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Improved grey wolf optimizer for optimal reactive power dispatch with integration of wind and solar energy

*The **aim** of this paper is to present a new improved grey wolf optimizer (IGWO) to solve the optimal reactive power dispatch (ORPD) problem with and without penetration of renewable energy resources (RERs). It is a nonlinear multivariable problem of optimization, with multiconstraints. The purpose is to minimize real power losses and improve the voltage profile of a given electric system by adjusting control variables, such as generator voltages, tap ratios of a transformer, switching VAr sources, without violating technical constraints that are presented as equalities and inequalities. **Methodology**. Metaheuristics are stochastic algorithms that can be applied to solve a wide variety of optimization problems without needing specific problem structure information. The penetration of RERs into electric power networks has been increased considerably to reduce the dependence of conventional energy resources, reducing the generation cost and greenhouse emissions. It is essential to include these sources in power flow studies. The wind and photovoltaic based systems are the most applied technologies in electrical systems compared to other technologies of RERs. Moreover, grey wolf optimizer (GWO) is a powerful metaheuristic algorithm that can be used to solve optimization problems. It is inspired from the social hierarchy and hunting behavior of grey wolves in the wild. **The novelty.** This paper presents an IGWO to solve the ORPD problem in presence of RERs. **Methods.** The IGWO based on enhancing the exploitation phase of the conventional GWO. The robustness of the method is tested on the IEEE 30 bus test system. For the control variables, a mixed representation (continuous/discrete), is proposed. The obtained **results** demonstrate the effectiveness of the introduced improvement and ability of the proposed algorithm for finding better solutions compared to other presented methods.* References 40, tables 3, figures 9.

Key words: **optimal reactive power dispatch, renewable energy resources, wind energy, solar energy, improved grey wolf optimizer.**

***Метою** статті є представлення нового покращеного оптимізатора сірого вовка (IGWO) для вирішення задачі оптимального розподілу реактивної потужності (ORPD) із застосуванням відновлюваних джерел енергії (RERs) та без них. Це нелінійне багатовимірне завдання оптимізації з безліччю обмежень. Мета полягає в тому, щоб мінімізувати реальні втрати потужності і покращити профіль напруги заданої електричної системи шляхом регулювання змінних керуючих, таких як напруги генератора, коефіцієнти відгалужень трансформатора, перемикання джерел реактивної потужності, не порушуючи технічних обмежень, які представлені у вигляді рівностей і нерівностей. **Методологія**. Метаевристика – це стохастичні алгоритми, які можна застосовувати для вирішення широкого спектра задач оптимізації без необхідності конкретної інформації про структуру проблеми. Проникнення RER в електромережі значно зросла задля зниження залежності від традиційних джерел енергії, зниження вартості генерації та викидів парникових газів. Вкрай важливо включити ці джерела до дослідження потоків потужності. Системи на основі вітру та фотоелектрики є найбільш застосовуваними технологіями в електричних системах порівняно з іншими технологіями RERs. Більш того, оптимізатор сірого вовка (GWO) – це потужний метаевристичний алгоритм, який можна використовувати для розв'язання оптимізації задач. Він натхненний соціальною ієрархією та мисливською поведінкою сірих вовків у дикій природі. **Новизна**. У цій статті представлено IGWO для вирішення проблеми ORPD при наявності RERs. **Методи**. IGWO, заснований на покращенні фази експлуатації звичайного GWO. Надійність методу перевірена на тестовій системі шини IEEE 30. Для керуючих змінних запропоновано змішане уявлення (безперервне/дискретне). **Отримані результати** демонструють ефективність введеного покращення та здатність запропонованого алгоритму знаходити кращі рішення порівняно з іншими методами.* Бібл. 40, табл. 3, рис. 9.

Ключові слова: **оптимальний розподіл реактивної потужності, відновлювані джерела енергії, енергія вітру, сонячна енергія, покращений оптимізатор сірого вовка.**

Introduction. The development of an optimal solution for the operation and management of electrical networks was initiated in 1958 by L.K. Kirchmayer [1], with the goal of minimizing the operational cost of supplying electrical energy to a given load. Thus, the problem evolved into a dispatch problem. At that time, significant progress had been made in the ordinary power flow, and the use of computers showed promising potential. Consequently, analysts tried to incorporate this success into the field of optimal power flow (OPF). In 1962, J. Carpentier introduced for the first time the OPF problem [2], which was further developed by H. Dommel and W. Tinney [3]. Since then, the OPF has generated significant interest among researchers focused on power system operation and planning.

The optimal reactive power dispatch (ORPD) problem is a specific case of the OPF problem and has an increasingly important role in enhancing the reliability, security, and economic efficiency of power systems [4, 5]. It is a multi-constraints nonlinear multivariable problem of optimization that aims to get the best profile of the voltage and reduction of power losses by adjusting a set of control variable values including the voltages of generator, shunt VAR reactive compensators and the tap changing of the transformers. Meanwhile, optimization constraints generator reactive power capabilities, voltages of load bus and power balance must be satisfied.

