Dingo Optimizer for Power Loss Minimization Using Optimal Power Flow

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ABSTRACT

This study introduces a new metaheuristic optimization method designed to address optimal power flow problems in power systems. The approach takes inspiration from the natural behavior of dingoes (Canis familiaris dingo). The Dingo Optimizer (DOA) is a bio-inspired algorithm that mimics the hunting behavior of dingoes, which involves three main strategies: exploration, surrounding, and exploitation. Optimal power flow (OPF) is the fundamental technique used for efficient and cost-effective power system operation and future planning. This proposed method is utilized to address the optimal power flow problem by ascertaining the ideal configuration of the control variables while ensuring compliance with the operational and physical limitations of the power system. The suggested method aims to minimize losses, using control variables including real and reactive power injections, transformer tap-changers, and voltage magnitudes. The suggested approach's performance and efficacy are confirmed by validation on the standard IEEE 30 and 14 bus test systems. Furthermore, the acquired outcomes are contrasted with those of three renowned algorithms, namely the whale optimization algorithm (WOA), particle swarm optimization (PSO), and the genetic algorithm (GA). The results demonstrate that DOA outperforms the compared algorithms with a reduced computational time.

1. INTRODUCTION

An electrical power system is partitioned into four distinct segments, which include generation, transmission, distribution, and consumption. The system is intricate and advanced due to its extensive size, dynamic nature, and intricate interaction of each element. Controlling and managing a power system is an exceedingly arduous and demanding task for utilities or operators. Efficient operation and control necessitate a wide array of system data, along with effective computing, operation, and measuring [1]. Load flow analysis, commonly referred to as optimal power flow studies, is considered to be a reliable and pragmatic approach in power system operation and planning for both current and hypothetical systems [2]. OPF, or Optimal Power Flow, is a mathematical problem that aims to provide the optimal solution for a given objective function. It achieves this by adjusting the controllable variables while ensuring that no operational or physical system constraints are violated, including both inequality and equality requirements. The power flow balance equations represent the equality constraints, whereas the bus voltages, real power, reactive power, transformer tap changer, and network line flows represent the inequality constraints [3].

Currently, the globe is confronting the issue of global warming and climate change as a result of the release of greenhouse gases from the combustion of fossil fuels. Under the KYOTO protocol commitment, all participating nations pledged to decrease their usage of fossil fuels as a means to reduce greenhouse gas emissions. Moreover, the escalating cost of fuel has resulted in a corresponding rise in the price of power. Discovering a cost-effective method to generate electricity that meets all the necessary physical and operational limitations is of utmost significance. The utilization of OPF is the optimal approach for reducing the expenses associated with energy generation while minimizing environmental impact. Consequently, both the utilities and the governments have given it their attention.

A variety of optimization techniques, both traditional and intelligent, have been utilized to address OPF difficulties. In addition, other commonly used conventional optimization approaches include linear programming [4], nonlinear programming [5], quadratic programming [6], and the interior point method [7]. OPF difficulties have been

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addressed using both traditional and intelligent approaches. Conventional methods, sometimes referred to as deterministic, have been extensively utilized in the past because of their superior convergent properties. The literature review of the most frequently employed conventional optimization methods is included in [8]. Nevertheless, they possess certain limitations. Attaining global optimality is a significant challenge for them as they tend to converge towards local optima or struggle to achieve global optimality effortlessly. They lack the capability to process binary or integer variables and rely on certain theoretical assumptions such as convexity, differentiability, and continuity, which may not be applicable to complex OPF situations [9]. In order to address these challenges, various computational intelligent methods have been rapidly developed with high performance and effectiveness. These methods include genetic algorithm (GA) [10], tabu search (TS) [11], particle swarm optimization (PSO) [12], cuckoo search algorithm (CSA) [13], differential evolution algorithm (DE) [14], simulated annealing (SA) [15], evolutionary programming (EP) [16], harmony search algorithm (HAS) [17], sine cosine algorithm [18], artificial bee colony (ABC) [19], and whale optimization algorithm (WOA) [20]. Furthermore, they are effectively employed in numerous applications as a substitute for traditional approaches. They possess the ability to achieve rapid convergence while ensuring global optimality in expansive solution domains.

