Multi-Objective Ant Lion Optimizer for Congestion Management and Real-Power Rescheduling in Power Systems

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Abstract: - This paper presents the congestion management problem in electrical networks during power line outages and overloads on other lines. The study focuses on congestion management in the IEEE 30 bus system and modifies the IEEE 30 bus system by applying a model for congestion management pricing, incorporating data from both transmission lines and generators. The research proposes a Multi-Objective Ant Lion Optimizer (MOALO) method to solve single and multi-objective optimization problems to find a solution for management pricing, comparing results with other research methods to show the effectiveness of the applied approach and the mathematical model representing congestion management.

Key-Words: - Congestion management; Generator rescheduling; Cost minimization; management pricing; Ant Lion Optimizer; Optimal power flow.

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1 Introduction

Electricity market issues have gained attention in studies by market liberation from monopoly, [1]. Researchers have developed mathematical models to control production prices through supply and demand, such as the widely used economic dispatch (ED), which controls production prices based on the energy of each production unit and the price per Megawatt, [2], [3].

However, economic dispatch (ED) remains limited as it doesn’t consider the carefully planned electrical network, including transmission lines' capacities and voltage limits in each bus. To address this, the economic dispatch model is introduced within the optimal power flow (OPF), [4], [5], [6]. Due to various things affecting power transmission lines, such as overloads and outages, this impacts the power flow in the system. Researchers introduce a model for congestion management (CM) to find a solution for outages and overloads by setting limits on each transmission line (Figure 1 and Figure 2), along with the increment and decrement prices for each generator experiencing production changes, [7].

Transmission congestion is a phenomenon that occurs in electricity markets. It happens when scheduled transactions on the market (production and load) result in a power flow on a transmission element exceeding its available capacity.

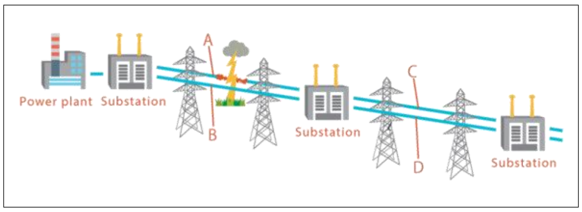

Fig.1: Outage on transmission line

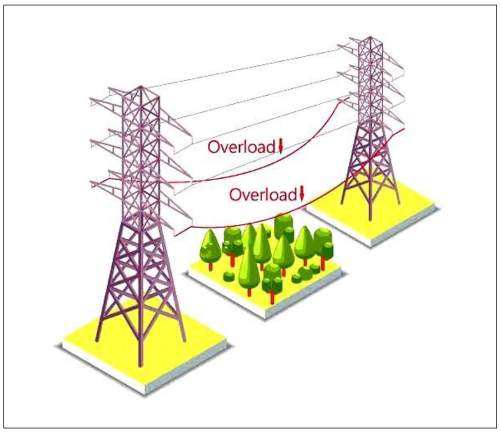

Fig.2: Overload in transmission line

To prevent physical overloads, network managers distribute production to avoid them. Its component is known as the marginal cost of transmission congestion from one node to another, [8].

For instance, any outage on one line will inevitably lead to increased load on other lines, exceeding energy limits and creating additional problems. Congestion management in electrical networks is crucial for efficiently managing power production units without introducing costly solutions, considering the existing constraints through a mathematical model to minimize the congestion management cost, [9].

There are many conventional optimization methods used for managing congested electrical power systems and congestion management in power markets. Authors made a review for some literature on Congestion Management in Power System [10], and for this problem, many techniques and optimization methods are used, like Particle Swarm Optimization (PSO) [11], [12], [13], Genetic Algorithm (GA) [14], and NSGA-II [15], and literature uses Unified Power Flow Controllers (UPFC) and Flexible Alternating Current Transformer System (FACTS) device for management of congestion [16], [17] to minimize costs of generation and relieve congestion systems. In [18], (PSO) has been used for real power when the fitness function of congestion management is described by the collection of objectives and with large penalty factors. In [19], the precedent fitness function has been used by the application of the Novel Satin Bowerbird Optimization Algorithm (SBO), by the Firefly algorithm (FFA) in [20], and by the Teaching-Learning-Based Optimization algorithm (TLBO) in [21]. The congestion management problem has been given an optimal solution by using the Pareto Optimal Front [22] to minimize the congestion management cost and the electrical losses with the application of the Evaporation Rate Water Cycle Optimization Algorithm (ERWCA).

