward, the main algorithms were introduced the Grey Wolf Optimization (GWO), its improved version (I-GWO), and the Whale Optimization Algorithm (WOA). Then, they were implemented on the IEEE 30 bus system to calculate the objective function with 13 decision variables and 7 restrictions. Finally, the main results were presented, where it is highlighted an improvement in the Objective Function of 0.45%, in comparison with the traditional Optimal Power Flow implemented in Matpower.**

Keywords*—*Metaheuristic, Optimization, Power Flow, Dispatch

Symbol nomenclature for the objective function and its constraints [1]

NOMENCLATURE

θ_{ij}	Voltage angle difference between buses i and j (rad).
B_{ij}	Transfer susceptance between bus i and j (p.u.).
F_Q	Active power loss in network (p.u.).
g_k	Transfer conductance between bus i and j (p.u.).
G_{ij}	Conductance of branch k (p.u.).
N_0	Set of numbers of total buses excluding slack bus.
N_B	Set of numbers of total buses.
N_C	Set of numbers of possible reactive power source installation buses.
N_D	Set of numbers of power demand buses.
N_E	Set of numbers of network branches.
N_G	Set of numbers of generator buses.
N_Q^{lim}	Set of numbers of buses on which injected reactive power outside limits
N_T	Set of numbers of transformer branches.
N_V^{lim}	Set of numbers of buses on which voltages outside limits.
N_i	Set of numbers of buses adjacent to bus i, including bus i.
N_{PQ}	Set of numbers of PQ buses.
N_{PV}	Set of numbers of PV buses.
P_s	Injected active power at slack bus (p.u.).
P_{Di}	Demanded active power at bus i (p.u.).
P_{gi}	Injected active power at bus i (p.u.).
P_{kloss}	Active power loss in branch k (p.u.).
Q_{Ci}	Reactive power source installation at bus i (p.u.).
Q_{Di}	Demanded reactive power at bus i (p.u.).
Q_{Gi}	Injected reactive power at bus i (p.u.).
S_L	Power flow in branch l (p.u.).
T_i	Tap position of transformer i.
V_i	Voltage magnitude of bus i (p.u.).
V_{PQ}	Voltage vectors of PQ buses (p.u.).
V_{PV}	Voltage vectors of PV buses (p.u.).

I. INTRODUCTION

The reactive power dispatch problem has a significant impact on the secure and economic operation of power systems, whose economical operation consists of two aspects: Active power regulation and reactive power dispatch. These aspects are considered as two separate problems: P and Q [2], [3]. The approach of P is to regulate active power outputs of generators to achieve the minimization of fuel costs, whereas Q problem aims to minimize the network power loss [4], [5]. These problems are subject to a number of inequality and equality constraints such as the bus voltages, the position of taps on the transformers, and the amount of reactive power which are self-restricted variables [6], [7].

To overcome these problems, researchers have proposed bio-inspired evolutionary algorithms, which are probabilistic search methods that simulate the natural biological evolution or the behavior of biological entities [8], [9]. The behavior of biological entities is guided by learning, adaptation, and evolution. In an attempt to reduce processing time and improve the quality of solutions, particularly to avoid being trapped in local optima, other tree recent emerging techniques inspired by different natural processes have been introduced: Gray Wolf Optimizer (GWO) algorithm [10], Improved GWO algorithm [11] and whale algorithm [12].

In this paper, an IEEE 30-bus system was employed to carry out the simulation study. The GWO algorithm performs well for reactive power dispatch and gives a satisfactory result within a proper search of time. Compared with Particle Swam Optimization method, the bio-inspired method is better in global optimization and it shows a great potential in power system economical operations.

The rest of this paper is organized as follows. Section II exposes the mathematical formulation of the problem statement. Section III exposes the algorithms in detail. Simulation results and comparison with other approaches are presented in Section IV and V. Finally, conclusions are outlined in Section VI.