In the past few decades, numerous optimization techniques have been studied to solve this kind of problems after using some simplifications and special treatments [6, 7]: gradient-based approach, linear programming, interior point, quadratic programming and non-linear programming. However, all these techniques have some of difficulties to solve the intricated problem of ORPD such as:

- trapping into the local minima;
- premature convergence;
- the algorithmic complexity;
- large iteration number;
- sensitivity to an initial search point;
- limited modeling capabilities (in handling nonlinear, discontinuous functions and constraints, etc.).

With the advancement of soft computing during the last years, these problems can be overcome by the introduction of many new stochastic search methods developed for global optimization problems.

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Metaheuristics are stochastic algorithms for solving a wide range of problems for which there is no known effective conventional methods. These techniques are often inspired from biology (evolutionary algorithms [8–13], differential evolution [14–18]), physics (simulated annealing [19, 20], Archimedes optimization algorithm [21]) and ethnology (ant colony optimization [22], particle swarm optimization (PSO) [23, 24], honey bee mating optimization [25], firefly algorithm [26], grey wolf optimizer (GWO) [27–30]). In order to improve the performance of optimization algorithms, some authors have proposed hybrid algorithms [31–34].

Nowadays, the contribution of renewable energy resources (RERs) in electric power system is intensively considered [35–40]. This integration leads to reducing greenhouse emissions, generation fuel cost, and enhancing the system operation. The most applied technologies for RERs are the wind and photovoltaic (PV) energy generation systems.

On the other side, GWO is a powerful metaheuristic method that has few parameters to be set, and it is easy to use it for solving ORPD problem.

The **aim** of this paper is to present a new improved grey wolf optimizer (IGWO) to solve ORPD problem with and without penetration of RERs. The IGWO is used to increase the diversity of solutions and resist premature convergence. The proposed algorithm is tested on the IEEE 30 bus test system.

Problem formulation. Minimization problems with constraints are generally expressed in the following form:

$$\begin{aligned}&\text{Minimize}: f(x),\\ &\text{Subject to}: h_i(x)=0, \quad i=0,...,m;\\ &\qquad g_j(x)\le 0, \quad j=0,...,n,\end{aligned} \tag{1}$$

where m is the number of equality constraints; n is the number of inequality constraints; $f(x)$ is the objective function; $h_i(x)$ is the equality constraint; $g_j(x)$ is the inequality constraint;

The number of variables is equal to the dimension of the vector $\boldsymbol{x}$.

The main objectives of the ORPD are to reduce transmission losses and improve the voltage profile in a power system. The total losses are represented as:

$$f(x)=p=\sum_{k\in N_B}P_{kLoss}=\sum_{k\in N_B}g_{ij}\left(V_i^2+V_j^2-2V_iV_j\cos\theta_{ij}\right), \tag{2}$$

where k is the branch between buses i and j; N_B is the set of branch numbers; P_{kLoss} is the active power loss of branch k; g_{ij} is the conductance of the branch existing between the buses i and j; V_i, V_j are the voltage profiles at bus i and j respectively; θ_{ij} is the phase angle of voltage between buses i and j.

The objective function $f(x)$ is constrained by a number of equality constraints (real and reactive power balance at each node) which are associated with the load flow:

$$P_{gi}-P_{di}-V_i\sum_{j\in N_i}V_j\left(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}\right)=0, i\in N_0, \tag{3}$$

$$Q_{gi}-Q_{di}-V_i\sum_{j\in N_i}V_j\left(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}\right)=0, i\in N_{PQ}, \tag{4}$$

Inequality constraints of control variables are given as:

$$T_{i\min}\le T_i\le T_{i\max},\ i\in N_T; \tag{5}$$

$$Q_{gi\min}\le Q_{gi}\le Q_{gi\max},\ i\in N_{cap}; \tag{6}$$

$$V_{i\min}\le V_i\le V_{i\max},\ i\in N_{PV}. \tag{7}$$

Inequality constraints of state variables are written as:

$$V_{i\min}\le V_i\le V_{i\max},\ i\in N_{PQ}; \tag{8}$$

$$Q_{gi\min}\le Q_{gi}\le Q_{gi\max},\ i\in N_{PV}, \tag{9}$$

where P_{gi} is the generated active power at bus i; Q_{gi} is the generated reactive power at bus i; P_{di} is the active power load at bus i; Q_{di} is the reactive power load at bus i; G_{ij} is the transfer conductance between buses i and j; B_{ij} is the transfer susceptance between buses i and j; N_i is the set of the bus numbers adjacent to bus i including bus i; N_0 is the set of the bus numbers except the swing bus; N_{PQ} is the set of PQ bus (load bus) numbers; N_{PV} is the set of PV bus (generator bus) numbers containing swing bus; T_i is the tap-setting of the transformer i; N_T is the set containing the numbers of tap-setting transformer branches; N_{cap} is the set of bus numbers containing shunt compensator banks.