2 Congestion Phenomenon in Transmission Networks

Transmission congestion is a phenomenon that occurs in electricity markets. It happens when scheduled transactions on the market (production and load) result in power flow on a transmission line exceeding its available capacity, [23]. To prevent physical overloads, network managers distribute production to avoid them. Its component is known as the marginal cost of transmission congestion from one node to another, [8].

2.1 Transit Limits Imposed on Transmission Network Facilities

In transmission networks, limits on the maximum power that can transit on a line may be imposed based on [24]:

- Thermal limits: For "short" lines (< 80 km), thermal limits are encountered first. The current flowing through the conductors causes heating (Joule effect), which, in case of heavy overload, can damage the conductors.
- Voltage limits: Voltage limits are more restrictive for "medium-length" lines (between 80 and 250 km) than thermal limits. The higher the active power flowing through these lines, the more a voltage drop phenomenon due to line impedance is observed. In critical cases, this can lead to a voltage collapse at the end of the line, requiring load shedding. These collapses can also lead to the loss of the entire network (blackout).
- Synchronism stability limits: These constraints appear for long lines (> 250 km). Disturbances on the network (loss of a generator, fault, etc.) can cause oscillations between two production centers connected by a long line. If these oscillations are not dampened, they can lead to line tripping.

2.2 Liberalized Markets Facing Network Limits

The development of large transmission networks was, until recently, ensured by national monopolies adapting their production facilities and strengthening their networks according to long-term consumption forecasts. Networks designed in a "monopolistic" logic were well-suited to the domestic market and known imports/exports, [25]. However, the liberalization of the electricity sector led to the internationalization of exchanges and the entry of new players into the market. This significantly changes the distribution of power transits on the network, making them more unpredictable and ultimately pushing a network, not yet adapted to this change, closer to its limits. This situation may arise where market demands, seeking networks to operate as "copper plates," clash with the physical realities of network operation, [26], [27].

3 Problem formulation

3.1 Objective Function

The main objective of this work is to minimize the congestion management cost by considering some constraints. The objective function of the problem is formulated as in equation (1):

$$FF = MC + pf_1 * \sum_{i,j \in n} (L_{ij} - L_{ij\max}) \quad (1)$$

$$MC = \sum_{i \in ng} (C_k.\Delta P_i^+ + D_k.\Delta P_i^-), \qquad and \quad \Delta P_i = P_i - P_i^* \quad (2)$$

$$L_{ij} = G_{ij} V_i \left[V_i - V_j \cos(\delta_i - \delta_j) \right] - V_i V_j B_{ij} \sin(\delta_i - \delta_j) \quad (3)$$

Subject to the following constraints:

$$\sum_{i=1}^{N} P_i = D + L \quad (4)$$

$$P_{i\min} \le P_i \le P_{i\max} \quad (5)$$

$$L_{ij} \le L_{ij\max} \quad (6)$$

$$V_{n\min} \le V_n \le V_{n\max} \quad (7)$$

Where:
P_i: real power generation of generator *i*.
P_i^*: real power generation of generator *i*.
ΔP_i^+: active power increment of generator *i*.
ΔP_i^-: active power decrement of generator *i*.
L_{ij}: power flow in line (*i-j*).
$L_{ij\,max}$: maximum power flow limit in line (*i-j*).
D: Total demand (MW);
L: Transmission losses (MW);
P_i^{min}, P_i^{max}: The power limits of generator *i* (MW);
V_n: Voltage of bus *n* (MW)
V_n^{min}, V_n^{max}: The voltage limits of bus *n* (MW);
Pf_1: penalty factor taken from the simulation procedure, [19].