Over the past twenty years, sophisticated search optimization techniques have been utilized to address OPF difficulties. Serhat et al. utilized gravitational search algorithms to address OPF issues using the IEEE 30 and 57 bus test systems, employing various objective functions. The achieved results were compared to alternative heuristic approaches [21]. Biswas et al. employed a differential evolution method that incorporated efficient handling approaches to address the OPF problem. The efficacy of the suggested approach was evaluated on IEEE 30, 57, and 118 bus systems, using diverse objective functions including cost, emission, power loss, and voltage stability [22]. Bouchekara introduced a black-hole-inspired method in [23] for solving OPF problems. The algorithm's performance was evaluated using the standard IEEE 30 bus test system and a genuine Nigerian 59 bus system. In addition, Taher et al. introduced an adapted shuffle frog leaping algorithm to address a multi-objective optimal power flow problem, taking into account the cost associated with emissions. The efficacy of the suggested method was assessed using the IEEE 30 bus test system [24]. A novel adaptive group search optimization technique was proposed to address the optimization of multi-objective functions, taking into account the total emission, operation cost, and N-1 security index. The technique was tested and confirmed using the IEEE 30 and 57 bus test systems [25]. In addition, a novel adaptation of PSO was utilized to address OPF issues using the IEEE 30 bus system. Meanwhile, the findings were compared to those obtained from various intelligent search techniques, including tabu search, simulated annealing, evolutionary programming, improved evolutionary programming, and particle swarm optimization [26]. PSO was employed in [27] to address the multi-objective OPF problem while considering voltage stability restrictions. The proposed technique underwent testing on the IEEE 30, 57, and 118 bus systems. A multi-objective differential evolution technique was employed to address the OPF issue related to flexible alternating current transmission system (FACTS) devices in IEEE 30 and 57 bus systems [28].

This study utilizes the DOA [29], a recently developed nature-inspired intelligent search algorithm, to address the OPF problem. The OPF problem is a non-linear optimization problem in a power system that involves both equality and inequality requirements. The goal is to reduce power loss by controlling variables such as voltage magnitude, reactive power, and transformer tap-changer. The algorithms' efficiency and reliability are demonstrated using the IEEE 14 and 30 bus systems. In addition, the results obtained from the proposed method are compared to those acquired from three other widely recognized intelligent search algorithms, namely GA, PSO, and WOA. The paper is structured into five distinct sections. The subsequent section outlines the problem formulation for minimizing losses and provides an explanation of the associated constraints. Furthermore, Section 3 offers a concise overview of the Department of Administration (DOA) and its operational protocols. The simulation results and discussions are presented in Section 4, whereas the conclusion is situated in Section 5.

2. MATERIALS AND METHODS

2.1. Objective function

The main aim of this research study is to address OPF difficulties in transmission systems by optimizing objective functions to find the best control variables, while ensuring that all constraints are met. The aim function is to minimize real power loss, which can be represented as follows:

$$\text{Minimize } f_i(x,u) \quad i = 1,2,...,N_{obj}, \tag{1}$$

$$\text{Subject to } g(x,u) = 0, h(x,u) \le 0. \tag{2}$$

where,

- f_i denotes the function of the objective i,
- N_{obj} denotes the amount of objective function,
- g denotes the equality constraints,
- h denotes the inequality constraints,
- x denotes the of dependent variables vector, and
- u denotes the independent variables vector.

2.2. Power loss formulation

Power losses are inevitable in a power system during its operation, and the cost of the generated electricity rises in proportion to the increase in active power losses. The core objective of this study is to reduce the amount of real power that is lost in transmission networks. Additionally, the active power loss can be ascertained by analyzing the power transfer between two bus systems, as seen in Fig. 1.

Line current I_{ik} is measured at bus i and considered as positive position and it can be formulated as:

$$I_{ik} = I_l + I_{i0} = y_{ik}(V_i - V_k) + y_{i0}V_i, \tag{3}$$

Similarly, line current I_{ki} is measured at bus k and considered ad positive position and it can be given by:

$$I_{ki} = -I_l + I_{k0} = y_{ik}(V_k - V_i) + y_{i0}V_k, \tag{4}$$

The apparent power from bus i to bus k and from bus k to bus i is expressed as:

$$S_{ik} = V_i I_{ik}^*, \tag{5}$$

$$S_{ki} = V_k I_{ki}^*, \tag{6}$$

As a result, the loss measured between two buses can be obtained by algebraic sum of power flow.

$$S_{loss} = S_{ik} + S_{ki}. \tag{7}$$

The aggregate power dissipation in a system is calculated by adding up all the power transfers inside the system. The power loss in the slack bus can be determined by adding up the power flow across the terminated bus [30]. Reactive power loss is disregarded in this paper, resulting in the objective function of reducing total real power loss as follows:

$$F_{Loss} = real\left(\sum_{i=1}^{n} S_{i\ loss}\right) \tag{8}$$

In this context, n is the bus branches' amount, and S_{loss} is the sum of complex power loss.