Control variables, including generator bus voltage, transformer tap settings, and switchable shunt capacitor banks, are inherently constrained. Meanwhile, load bus voltages and reactive power generation are state variables; with their limitations incorporated into the objective function as quadratic penalty terms, forming a penalty function:

$$\begin{aligned}\min F(x)=p+\sum_{i\in N_{PQ}}\lambda_{V_i}(V_i-V_i^{\lim})^2+\\ +\sum_{i\in N_{PV}}\lambda_{Q_{gi}}(Q_{gi}-Q_{gi}^{\lim})^2.\end{aligned} \tag{10}$$

This new formulation of the objective function is constrained by the equality constraints (3) – (4) and inequality constraints of control variables (5) – (7). The coefficients λ_{V_i} and $\lambda_{Q_{gi}}$ serve as penalty factors:

$$V_i^{\lim}=\begin{cases}V_{i\min} & \text{if} \quad V_i<V_{i\min};\\ V_{i\max} & \text{if} \quad V_i>V_{i\max};\\ V_i & \text{if} \quad V_{i\min}\le V_i\le V_{i\max};\end{cases} \tag{11}$$

$$Q_{gi}^{\lim}=\begin{cases}Q_{gi\min} & \text{if} \quad Q_{gi}<Q_{gi\min};\\ Q_{gi\max} & \text{if} \quad Q_{gi}>Q_{gi\max};\\ Q_{gi} & \text{if} \quad Q_{gi\min}\le Q_{gi}\le Q_{gi\max}.\end{cases} \tag{12}$$

Mathematical modelling of RERs.

1) *Model of wind power.* A wind turbine generates power output according to the wind speed it encounters. The relationship between output power and wind speed (v_w) is expressed as [36, 37]:

$$P_{wt}(v_w)=\begin{cases}0 & \text{for} \quad v_w\le v_{w,in}\ \text{and} v_{w,out}\le v_w;\\ P_{wr}\left(\dfrac{v_w-v_{w,in}}{v_{w,r}-v_{w,in}}\right) & \text{for} \quad v_{w,in}\le v_w\le v_{w,r};\\ P_{wr} & \text{for} \quad v_{w,r}\le v_w\le v_{w,out},\end{cases} \tag{13}$$

where P_{wr} is the rated power generated by the wind turbine while $v_{w,in}$, $v_{w,r}$ and $v_{w,out}$, denote the cut-in, rated, and cut-out wind speed, respectively.

The active and reactive generated powers of the wind farm are depicted as [37]:

$$P_{wf}=P_{wt}\cdot N_{wt};\quad Q_{wf}=\frac{P_{wf}}{\cos\phi}\sqrt{1-\cos\varphi}, \tag{14}$$

where P_{wf} , Q_{wf} are the active and reactive power respectively generated by the wind farm; N_{wt} is the number of the wind turbines connected in a wind farm; $\cos\varphi$ is the power factor.

2) *Model of solar power*. The output of the solar PV units also fluctuates due to daily and seasonally variation in solar irradiation, which causes a change in the power system. The solar irradiance G_s to energy conversion is given by following relationship with maximum output power limited to the PV unit rated power P_{sr}:

$$P_s(G_s)=\begin{cases} P_{sr}\left(\dfrac{G_s^2}{G_{std}\cdot R_c}\right) & \text{for} \quad 0\le G_s\le R_c\,; \\ P_{sr}\left(\dfrac{G_s}{G_{std}}\right) & \text{for} \quad G_s\ge R_c\,, \end{cases} \tag{15}$$

where P_{sr} is the equivalent rated power output of the PV generator; R_c, is the certain irradiance point set as 120 W/m^2; G_{std} is the solar irradiation in standard environment, set as 1000 W/m^2.

3) *Effect of the wind and solar powers in ORPD*. Wind and solar power significantly influence the dispatch solution of the ORPD problem. The integrated mathematical formulation of ORPD, which includes wind farms and PV systems, is presented in (16). It's important to note that this equation describes a balanced power flow in the system, taking into account RERs:

$$\begin{cases} P_{gi}+P_{wf}+P_s=P_{di}+V_i\sum\limits_{j\in N_i}V_j\left(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}\right); \\ Q_{gi}+Q_{wf}+Q_s=Q_{di}+V_i\sum\limits_{j\in N_i}V_j\left(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}\right). \end{cases} \tag{16}$$

Today, PV inverters operate with a very small amount of reactive power, resulting in a power factor that is very close to the unit. As a result, PV installations only inject active power into the grid.

Grey wolf optimizer. GWO is a metaheuristic optimization method that mimics the social hierarchy and hunting mechanism of grey wolves. This algorithm was first introduced in [27]. Wolves are classified into 4 main groups:

- Alpha (α) – the leader of the pack;
- Beta (β) – the second in command;
- Delta (δ) – the third in command;
- the remaining wolves are considered Omegas (ω).