II. PROBLEM STATEMENT

The optimal power flow consists in dispatching a series of generators to minimize or maximize an objective function subject to equality and inequality restrictions [13]. For this comparison of algorithms in optimal reactive power dispatch (ORPD), a test system of 30 nodes is considered as, provided by the MatPower tool. The file used can be found under the name ORPD30bus. This optimization aims to configure the control variables that relate the reactive output power in generators. The objective function aims to minimize active power losses. The function was taken from [1], and is described in (1).

$$f_Q = \sum_{k \in N_E} g_k \left(V_i^2 + V_j^2 - 2V_i V_j cos\theta_{ij} \right) \tag{1}$$

The minimization function is subject to a number of inequality and equality constraints, which are described in equations (2) to (8).

$$0 = P_{Gi} - P_{Di} - V_i \sum_{j \in N_i} V_j \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) \quad \mathrm{i} \in N_o \tag{2}$$

$$0 = Q_{Gi} - Q_{Di} - V_i \sum_{j \in N_i} V_j \left(G_{ij} sin\theta_{ij} + B_{ij} cos\theta_{ij} \right) \quad i \in N_{PQ} \tag{3}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \quad i \in N_B \tag{4}$$

$$T_k^{min} \leq T_k \leq T_k^{max} \quad k \in N_T \tag{5}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad i \in N_G \tag{6}$$

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \quad i \in N_C \tag{7}$$

$$S_l \leq S_l^{max} \quad l \in N_l \tag{8}$$

In this reactive power dispatch problem, the bus voltages, the position of the taps on the transformers, and the amount of reactive power are self-restricted variables. On the other hand, the voltages on the buses and the reactive power injected are restricted by their adherence to the objective function as positive constant penalty terms. Therefore, the generalization of the objective function is obtained in (9).

$$F_Q = f_Q + \sum_{i \in \mathrm{N}_\mathrm{V}^{\mathrm{lim}}} \lambda (V_i - V_i^{lim})^2 + \sum_{i \in \mathrm{N}_\mathrm{Q}^{\mathrm{lim}}} \lambda (Q_{Gi} - Q_{Gi}^{lim})^2 \tag{9}$$

$$V_i^{lim} = \begin{cases} V_i^{max}; & V_i > V_i^{max} \\ V_i^{min}; & V_i < V_i^{min} \end{cases} \tag{10}$$

$$Q_{Gi}^{lim} = \begin{cases} Q_{Gi}^{max}; & Q_{Gi} > Q_{Gi}^{max} \\ Q_{Gi}^{min}; & Q_{Gi} < Q_{Gi}^{min} \end{cases} \tag{11}$$

III. THEORICAL FRAMEWORK

The work consigned in this review allows identifying the characteristics of some meta-heuristic algorithms that stand out compared with others in the optimization process. In this context, it is valid to refer to the simplicity of meta-heuristics and the flexibility around its application to different problems without special changes in the structure of the algorithm, which implies representing the problem around the input and output variables [14]. Additionally, meta-heuristic algorithms use no derivation mechanisms so they can become relevant in real problems with high computational cost.

The Grey Wolf Optimizer (GWO) works through a set of agents that start at a random location and, over a course of iterations, they improve the search for the optimum. This implies multiple advantages in terms of finding space and in the results that agents can share. On the other hand, this algorithm may avoid local optimal solutions by sharing information with each other.

A. *Mathematical model of the GWO algorithm*

This model considers a set of hierarchical solutions that will define the optimization. Equation 12 shows the coefficients of vectors A and B, that is the opposition of the optimum Xp to one of the solutions to which it is going to be approximated (Grey Wolf).