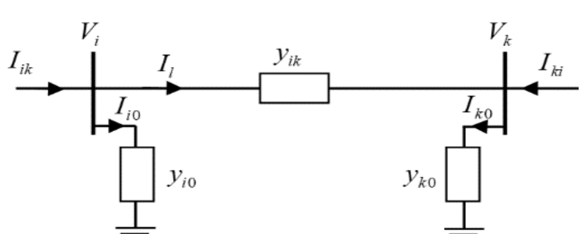

Fig. 1. Power flow diagram between two buses.

2.3. System variable constraints

The system variable constraints contain inequality restrictions of active power injection (P_i), imaginary power injected (Q_i), magnitude of the bus voltage ($|V_i|$), and transformer tap-changer position (T_i). The variables undergo optimization and their values are constrained by the given constraints during the optimization process. The system variable restrictions are expressed in the following manner:

$$P_{i\min} \le P_i \le P_{i\max}, \tag{9}$$

$$Q_{i\min} \le Q_i \le Q_{i\max}, \tag{10}$$

$$\left|V_{i\min}\right| \le \left|V_i\right| \le \left|V_{i\max}\right|, \tag{11}$$

$$T_{i\min} \le T_i \le T_{i\max}. \tag{12}$$

2.3. Power balance constraints

The optimal power flow problem must satisfy the system power flow equations, which can be represented as follows:

$$P_{G,i} - P_{D,i} - P_{L,i} = 0, \tag{13}$$

$$Q_{G,i} - Q_{D,i} - Q_{L,i} = 0. \tag{14}$$

where,

$P_{G,i}, Q_{G,i}$ are active and imaginary power generation at bus i,

$P_{D,i}, Q_{D,i}$ are active and imaginary demands at bus i,

$P_{L,i}, Q_{L,i}$ are real and imaginary power loss at bus i.

3. DINGO OPTIMIZER ALGORITHM

Canis lupus dingo is the scientific name for the dog commonly referred to as the dingo. They are social, intelligent, and skilled predators. Moreover, dingoes hunt in packs of 12 to 15 [29]. Throughout their daily existence, dingoes communicate using the various sensory capabilities of the air. In addition, dingoes produce auditory feedback as a means of exchanging information with others in order to establish the DOA process's shared community details. Exploration and exploitation are the two most important aspects of the optimization process. During the exploration phase, numerous potential solutions are targeted in the search spaces. In addition, exploitation enables the search for optimal solutions within the search space provided.

3.1. Mathematical Model

The mathematical formulation of encircling, searching, and attacking the prey of the DOA is described in this section.

$$\overrightarrow{D_d} = \left|\vec{A} \cdot \overrightarrow{P_P}(x) - \vec{P}(i)\right|, \tag{15}$$

$$\vec{P}(i+1) = \overrightarrow{P_P}(i) - \vec{B} \cdot \vec{D}(d), \tag{16}$$

$$\vec{A} = 2 \cdot \overrightarrow{a_1}, \tag{17}$$

$$\vec{B} = 2\vec{b} \cdot \overrightarrow{a_2} - \vec{b}, \tag{18}$$

$$\vec{b} = 3 - \left(I * \left(\frac{3}{Max.Iteration}\right)\right). \tag{19}$$

where,

$\overrightarrow{D_d}$ is distance between the prey and dingo,

$\overrightarrow{P_p}$ is the prey's position vector,

$\vec{P}$ is the dingo's position vector,

$\vec{A}$ is the coefficient vector,

$\vec{B}$ is the coefficient vector,

$\vec{a}_1$ is the random vector in [0,1],

$\vec{a}_2$ is the random vector in [0,1],

$\vec{b}$ is the linearly decrement from 3 to 0 at every position,

I is 1,2,3,……, $I_{\max}$,

Max.Iteration is the maximum numbers of the iterations.

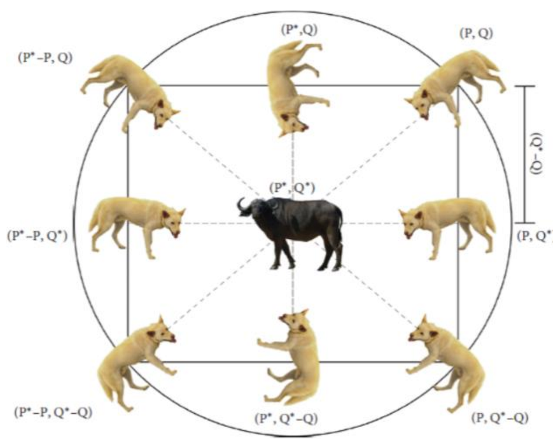

Fig. 2. Vectors of dingoes' position in 2D [29].