The positions of the wolves are updated based on the positions of the 3 best wolves (Alpha, Beta and Delta). The GWO search algorithm begins with a group of search agents, also known as design solutions (X).

The reproduction process involves the following 3 main operators: *social hierarchy*, *encircling prey* and *hunting*.

1) *Social hierarchy*. The social hierarchy of grey wolves classifies them into 4 groups based on their objective function values. The groups are Alpha (α) for the best, Beta (β) for the second best, and Delta (δ) for the third best, while the remaining wolves are assigned to the Omega (ω) group.

2) *Encircling prey*. The process of encircling prey by grey wolves for hunting can be mathematically defined as:

$$D=\left|\, C\cdot X_p(t)-X(t)\,\right|\;; \tag{17}$$

$$X(t+1)=X_p(t)-A\cdot D\,, \tag{18}$$

where:

$$A=2\cdot a\cdot r_1-a\;; \tag{19}$$

$$C=2\cdot r_2\,, \tag{20}$$

where t is the current iteration; A, C are the coefficient vectors; X_p is the position vector of the prey; X is the position vector of a grey wolf; r_1, r_2 are the uniform random vectors whose elements are generated randomly within the range [0, 1] [27]. The magnitude of A is allowed to be large initially to encourage exploration and it is gradually reduced to get good exploitation in later iterations.

The components of a are linearly decreased from 2 to 0 throughout the optimization process. It can be formulated as:

$$a=2-\frac{2\cdot t}{\text{maximum number of iterations}}\,. \tag{21}$$

3) *Hunting*. In the hunting phase, the positions of the grey wolves Alpha (X_α), Beta (X_β) and Delta (X_δ), as defined in the social hierarchy play a crucial role. These 3 agents collectively influence a new search at iteration t, which is referred to as the hunting operator as:

$$D_\alpha=\left|\, C_1\cdot X_\alpha(t)-X(t)\,\right|\;; \tag{22}$$

$$D_\beta=\left|\, C_2\cdot X_\beta(t)-X(t)\,\right|; \tag{23}$$

$$D_\delta=\left|\, C_3\cdot X_\delta(t)-X(t)\,\right|\;; \tag{24}$$

$$X_1=X_\alpha(t)-A_1\cdot D_\alpha\;; \tag{25}$$

$$X_2=X_\beta(t)-A_2\cdot D_\beta\,; \tag{26}$$

$$X_3=X_\delta(t)-A_3\cdot D_\delta\,. \tag{27}$$

A new grey wolf position, or the next generation, can then be determined as:

$$X(t+1)=\frac{X_1+X_2+X_3}{3}\,. \tag{28}$$

Once all new agents or design solutions are generated, the function evaluations of these agents are carried out. The process is repeated until a termination condition is met. A pseudo-code for the GWO algorithm applied to ORPD is illustrated in Fig. 1.

```
Initial system data, Number of search agent, Number of iterations,
Initialize the grey wolf population Xi within the limits of their control variables.
Initialize a, A, C.
Evaluate the fitness of each search agent (run Newton–Raphson load flow)
Determine:
Xα = the best search agent
Xβ = the second best search agent
Xδ = the third best search agent
while (t<max number of iterations)
for each search agent
Update the position of the current search agent by equation (28) (within their limits of control variables)
end for
Update a, A, C.
Calculate the fitness of all search agents (using Newton–Raphson load flow)
Update Xα, Xβ, Xδ
t = t + 1
end while
return Xα.
```

Fig. 1. Pseudo code of the GWO algorithm for ORPD

Improved grey wolf optimizer. In this work, the reproduction process of the original GWO is modified. Rather than averaging the positions of X_1, X_2 and X_3 as with (28), the reproduced solution $X(t + 1)$ has 2 possible choices to be modified as shown in (29). Those choices have equal probability to take place. The modification of this step is expected to provide better population diversity.

$$X(t+1)=\begin{cases}\dfrac{X_1+X_2}{2} & \text{if} \quad p<0.5\,; \\ \dfrac{X_1+X_2+X_3}{3} & \text{if} \quad p\geq 0.5\,, \end{cases} \tag{29}$$

where $p\in[0, 1]$ is the uniform random number generated a new for each agent.

Simulation and results.

1) *Data of the studied network*. In this section, we evaluate the IGWO algorithm for solving the ORPD problem with and without integration of RERs: wind and solar energy. This assessment utilizes the IEEE 30-bus test system, which includes 30 buses, 41 branches, 6 generators, 4 tap-setting transformers, and 9 VAR switching sources. Bus 1 is the swing bus, while buses 2, 5, 8, 11, and 13 are designated as PV buses. The possible locations for reactive power installations are buses 10, 12, 15, 17, 20, 21, 23, 24, and 29. The tap-setting transformers are located on branches (6–9), (6–10), (4–12) and (28–27). System data is referenced from sources [17, 24]. The used base of power is S_B = 100 MVA.