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t) \right| \tag{12}$$

$$\vec{X}(t+1) = \overrightarrow{X_p} - \vec{A}.\vec{D} \tag{13}$$

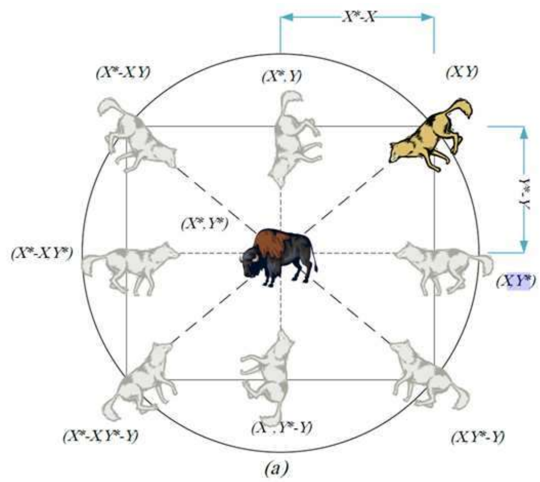

Fig. 1. Agent positioning [10]

The iterations of equations (12) and (13) allow updating the position of the solution (X, Y), according to the position of the optimum (X *, Y *). Fig. 1 shows the positioning of different agents whose location will be adjusted throughout the iterations in vectors A and C.

To simulate the iterative optimization process of the agents, the algorithm proposes a main solution (Alpha) and a population of secondary agents (beta and delta) that will update their position according to the search for the best agent (alpha).

B. *Improved GWO algorithm*

The presented algorithm has some disadvantages related to the low scanning and slow convergence rates. In the recent years, there have been different improvements focused on improving the functioning of the GWO. Among these improvements, researchers have proposed evolutionary elimination mechanisms that allow the algorithm to avoid local optimum, thus accelerating the convergence speed and improving the precision of this convergence point [15]. Another improvement proposal focuses on the combination of the GWO algorithm with PSO, which preserves the information of the optimal position of each search agent and prevents the algorithm from falling into local optimum.

To solve the aforementioned problems, an improvement in the GWO algorithm (IGWO) uses a Gaussian disturbance to expand the search range and a cosine factor to avoid falling into local optimum and improve the precision of the solution. To improve these characteristics of the GWO, an adaptive crossover operation and genetic mutations operations are proposed, that avoid local optimum and premature convergence. The adaptive probability of the genetic operators will ensure that the algorithm obtain global optimization. The probabilities of crossover and mutation are described in (14) and (15) [11].

$$P_c = \begin{cases} 0.75 - \frac{1}{|f_{best} - f_{mean}|}, & |f_{best} - f_{mean}| > \varepsilon_1 \\ 0.5, & else \end{cases} \quad (14)$$

$$P_m = \begin{cases} 0.075 - \frac{1}{|f_{best} - f_{mean}|}, & |f_{best} - f_{mean}| > \varepsilon_2 \\ 0.05, & else \end{cases} \quad (15)$$

f_{best} is the best fit of the current population, f_{mean} is the average fit of the current population, and E1 and e2 are precision parameters. To complete the arithmetic crossing operations, according to the probability parameter P_c, two random individuals are selected from the Alpha agents as shown in (16).

$$X' = \lambda_1 \cdot X_a + (1 - \lambda_1) \cdot X_b \quad (16)$$

where X_a and X_b are positions of the Alpha agents. X' is the position of the new generated individual and the value of λ is a random parameter. Regarding the mutation operation, it focuses on preventing convergence at local points; in this sense, by taking into account the parameter P_m, the mutation of the population is achieved according to the following equation [11]:

$$X'' = X_i \cdot (1 + \lambda_2)''' \quad (17)$$

C. Mathematical model of the whale algorithm (WOA)

Similar to the GWO algorithm, this metaheuristic has characteristics that make it easy to implement in single-objective problems. Imitating the way of whaling, the bio-inspired model proposes a series of steps to achieve the global optimum.

1) Limit the optimal: Similar to the process described in the GWO algorithm, equation (12), also implemented in WOA, describes the positioning elements of the best solution obtained and the current iteration [12]. Additionally, the equation (18) allows calculating the vector coefficients, executing the attack task of the algorithm, in which the value of a is decreased by limiting the value of A to an interval *[-a, a]*.

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (18)$$

2) Position update spiral: As shown in Fig. 2, the method calculates the distance between the whale coordinates (X, Y) and the optimum (X *, Y *). The equation (19) that simulates the helix process is described below.