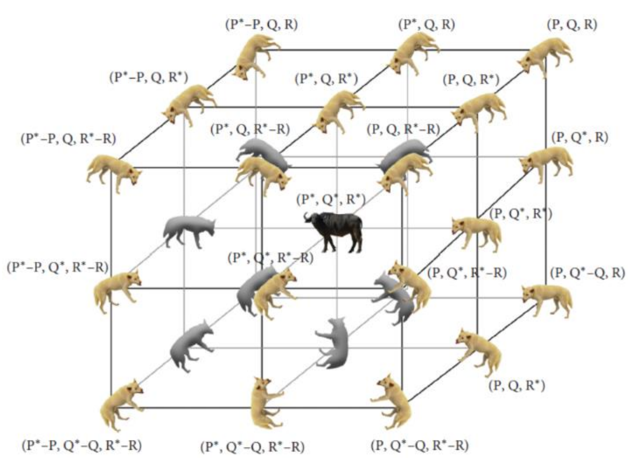

Fig. 3. Vectors of dingoes' position in 3D [29].

Dingoes share information and location to encircling the prey as shown in Fig. 2. The prey is located in position (P^*,Q^*) and a dingo can update its position to location (P^*,Q^*). All the possible location are determined around the best agent by changing the values of vector $\vec{A}$ and $\vec{B}$. Also, Figure 3 illustrates the clear explanation in 3D space how random vector $\vec{a}_1$ and $\vec{a}_2$ enable the dingoes to enter in any location between the points. In search space, the agent conceptually doesn't have the calculation the position of the prey known as the optimal point. Hence, the alpha, beta, and other dingoes in the pack are assumed to have good knowledge about potential location of the prey.

The alpha dingo always commands to hunt with the participation of beta and other dingoes sometimes. As a result, the first two best values have been achieved so far. Other dingoes need to update their position randomly and compute the position of their prey, as illustrated in Fig. 4. The mathematical formulation and equation of the process are expressed in the following:

$$\vec{D}_\alpha = \left|\vec{A}_1 \cdot \wedge\vec{P}_\alpha - \vec{P}\right|, \tag{20}$$

$$\vec{D}_\beta = \left|\vec{A}_2 \cdot \wedge\vec{P}_\beta - \vec{P}\right|, \tag{21}$$

$$\vec{D}_o = \left|\vec{A}_3 \cdot \wedge\vec{P}_o - \vec{P}\right|, \tag{22}$$

$$\vec{P}_1 = \left|\vec{P}_\alpha \cdot \vec{B} - \vec{D}_\alpha\right|, \tag{23}$$

$$\vec{P}_2 = \left|\vec{P}_\beta \cdot \vec{B} - \vec{D}_\beta\right|, \tag{24}$$

$$\vec{P}_3 = \left|\vec{P}_o \cdot \vec{B} - \vec{D}_0\right|. \tag{25}$$

The intensity of each dingo can be calculated as described in the following equations.

$$\vec{I}_\alpha = \log\left(\frac{1}{F_\alpha - (1E - 100)} + 1\right), \tag{26}$$

$$\vec{I}_\beta = \log\left(\frac{1}{F_\beta - (1E - 100)} + 1\right), \tag{27}$$

$$\vec{I}_o = \log\left(\frac{1}{F_o - (1E - 100)} + 1\right). \tag{28}$$

where,

F_α is the alpha dingo's fitness value,

F_β is the beta dingo's fitness value,

F_o is other dingoes' fitness value.

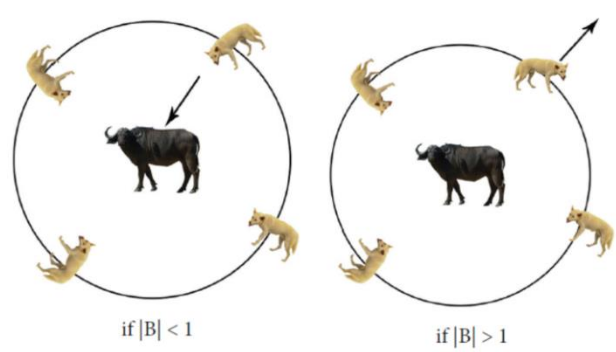

Fig. 4. Vector position of dingo for hunting prey [29].