2) *Load flow calculation*. At the beginning, the load flow calculation is done without consideration of the powers of RERs. The Newton–Raphson method results, shown in Table 1, indicate a total transmission loss of 5.8223 MW. Voltages exceeding the acceptable limits are observed at buses V_{19} – V_{27}, V_{29} and V_{30}. It is crucial to adjust the control variables to minimize transmission losses and enhance the voltage profile in the network. It should be noted that constraints for control and state variables are shown in Table 2, 3 respectively.

Table 1

Load flow results

Bus	Voltage		Load		Generation	
	V, pu	θ, °	P_d, pu	Q_d, pu	P_g, pu	Q_g, pu
1	1.0500	0	0	0	0.9922	–0.0153
2	1.0400	–1.7623	0.217	0.127	0.8000	0.1564
3	1.0279	–3.9323	0.024	0.012	0	0
4	1.0222	–4.6963	0.076	0.016	0	0
5	1.0100	–6.4824	0.942	0.190	0.5000	0.1641
6	1.0166	–5.4355	0	0	0	0
7	1.0059	–6.3969	0.228	0.109	0	0
8	1.0100	–5.6272	0.300	0.300	0.2000	0.1354
9	0.9755	–7.0162	0	0	0	0
10	0.9547	–9.1959	0.058	0.020	0	0
11	1.0500	–4.6886	0	0	0.2000	0.3800
12	0.9976	–8.7884	0.112	0.075	0	0
13	1.0500	–7.2567	0	0	0.2000	0.3954
14	0.9773	–9.7952	0.062	0.016	0	0
15	0.9680	–9.7932	0.082	0.025	0	0
16	0.9718	–9.2538	0.035	0.018	0	0
17	0.9540	–9.4522	0.090	0.058	0	0
18	0.9501	–10.3964	0.032	0.009	0	0
19	0.9429	–10.5331	0.095	0.034	0	0
20	0.9450	–10.2636	0.022	0.007	0	0
21	0.9408	–9.7516	0.175	0.112	0	0
22	0.9413	–9.7419	0	0	0	0
23	0.9467	–10.1714	0.032	0.016	0	0
24	0.9274	–10.2804	0.087	0.067	0	0
25	0.9204	–10.3073	0	0	0	0
26	0.9008	–10.8220	0.035	0.023	0	0
27	0.9257	–10.0102	0	0	0	0
28	1.0116	–5.8711	0	0	0	0
29	0.9035	–11.5199	0.024	0.009	0	0
30	0.8907	–12.6115	0.106	0.019	0	0
Total real losses: 5.8223 MW						

Table 2

Control variables and losses obtained from execution of GWO and IGWO with and without integration of RERs, CPVEIHBMO [25] and PSOGWO [34]

Control variables	Min	Max	Initial	GWO without RERs	IGWO without RERs	GWO with RERs	IGWO with RERs	CPVEIHBMO [25]	PSOGWO [34]
V_1, pu	0.95	1.1	1.05	1.0701	1.0714	1.0638	1.0624	1.0254	0.9615
V_2, pu	0.95	1.1	1.04	1.0615	1.0616	1.0605	1.0578	1.0352	1.0020
V_5, pu	0.95	1.1	1.01	1.0378	1.0389	1.0444	1.0407	1.0563	0.9437
V_8, pu	0.95	1.1	1.01	1.0390	1.0394	1.0442	1.0429	1.0273	0.9623
V_{11}, pu	0.95	1.1	1.05	1.0939	1.0799	1.0807	1.0640	1.0287	0.9476
V_{13}, pu	0.95	1.1	1.05	1.0378	1.0599	1.0401	1.0630	1.0756	1.0464
T6–9	0.9	1.1	1.078	0.9813	1.0375	0.9875	1.0188	0.9983	0.9746
T6–10	0.9	1.1	1.069	1.0875	0.9313	1.0438	0.9063	0.9748	1.0105
T4–12	0.9	1.1	1.032	1.0063	0.9875	0.9938	1.0000	0.9726	0.9776
T28–27	0.9	1.1	1.068	1.0063	0.9688	0.9813	0.9750	1.0817	0.9392
Q_{gc10}, pu	0	0.05	0	0.0160	0.0250	0.0250	0.0135	0.0482	0.0040
Q_{gc12}, pu	0	0.05	0	0.0260	0.0295	0.0025	0.0465	0.0483	0.0580
Q_{gc15}, pu	0	0.05	0	0.0255	0.0370	0.0490	0.0280	0.0476	0.0342
Q_{gc17}, pu	0	0.05	0	0.0500	0.0370	0.0215	0.0150	0.0485	0.0272
Q_{gc20}, pu	0	0.05	0	0.0475	0.0200	0.0005	0.0115	0.0498	0.0016
Q_{gc21}, pu	0	0.05	0	0.0215	0.0285	0.0385	0.0350	0.0499	0.0720
Q_{gc23}, pu	0	0.05	0	0.0035	0.0035	0.0035	0.0110	0.0489	0.0347
Q_{gc24}, pu	0	0.05	0	0.0475	0.0460	0.0490	0.0330	0.0499	0.0111
Q_{gc29}, pu	0	0.05	0	0.0425	0.0185	0.0105	0.0365	0.0499	0.0157
Total real losses, MW			5.8223	4.9496	4.9015	2.5374	2.5193	5.3243	5.0903