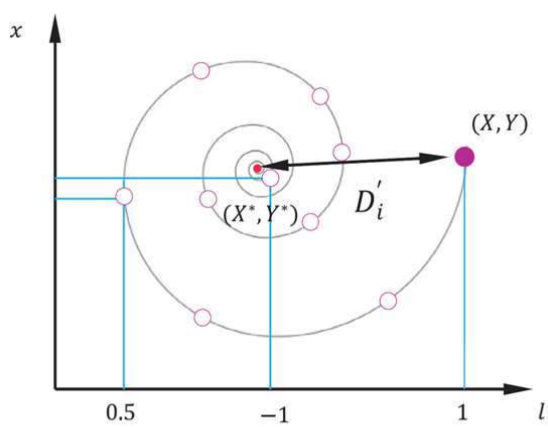

Fig. 2. Position update spiral [12]

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X^*}(t) \quad (19)$$

$$\overrightarrow{D'} = |\overrightarrow{X^*}(t) - \vec{X}(t)| \quad (20)$$

where D' indicates the distance of the nth best solution obtained, b is a constant to define the shape of the logarithmic spiral and l is a random number between *[-1, 1]*.

IV. Reference Power System

For the project development, the 30-bus system given by the IEEE was considered, which is mainly used for Reliability studies in Power Systems. This system is presented in Fig. 3.

This model was adapted from the common database of IEEE, which corresponds at the same time to the data used in the Optimal Power Flow and free software Matpower, developed for MATLAB [16].

The system consists of Fossil Fuel Generators and **synchronous capacitors**, for Voltage Level Control, considering the optimum performance level of the power system. At the same time, power transformers have **TAP changers** that could perform the same function. This represents a total of 30 nodes and 41 transmission lines [17], [18].

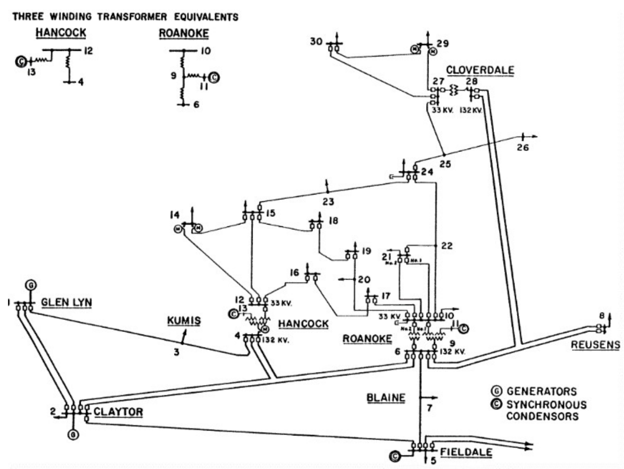

Fig. 3. 30-bus IEEE power system proposed [17]

V. Results and Analysis

For this optimization problem, a reference code was used where the 30-bus system was analyzed by Heuristic Algorithms. In other words, in Matpower 3.2 the power flux calculation was adapted to use the variables given by the optimization model as inputs. Since this code was originally designed to work with Particle Swarm Optimization (PSO), the objective function and its restrictions were modified to allow their calculation using other meta-heuristic methods. The decision variables considered are presented in the next list:

- **Generator bus voltages:** Limited by the generation limit of the zone and the voltage levels given by the 30-bus model in Matpower.
- **Transformer TAPs:** Used for voltage regulation in the system and as additional support related to generation variability.
- **Capacitive compensation:** Associated with the increase or decrease of voltage levels of the nearest

nodes to meet the power grid limits and to reduce line loses.

In total, 13 decision variables were presented, and their limits were constrained by the initial system data than consider the generation constraints, line properties and the effects of capacitive compensation. The performance test was done with three meta-heuristic algorithms created based on animal behavior and built with the Mathworks database.

The implemented algorithms correspond to the traditional Grey Wolf Optimization (GWO) [10], its improved version (I-GWO) [11] and the Whale Optimization Algorithm [12]. These algorithms were chosen based on their performance in terms of convergence to the Optimal Reactive Power Dispatch. which, Unlike the referenced PSO procedure in [16] these algorithms, converged to a close value to the reference calculated by the Newton-Raphson method in Matpower.