Dingoes attack the prey to finish the hunting when there is no update of the positions in search space. They mostly hunt the prey based on the location of the pack by traveling forward for hunting and striking the predators. is applied to the random values. If it is less than -1, it means that the prey is moving away from the search agents. However, if it is greater than 1, the pack will go nearer to the prey.

3.2. Proposed algorithm

DOA algorithm for solving the optimization problem has the several processes as described in the following steps.

Input: the population of dingo $D_n (n = 1, 2, ..., n)$

Output: the best dingo position

1. Generate initial search agents D_{in}
2. Initiate the value of $\vec{b}$, $\vec{A}$, and $\vec{B}$
3. **While** Termination condition does not reach do
4. Evaluate each dingo's fitness and intensity cost
5. $D_\alpha =$ Dingo with the best search
6. $D_\beta =$ Dingo with the second-best search
7. $D_o =$ Dingo search result afterward
8. Iteration1
9. Repeat
10. **For** i=1: D_{in} do
11. Renew the latest search agent status
12. **End for**
13. Estimate the fitness and intensity cost of dingoes
14. Record the values of $S_\alpha, S_\beta, S_\delta$
15. Record the values of $\vec{b}$, $\vec{A}$, and $\vec{B}$
16. Iteration = Iteration + 1
17. Check if Iteration $\geq$ Stopping criteria
18. Output
19. **End while**

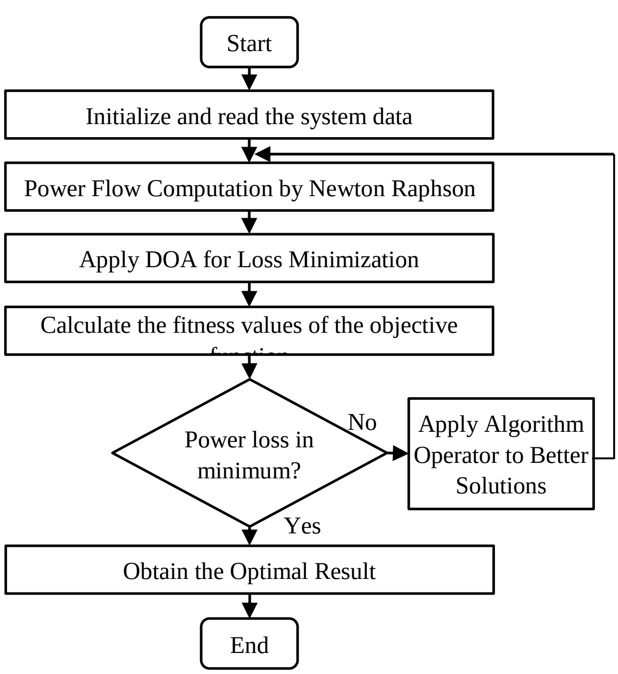

Fig. 5. Flowchart of the proposed algorithm.

In this research paper, the DOA algorithm is applied mainly for solving OPF problems for computing the optimal values of real and reactive power injection, power transformer tap-changer position, and bus voltage magnitude, while active power loss minimization is the objective function. Fig. 5 illustrates the flowchart of DOA for solving the specified OPF problems.

4. RESULTS AND DISCUSSIONS

In this section, the IEEE 30 and 14 bus test systems were employed in order to verify the effectiveness and performance of the proposed methods. Transmission system with a 230kV system voltage and a 100MVA base applied to the proposed algorithm. Moreover, to compare the accuracy of the algorithm, four well-known methods of optimization techniques, comprising GA, PSO, WOA, and DOA, were applied to solve the problems. Furthermore, the proposed algorithms were implemented in 2014a, and the tested cases were simulated using the same computer, which was a Core i5-6200U with 8GB of memory. All four algorithms were set to the same value for the population and iteration in order to compare their efficiency and robustness. In addition, the maximum and minimum voltage of the generator bus were limited from 0.95 to 1.05 p.u. for controlling the voltage level in the standard range, while the tap changer of the power transformer was considered from 0.9 to 1.1 p.u. Furthermore, all the methods were tested with 30 trials to get the maximum, minimum, and optimal values.

4.1. 14 bus system

In this section, 14 bus standard-tested systems were employed with the proposed algorithm, as shown in [31]. Bus 1 and 2 are the slack and voltage-controlled buses, respectively, while the others are load buses. Moreover, buses 3, 6, and 8 are the locations for installing the reactive power compensator. In addition, the tested system has three power transformers with five tap changers, which are located in the branches 4-7, 4-9, 5-6, 7-8, and 7-9.