3) *Treatment of control variables, initiation and evaluation steps*. Each potential solution (search agent) is represented by a vector $\boldsymbol{X}$ that includes the values of control parameters such as generator voltages V_{gi}, transformer taps T_i and the reactive power of switchable shunt capacitors Q_{gci}. This vector is expressed as:

$$\boldsymbol{X}=\left[V_{g_1}\ldots V_{g_{N_{PV}}}\middle|T_1\ldots T_{N_T}\middle|Q_{gc1}\ldots Q_{gcN_{cap}}\right]. \tag{30}$$

Generator voltages are treated as continuous variables, whereas transformer taps and reactive power settings are considered discrete. During the initialization phase of both the GWO and IGWO approaches, initial solutions are generated using uniform random variables:

$$X_i = X_{i\,\min} + rnd \cdot \left(X_{i\,\max} - X_{i\,\min}\right), \qquad (31)$$

where $0 < rnd < 1$ is the random value.

To handle discrete variables, we adjust the variable value using the following formulation:

$$X_i = X_{i\,\min} + NX_i \cdot \Delta X_i\,, \qquad (32)$$

where N is the set of the total number of buses; NX_i is the integer number represents the variation number of the variable X_i; ΔX_i is the step size of the variable X_i.

In this paper, each transformer has 32 discrete settings, while each of the nine shunt compensator banks offers 100 possible configurations. To evaluate any solution, the fitness function value is determined by running a load-flow analysis using the Newton–Raphson method.

Table 3

Dependent variables obtained from execution of GWO and IGWO with and without integration of RERs

Dependent variables, pu	Min	Max	Initial	GWO without RERs	IGWO without RERs	GWO with RERs	IGWO with RERs
V_3	0.95	1.05	1.0279	1.0495	1.0498	1.0500	1.0500
V_4	0.95	1.05	1.0222	1.0441	1.0441	1.0463	1.0465
V_6	0.95	1.05	1.0166	1.0408	1.0403	1.0454	1.0430
V_7	0.95	1.05	1.0059	1.0319	1.0320	1.0473	1.0443
V_9	0.95	1.05	0.9755	1.0499	1.0408	1.0491	1.0448
V_{10}	0.95	1.05	0.9547	1.0221	1.0413	1.0282	1.0467
V_{12}	0.95	1.05	0.9976	1.0286	1.0497	1.0339	1.0499
V_{14}	0.95	1.05	0.9773	1.0164	1.0378	1.0231	1.0389
V_{15}	0.95	1.05	0.9680	1.0143	1.0357	1.0234	1.0389
V_{16}	0.95	1.05	0.9718	1.0202	1.0402	1.0249	1.0419
V_{17}	0.95	1.05	0.9540	1.0190	1.0377	1.0231	1.0408
V_{18}	0.95	1.05	0.9501	1.0081	1.0269	1.0194	1.0368
V_{19}	0.95	1.05	0.9429	1.0076	1.0249	1.0201	1.0386
V_{20}	0.95	1.05	0.9450	1.0129	1.0292	1.0213	1.0403
V_{21}	0.95	1.05	0.9408	1.0115	1.0315	1.0189	1.0368
V_{22}	0.95	1.05	0.9413	1.0121	1.0322	1.0196	1.0373
V_{23}	0.95	1.05	0.9467	1.0064	1.0280	1.0156	1.0320
V_{24}	0.95	1.05	0.9274	1.0035	1.0252	1.0127	1.0283
V_{25}	0.95	1.05	0.9204	1.0079	1.0327	1.0195	1.0352
V_{26}	0.95	1.05	0.9008	0.9900	1.0152	1.0018	1.0178
V_{27}	0.95	1.05	0.9257	1.0194	1.0458	1.0324	1.0480
V_{28}	0.95	1.05	1.0116	1.0378	1.0360	1.0407	1.0397
V_{29}	0.95	1.05	0.9035	1.0120	1.0318	1.0159	1.0392
V_{30}	0.95	1.05	0.8907	0.9952	1.0184	1.0032	1.0236
Q_{g1}	–0.2	0.25	–0.0153	–0.0447	–0.0158	–0.0521	–0.0360
Q_{g2}	–0.2	1	0.1564	0.1286	0.1055	0.0974	0.0589
Q_{g5}	–0.15	0.8	0.1640	0.2084	0.2218	0.1786	0.1678
Q_{g8}	–0.15	0.6	0.1353	0.2618	0.2951	0.2877	0.3155
Q_{g11}	–0.1	0.5	0.3800	0.2350	0.2067	0.1678	0.1017
Q_{g13}	–0.15	0.6	0.3954	0.0710	0.0797	0.0488	0.1016

4) *System without integration of RERs*.