For this first analysis, 50 search agents and 200 iterations were considered to compare the behavior of the algorithms measured in their final value and the total calculation time. According to the plot in Figure 4, after the twentieth iteration of the objective function, the values began to approach **18**, except for the GWO, where this behavior began to appear in the **180th iteration**, showing the first differences between each algorithm and the performance in the ORPD.

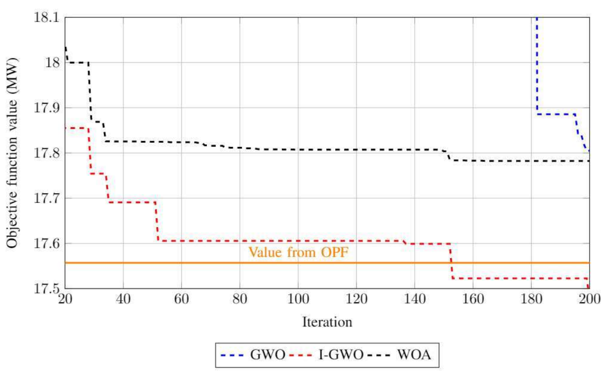

Fig. 4. Simulation results for each of the Algorithm

These results were compared with the value obtained by the Newton-Raphson method in Table I, showing the decision variables and their per-unit values in the case of Generator Voltage **(Vgn)** and Transformer Taps **(Tn)** along with the reactive compensation **(QCn)** in MVar and the Objective function **Fxmin** in MW. The main difference between the mathematical model method and metaheuristics is the calculation time, which varies between 35 and 478 seconds on a computer with Intel Core i5-7200U logical processor with 8 GB RAM memory. In contrast, the mathematical calculation lasted less than 1 second, as there is also the base to the iterative process of each of the algorithms.

Some of the decision variable values are similar to the Newton-Raphson method, as evidenced by a difference of less than 1% in the case of the slack node **Vg1**. However, only in the **I-GWO** a lower value of the objective function was obtained, thus demonstrating that it is possible to obtain a better reactive power dispatch with a method different from the traditional power flow. At the same time, as shown in Fig. 4, after a certain number of iterations, the algorithms start to minimize the objective function at a slower pace, related to their iterative nature and as the penalty functions get lower.

TABLE I. OPTIMIZATION RESULTS PER DECISION VARIABLE

	Original	GWO	IGWO	WOA
Vg1	1.06	1.061	1.0613	1.0616
Vg2	1.045	1.0306	1.0341	1.0319
Vg5	1.01	0.9981	1.0036	0.9944
Vg8	1.01	1.0091	1.0066	1.0038
Vg11	1.082	1.0413	1.0595	1.0315
Vg13	1.071	0.9889	1.0588	1.0278
T1	0.978	1.0374	1.0426	1.0432
T2	0.969	1.049	0.9557	0.9843
T3	0.932	1.0267	0.989	1.0294
T4	0.968	0.9872	0.971	1.0369
QC3	0	20.6905	2.2434	18.7021
QC10	19	18.8579	21.8108	21.4452
QC24	4.3	24.4423	15.0914	24.4391
Fxmin	17.557	17.8049	17.4774	17.7824

Related to this analysis in Table II, the results concerning the simulation with a different number of search numbers and the maximum number of iterations are presented for each of the algorithms. The measurement time in seconds corresponds to the time spent for each Matlab function associated with the meta-heuristic algorithms, including the corresponding power flows in Matpower.