Table 1. Controlled variables of 14 bus system

Controlled variables		Limitations	
		Min	Max
Generator (MW)	*P*	10	60
Reactive power (MVar)	*Q*	0	40
Bus voltage (p.u.)	*V*	0.95	1.05
Tap-changer (p.u.)	*T*	0.9	1.1

Table 2. Parameters setting values of each method of 14 bus system

Parameters	Algorithms			
	GA	PSO	WOA	DOA
Population	50	50	50	50
Max. iteration	200	200	200	200

Table 3. Simulated result comparison of 14 bus system

Methods	Before (MW)	After (MW)			Computed time (s)
	Loss	Loss	Saving	Deduction (%)	
GA	14.72	12.73	1.99	13.51	352.83
PSO		12.75	1.95	13.24	407.34
WOA		12.72	2	13.58	240.43
DOA		12.71	2.01	13.65	188.46

Table 4. The optimal solutions by the different algorithms of 14 bus system

Controlled variables		GA			PSO			WOA			DOA		
		Max	Min	Opt.	Max	Min	Opt.	Max	Min	Opt.	Max	Min	Opt.
Generator (MW)	P2	59.92	59.24	59.61	59.20	58.67	58.94	59.96	59.79	59.90	59.98	59.85	59.96
Bus voltage (p.u.)	V1	1.05	0.98	1.03	1.03	1.00	1.01	1.03	1.01	1.03	1.05	1.03	1.04
	V2	1.06	0.99	1.02	1.02	0.99	1.00	1.02	0.99	1.03	1.06	1.04	1.05
Reactive power (MVar)	Q3	12.40	9.67	10.72	14.43	12.56	13.11	14.43	12.56	11.49	10.83	12.17	11.45
	Q6	34.76	32.50	33.50	34.68	33.40	33.84	34.68	33.40	32.99	39.32	37.68	38.10
	Q8	21.43	19.67	20.43	17.87	14.45	16.80	17.87	14.45	20.21	15.43	13.75	14.10
Tap-changer (p.u.)	T(4-7)	1.1	1.08	1.09	1.09	1.07	1.08	1.09	1.07	1.1	1.1	1.08	1.1
	T(4-9)	1.1	1.09	1.1	1.02	0.99	1.01	1.02	0.99	1.07	1.1	1.09	1.1
	T(5-6)	1.09	1.08	1.09	1.07	1.03	1.05	1.07	1.03	1.1	1.1	1.08	1.1
	T(7-8)	1.06	1.05	1.05	1.04	1.00	1.02	1.04	1.00	1.05	1.07	1.05	1.06
	T(7-9)	1.09	1.07	1.09	1.09	1.07	1.07	1.09	1.07	1.1	1.1	1.08	1.1
Real Power loss (MW)		12.74	12.73	12.73	12.75	12.74	12.74	12.74	12.71	12.72	12.72	12.71	12.71
Loss Saving (MW)		1.98	1.99	1.99	1.97	1.98	1.98	1.98	2.01	2	2	2.01	2.01
Computed Time (s)		380.45	335.67	355.77	435.56	385.45	407.45	265.45	237.69	252.67	203.56	167.54	188.46

Table 5. Controlled variable constraints of 30 bus system

Controlled variables		Limitations	
		Min	Max
Generator (MW)	*P*	20	80
Reactive power (MVar)	*Q*	0	50
Bus voltage (p.u.)	*V*	0.95	1.05
Tap-changer (p.u.)	*T*	0.9	1.1

Table 6. Parameters settings of each method of 30 bus system

Parameters	Algorithms			
	GA	PSO	WOA	DOA
Population	100	100	100	100
Max. iteration	350	350	350	350

Table 7. Simulated result comparison of 30 bus system

Methods	Before (MW)	After (MW)			Computed time (s)
	Loss	Loss	Saving	Deduction %	
GA	6.50	1.70	4.80	73.84	2303.37
PSO		1.72	4.78	73.53	2505.76
WOA		1.67	4.83	74.30	1682.98
DOA		1.66	4.84	74.46	1306.65

Table 1 describes the limitations and controlled variables applied in the algorithms; also, the real and reactive power injection are limited from 10 to 60 MW and 0 to 40 MVAR, respectively. Meanwhile, Table 2 shows the values of the setting parameters for 14 bus systems. Each method was set at 50 and 200 population and maximum iterations, respectively.