4.1) *Application of GWO*. The GWO results are presented in Table 2, 3. The obtained results are based on:

- grey wolf population size: 100;
- maximum number of iterations: 500.

The optimization led to a significant reduction in total real losses, improving by 14.98 % from 5.8223 MW (initial case of load flow calculation) to 4.9496 MW. The voltage profile has been enhanced, and all constraints have been respected. The convergence characteristics of the algorithm are illustrated in Fig. 2, 3.

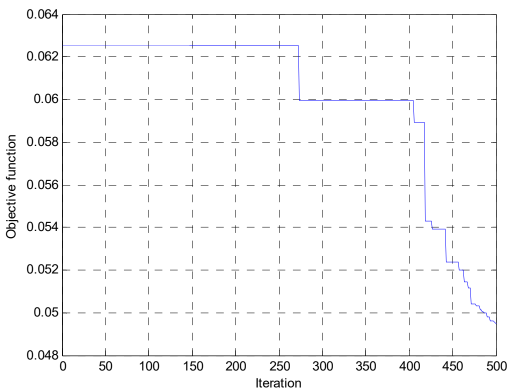

Fig. 2. Convergence of the objective function using GWO without RERs

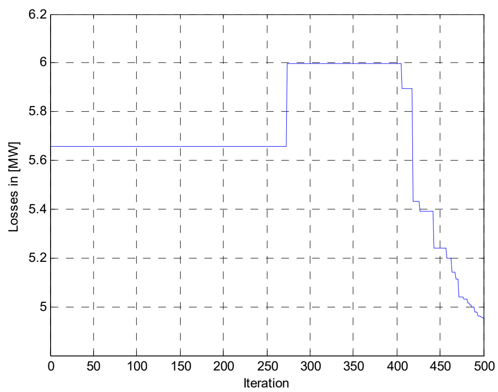

Fig. 3. Convergence of active losses using GWO without RERs

4.2) *Application of IGWO*. The IGWO without integration of RERs results are given in Table 2, 3 and Fig. 4, 5. Hence, we can clearly perceive the superiority of IGWO over GWO, where all the constraints are also respected and the losses are moved from 4.9496 MW to 4.9015 MW, with a minimization in total active losses of 15.81 % compared to the initial load flow case.

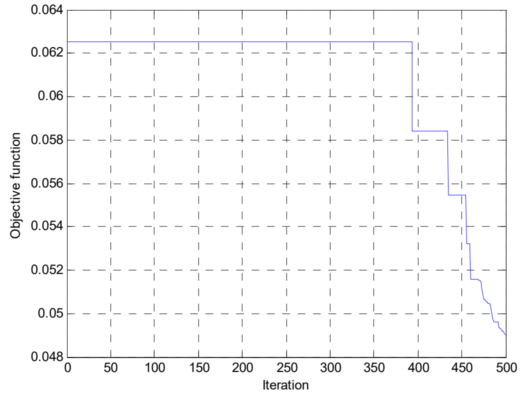

Fig. 4. Convergence of the objective function using IGWO without RERs

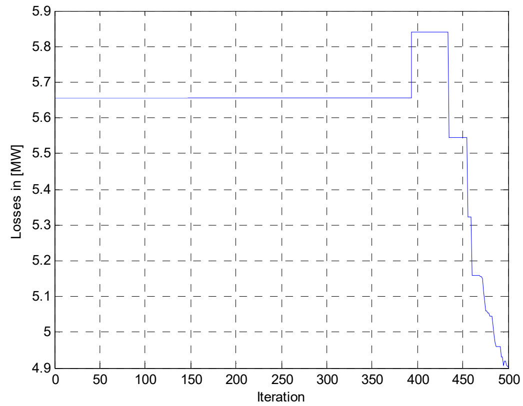

Fig. 5. Convergence of active losses using IGWO without RERs

5) *System with integration of RERs*. In this paper, RERs are added on buses 7 and 19. Wind speed and solar radiation data are taken from [35]. In bus 7, there is a wind farm, which consists of 30 wind turbines with a rated power of 3 MW for each one. The wind turbine cut-in, cut-out, and the rated speeds respectively are: $v_{w,in}$ = 3 m/s; $v_{w,out}$ = 25 m/s; $v_{w,r}$ = 16 m/s. The annual average wind speed from the location of this wind farm is taken as 7.536 m/s, which leads to an overall power output of 31.41 MW according to (13) and (14). In this work a power factor of 0.95 is considered for this wind farm.

The solar power plant is added on bus 19, where the PV array output power P_{sr} is assumed to be 30 MW, R_c is set as 120 W/m^2 and the annual average radiation from this location is taken as G_s = 471.76 W/m^2. Using (15) the total power generation for this plant in this location is 14.153 MW. Unity power factor is considered for the solar farm.