TABLE II. CALCULATION RESULTS RELATED TO ITERATIONS AND NUMBER OF SEARCH AGENTS

Number of Search Agents	Iterations	Algorithm	Execution Time (s)	Objective Function (MW)
25	100	WOA	40.58	20.81
25	100	I-GWO	74.38	17.62
25	100	GWO	35.69	24.96
50	100	WOA	71.89	18.62
50	100	I-GWO	125.30	17.86
50	100	GWO	55.95	19.23
25	200	WOA	64.15	18.27
25	200	I-GWO	123.69	17.53
25	200	GWO	64.17	25.37
50	200	WOA	128.66	18.27
50	200	I-GWO	284.01	17.61
50	200	GWO	136.12	17.89
25	500	WOA	131.18	18.01
25	500	I-GWO	228.48	17.49
25	500	GWO	124.88	18.96
50	500	WOA	259.27	27.27
50	500	I-GWO	478.17	17.49
50	500	GWO	233.58	17.72

Firstly, as the number of agents increases the I-GWO final value gets closer to a lower value from the reference point. This phenomenon is similar to the maximum number of iterations, getting to the lowest of 17.49. However, in the other two methods, the final result does not have a direct relationship between those parameters. For example, the WOA value of 27.47 MW with 50 search agents and 500 iterations is the highest of all the calculated methods while the other two algorithms both reach a minimum.

In contrast the I-GWO spends almost double the time concerning the other methods, something that must be considered in real-world applications as the power dispatch could be developed as fast as 5 minutes in some recent applications [2], [19], [20]. This time interval is related to the PC's logical processor and RAM, as in this case, a personal laptop was used.

VI. Conclusions

The bio-inspired optimization algorithms could be used as a tool to identify the best operation conditions related to the Reactive Power Dispatch and as a different approach to the Optimal Power Flow calculation by Matpower. However, it is important to consider the total calculation time, since as these algorithms could be used in real-time dispatch and power systems are becoming more complex, with new technologies such as renewable energy generation, network contingencies, distribution network expansion, among others.

Specifically, the application of these new meta-heuristic algorithms in the IEEE 30 bus system shows there are still challenges to obtain an objective function value close to the obtained in the traditional Newton-Raphson power flow. The nature of iterations makes the GWO and WOA volatile as the results change as presented in Table II with a different number of search agents and iterations. However, the Improved GWO shows a constant behavior as the increase of those variables makes the final result lower than the original power flow.

Secondly, the final value of the objective function of the three meta-heuristics methods compared with the initial calculation differs in less than 2%, which indicates that these methods have high accuracy. However, a major concern is the total calculation time that could be solved with better computing equipment or with the improvement of the MATLAB code calculation.

Finally, With the analysis of the 30 IEEE bus system and the use of these relative new bio-inspired algorithms in the ORPD, the next step is including more restrictions associated with behaviors such as renewable energy effects, uncertainty in measurement and Unit-Commitment. Moreover, it is important to consider the available calculation time, software and hardware as more decision variables (with larger systems) and problem properties increase the total calculation and even could lead to non-convergence.

References

[1] Y. Amrane and M. Boudour, "Optimal reactive power dispatch based on particle swarm optimization approach applied to the Algerian electric power system," in *2014 IEEE 11th International Multi-Conference on Systems, Signals Devices (SSD14)*, 2014, pp. 1–6, doi: 10.1109/SSD.2014.6808822.

[2] X. Jin, C. Zhang, H. Chen, and X. Xu, "Optimal reactive power dispatch considering wind turbines," in *2014 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2014, pp. 1–5, doi: 10.1109/APPEEC.2014.7066046.

[3] Q. Li, Q. Cao, and Y. Zhang, "Robust Optimal Reactive Power Dispatch against Line Parameters Uncertainty," in *2018 International Conference on Power System Technology (POWERCON)*, 2018, pp. 3729–3733, doi: 10.1109/POWERCON.2018.8602192.

[4] K. Yang, Y. Gong, P. Zhang, and Z. Liu, "A reactive power compensation method based on tracing the power flow and loss function of power system," in *2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2015, pp. 615–619, doi: 10.1109/DRPT.2015.7432309.

[5] F. R. Cabezas Soldevilla and F. A. Cabezas Huerta, "Minimization of Losses in Power Systems by Reactive Power Dispatch using Particle Swarm Optimization," in *2019 54th International Universities Power Engineering Conference (UPEC)*, 2019, pp. 1–5, doi: 10.1109/UPEC.2019.8893527.