The simulated results of the four methods are illustrated in Table 3. It was observed that the power loss before the optimization implementation was 14.72 MW. After the optimization, the losses were 12.73MW, 12.75MW, 12.72MW, and 12.71MW, which were obtained from GA, PSO, WOA, and DOA, respectively. The loss savings from GA, PSO, WOA, and DOA were respectively 1.99 MW, 1.97 MW, 2 MW, and 2.01 MW.

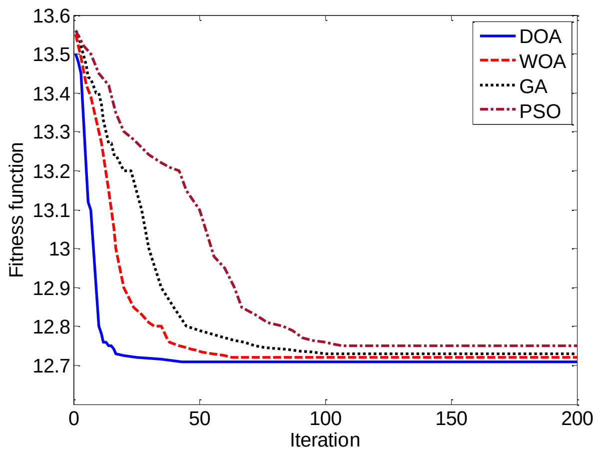

Fig. 6. 14 bus system's convergence characteristics.

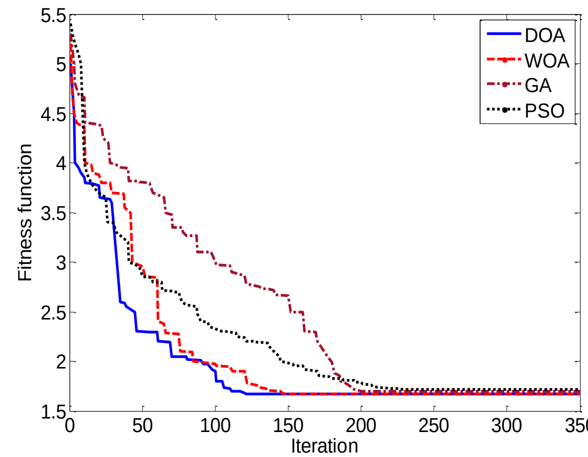

Fig. 7. 30 bus system's convergence characteristics.

It was observed that DOA provided the highest loss savings of the three compared methods. Moreover, DOA could achieve convergence with less computation than the compared methods. All of the optimum values of the controlled parameters were found to be within the limitation.