5.1) *Application of GWO*. The convergence characteristics of the GWO algorithm with integration of RERs are shown in Fig. 6, 7. The simulation results are resumed in Table 2, 3. The penetration of RERs has reduced the active power loss in the system largely to 2.5374 MW, with a minimization of 56.41 % compared to the initial load flow case. All the constraints are respected again.

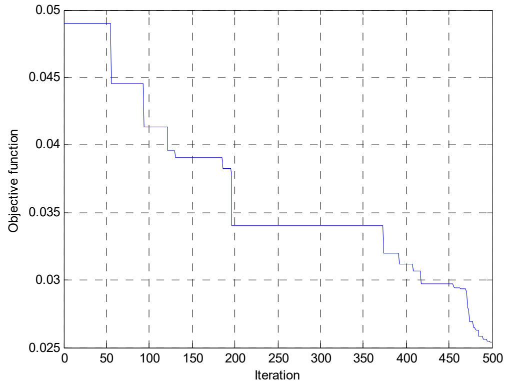

Fig. 6. Convergence of the objective function using GWO with RERs

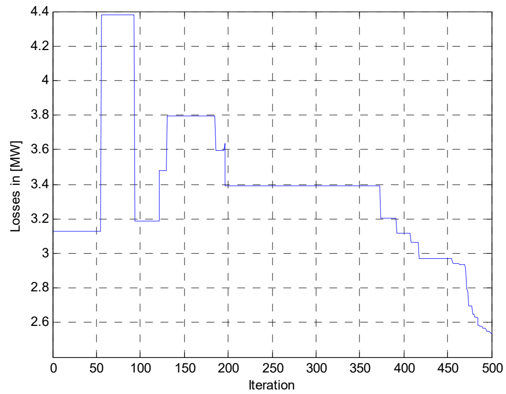

Fig. 7. Convergence of active losses using GWO with RERs

5.2) *Application of IGWO*. The IGWO results are presented in Table 2, 3, with addition of convergence characteristics in Fig. 8, 9. Power losses have continued to decrease. One can clearly perceive an important improvement of 56.73 % in total real losses, ranging also from 5.8223 MW in the case of load flow calculation to 2.5193 MW in our current case. The voltage profile has been improved and all the constraints have been respected.

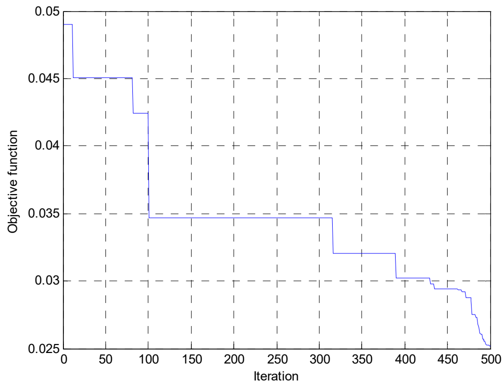

Fig. 8. Convergence of the objective function using IGWO with RERs

Table 2 presents a comparison of our applied algorithms with results obtained from:

- the new multi-objective strategy (Case IV) based on the Chaotic Parallel Vector Evaluated Interactive Honey Bee Mating Optimization (CPVEIHBMO) technique, as described in [25];
- the hybrid GWO-PSO optimization technique (Case I) discussed in [34].

The comparison highlights the effectiveness and superiority of the IGWO approach.

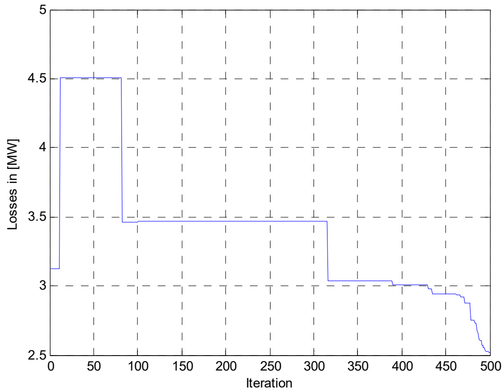

Fig. 9. Convergence of active losses using IGWO with RERs

Conclusions. The ORPD problem is a nonlinear multivariable optimization problem with both equality and inequality constrains. To solve this problem, the paper has proposed GWO and a new IGWO with and without incorporating of wind and solar energy systems.

In this work, the modification in the reproduction process step of IGWO is expected to provide better population diversity.

To make the ORPD problem more practical, control variables are represented in a mixed format, combining continuous and discrete values. Specifically, generator voltages are treated as continuous, while reactive power installations and transformer taps are considered discrete. The robustness of the proposed methods is evaluated using the standard IEEE 30-bus test system. The results demonstrate that IGWO offers notable advantages over GWO. The results also show that the introduction of RERs into the network, combined with control variable adjustments through the algorithm, leads to a more significant reduction in active power loss and voltage deviation compared to scenarios without RERs.

Conflict of interest. The author declares that there is no conflict of interest.

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