[6] M. H. Sulaiman and Z. Mustaffa, "Cuckoo Search Algorithm as an optimizer for Optimal Reactive Power Dispatch problems," in *2017 3rd International Conference on Control, Automation and Robotics (ICCAR)*, 2017, pp. 735–739, doi: 10.1109/ICCAR.2017.7942794.

[7] B. Gaur, R. Ucheniya, and A. Saraswat, "Real Power Transmission Loss Minimization and Bus Voltage Improvement Using UPFC," in *Advances in Communication, Devices and Networking*, 2020, pp. 1–9.

[8] Y. Tian, S. Peng, X. Zhang, T. Rodemann, K. C. Tan, and Y. Jin, "A Recommender System for Metaheuristic Algorithms for Continuous Optimization Based on Deep Recurrent Neural Networks," *IEEE Trans. Artif. Intell.*, vol. 1, no. 1, pp. 5–18, 2020, doi: 10.1109/TAI.2020.3022339.

[9] S. Sharma, R. Kapoor, and S. Dhiman, "A Novel Hybrid Metaheuristic Based on Augmented Grey Wolf Optimizer and Cuckoo Search for Global Optimization," in *2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC)*, 2021, pp. 376–381, doi: 10.1109/ICSCCC51823.2021.9478142.

[10] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[11] W. Long, S. H. Cai, J. J. Jiao, and T. Bin Wu, "An Improved Grey Wolf Optimization Algorithm," *Tien Tzu Hsueh Pao/Acta Electron. Sin.*, vol. 47, no. 1, pp. 169–175, 2019, doi: 10.3969/j.issn.0372-2112.2019.01.022.

[12] S. Mirjalili and A. Lewis, "The Whale Optimization Algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, May 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[13] J. M. López Lezama and L. A. Gallego Pareja, "Flujo de potencia óptimo usando el método del gradiente para reducción de pérdidas en sistemas de potencia," *Ing. y Cienc. - ing.cienc.*, vol. 4, no. 7, pp. 71–85, 2008.

[14] P. Charles, F. Mehazzem, and T. Soubdhan, "A Review on Optimal Power Flow Problems: Conventional and Metaheuristic Solutions," in *2020 2nd International Conference on Smart Power Internet Energy Systems (SPIES)*, 2020, pp. 577–582, doi: 10.1109/SPIES48661.2020.9242994.

[15] Y. Li, X. Lin, and J. Liu, "An improved gray wolf optimization algorithm to solve engineering problems," *Sustain.*, vol. 13, no. 6, pp. 1–23, 2021, doi: 10.3390/su13063208.

[16] "Optimal Reactive Power Dispatch(ORPD) using Particle Swarm Optimization(PSO) - File Exchange - MATLAB Central." https://la.mathworks.com/matlabcentral/fileexchange/41265-optimal-reactive-power-dispatch-orpd-using-particle-swarm-optimization-pso.

[17] I. Totonchi, H. Al Akash, A. Al Akash, and A. Faza, "Sensitivity analysis for the IEEE 30 bus system using load-flow studies," 2013, doi: 10.1109/EPECS.2013.6713060.

[18] C. J. Angeles, E. J. Mercader, G. E. Tan, M. C. Pacis, and R. F. Bersano, "Fault evaluation and performance of an IEEE Bus 30 power distribution network with distributed generation (DG)," in *2017IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2017, pp. 1–6, doi: 10.1109/HNICEM.2017.8269543.

[19] E. A. Bakirtzis, P. N. Biskas, D. P. Labridis, and A. G. Bakirtzis, "Multiple Time Resolution Unit Commitment for Short-Term Operations Scheduling Under High Renewable Penetration," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 149–159, 2014, doi: 10.1109/TPWRS.2013.2278215.

[20] Y.-M. Zhang, C.-R. Chen, and C.-Y. Lee, "Solution of the optimal reactive power dispatch for power systems by using novel charged system search algorithm," in *2018 7th International Symposium on Next Generation Electronics (ISNE)*, 2018, pp. 1–4, doi: 10.1109/ISNE.2018.8394748.