Table 8. The optimal solutions by the different algorithms of 30 bus system

Controlled variables		GA			PSO			WOA			DOA		
		Max	Min	Opt.	Max	Min	Opt.	Max	Min	Opt.	Max	Min	Opt.
Units (MW)	P2	33.49	33.40	33.46	32.07	32.03	32.04	33.48	33.41	33.45	35.17	35.03	35.06
	P5	75.80	75.70	75.74	77.84	77.67	77.77	75.79	75.75	75.77	79.98	79.81	79.88
	P8	39.69	39.65	39.67	38.54	38.43	38.51	39.66	39.66	39.66	35.07	34.96	35.04
	P11	79.95	79.85	79.90	79.87	79.59	79.78	79.90	79.86	79.87	80.02	79.92	79.95
	P13	53.15	53.10	53.13	53.87	53.80	53.85	53.15	53.11	53.12	51.81	51.11	51.29
Bus voltage (p.u.)	V1	1.05	1.05	1.05	1.05	1.02	1.03	1.05	1.05	1.05	1.01	0.99	1.00
	V2	1.01	0.99	1.00	1.02	1.01	1.01	1.01	1.00	1.00	1.05	1.01	1.03
	V5	1.06	1.04	1.05	1.02	1.01	1.01	1.04	1.04	1.04	1.03	1.01	1.02
	V8	1.03	1.01	1.02	1.06	1.04	1.05	1.02	1.02	1.02	1.01	1.00	1.01
	V11	1.05	1.04	1.04	1.00	1.00	1.00	1.05	1.04	1.04	1.05	1.01	1.03
	V13	1.06	1.04	1.05	1.06	1.04	1.05	1.06	1.05	1.05	1.03	1.03	1.03
Reactive power (MVar)	Q10	7.59	7.49	7.53	29.86	29.83	29.85	7.57	7.51	7.54	18.62	18.23	18.54
	Q12	38.01	37.90	37.95	21.35	21.01	21.09	37.98	37.93	37.94	45.38	45.03	45.27
	Q15	3.85	3.83	3.84	1.76	1.72	1.74	3.85	3.83	3.84	6.23	6.08	6.12
	Q17	4.50	4.37	4.43	13.86	13.81	13.84	4.48	4.45	4.46	6.88	6.80	6.85
	Q20	5.53	5.50	5.52	5.01	5.01	5.01	5.52	5.50	5.51	5.75	5.64	5.69
	Q21	13.79	13.70	13.74	1.44	1.35	1.42	13.75	13.72	13.73	11.60	11.45	11.47
	Q23	1.78	1.71	1.75	3.55	3.47	3.50	1.77	1.73	1.76	1.85	1.81	1.84
	Q24	7.95	7.90	7.93	8.14	8.10	8.11	7.92	7.90	7.91	9.15	9.03	9.08
	Q29	3.72	3.69	3.71	4.18	4.12	4.13	3.70	3.70	3.70	3.74	3.70	3.72
Tap-changer (p.u.)	T(1-9)	1.10	1.08	1.09	1.09	1.09	1.09	1.10	1.08	1.09	1.12	1.02	1.04
	T(6-10)	1.10	1.08	1.09	1.09	1.08	1.09	1.10	1.08	1.09	1.01	1.00	1.00
	T(4-12)	1.10	1.08	1.09	1.07	1.07	1.07	1.09	1.09	1.09	1.06	1.01	1.03
	T(27-28)	1.10	1.08	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.08	1.02	1.04
Real Power loss (MW)		1.71	1.70	1.70	1.73	1.72	1.72	1.68	1.66	1.67	1.67	1.66	1.66
Loss Saving (MW)		4.79	4.80	4.80	4.77	4.78	4.78	4.82	4.84	4.83	4.83	4.84	4.84
Computed Time (s)		2376.8	2270.7	2307.5	2425.4	2350.6	2406.9	1753.2	1642.4	1704.3	1367.4	1278.7	1303.5

Besides, the optimal real power injected was in bus 2, while the reactive power was located in buses 3, 6, and 8.

The convergence characteristics of each method of the 14-bus system were described in Fig. 6, and it was shown that DOA has better convergence with the fastest reach, followed by WOA, GA, and PSO in terms of iterations.

4.2. 30 bus system

The last tested system is the 30 bus system, as illustrated in [31]. It has a slack bus, five generator buses, and 24 load buses with 41 branches. Bus 1 is considered the slack bus, while buses 2, 4, 5, and 6 are the generator buses. Furthermore, the controlled variables and their limitations applied in the algorithm are shown in Table 5.

Table 6 shows the values of the setting parameters for 30 bus systems. The population of search agents was set at 100, while the maximum iteration was set at 350. The reactive power installations are located on buses 10, 12, 15, 17, and 20, 21, 23, 24, and 29, while the power transformer tap changer is located on branches 6-9, 6-10, 4-12, and 27-28. The size of the generator and reactive power are considered to be between 20 and 80 MW and 0 and 50 MVAR, respectively. Furthermore, the voltage magnitude of the generator bus is limited to 0.95 to 1.05 p.u. with a 5% tolerance.

The simulated results of each method are shown in Table 7. It was noticed that the total real power loss before the OPF implementation was 6.50 MW, while the loss after optimization was 170 MW, 1.72 MW, 1.67 MW, and 1.66 MW, which were obtained respectively from GA, PSO, WOA, and DOA. As a result, DOA could provide the highest loss savings, followed by WOA, GA, and PSO, respectively. DOA also reached optimal results with the fastest computation time. Table 8 describes the optimal results of the 30 bus system, and it was observed that all the optimal values with 30 iterations running of the controlled variables are within the limitation. In Fig. 7, the characteristics of how each method of the 30 bus system converges were shown. It was shown that DOA converges the fastest, followed by WOA, GA, and PSO in terms of how many times the method is run.

5. CONCLUSIONS

This work introduces methods for addressing optimal power flow problems, specifically focusing on the mitigation of real transmission power losses. To facilitate comparison, four algorithms, namely GA, PSO, WOA, and DOA, were employed to address the single objective problem. The algorithms were utilized on the IEEE 14 and 30 bus systems to showcase their performance and effectiveness. The attained outcomes were examined against each method, showcasing that the current power loss has been minimized in conjunction with the manageable variables. Furthermore, it is worth noting that DOA is the most efficient approach for resolving OPF, as it has the capability to generate substantial cost reductions within a minimal timeframe.

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