4 Multi-Objective Ant Lion Optimizer Methodology

The Multi-Objective Ant Lion Optimizer (MOALO) was developed in 2016 by [28]. This is an updated version of the Ant Lion Optimizer (ALO), which was first introduced by [29] in 2015. A stochastic method of Ant Lion Optimizer (ALO) was developed in response to ant lion hunting behavior, [29] (Figure 3).

4.1 Ant Lion Optimization

In Figure 4, the ants, representing the prey, are defined by the Mant matrix of size *n*×*d* (Equation (8)). These ants move randomly in the search space using equation (8). Their random movements are influenced by the traps set by ant lions, as described in equations (10-12). It is assumed that these antlions also hide somewhere in the search space, with their positions considered to be the best positions that provide optimal fitness values. The antlions are represented by the Mantlion matrix of size *n*×*d* (Equation (9)), where MOAL in (Equation (10)) is the matrix for saving the fitness of each antlion.

$$M_{OA} = \begin{bmatrix} f\left(\left[A_{1,1}, A_{1,2}, \ldots, A_{1,d}\right]\right) \\ f\left(\left[A_{1,1}, A_{1,2}, \ldots, A_{1,d}\right]\right) \\ \vdots \\ \vdots \\ f\left(\left[A_{1,1}, A_{1,2}, \ldots, A_{1,d}\right]\right) \end{bmatrix} \quad (8)$$

$$M_{\text{Antlion}} = \begin{bmatrix} AL_{1,1} & AL_{1,2} & \cdots & \cdots & AL_{1,d} \\ AL_{1,1} & AL_{2,2} & \cdots & \cdots & AL_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ AL_{n,1} & AL_{n,2} & \cdots & \cdots & AL_{n,d} \end{bmatrix} \quad (9)$$

$$M_{OAL} = \begin{bmatrix} f\left(\left[AL_{1,1}, AL_{1,2}, \ldots, AL_{1,d}\right]\right) \\ f\left(\left[AL_{1,1}, AL_{1,2}, \ldots, AL_{1,d}\right]\right) \\ \vdots \\ \vdots \\ f\left(\left[AL_{1,1}, AL_{1,2}, \ldots, AL_{1,d}\right]\right) \end{bmatrix} \quad (10)$$

4.1.1 Ants' Random Walks

The ALO algorithm emulates the interplay observed among lion ants and regular ants within the trap scenario. In these interaction models, ants are mandated to traverse the search space, while other ants are sanctioned to pursue and enhance their fitness using traps. Given the stochastic nature of ant movement during food foraging in nature, a random walk is selected as the modeling approach for ant locomotion, wherein:

$$X(t) = \left[0, cumsum(2r(t_1) - 1), \begin{matrix} cumsum(2r(t_2) - 1), \\ \ldots, cumsum(2r(t_T) - 1) \end{matrix} \right] \quad (11)$$

Where *consumer* calculates the cumulative sum, *n* is the maximum number of iterations, *t* represents the step size or random iteration, and *r(t)* is a stochastic function defined as follows:

$$r(t) = \begin{cases} 1 & if \;\; rand > 0.5 \\ 0 & if \;\; rand \le 0.5 \end{cases} \quad (12)$$

And rand is a randomly generated number with a uniform distribution in the interval [0,1].

4.1.2 Ant Random Walks

Random walks are all based on equation (13). Ants update their position X^t_i with a random walk at each optimization step, normalized using the following equation (min-max normalization) to keep them within the search space:

$$X_i^t = \frac{\left(X_i^t - a_i\right) \times \left(d_i - c_i^t\right)}{\left(d_i^t - a_i\right)} + c_i \tag{13}$$

a_i: is the random walk minimum of i^{th} variable;
b_i: is the random walk maximum in i^{th} variable;
c_i^t: is the i-th variable minimum at t^{th} iteration;
d_i^t: indicates the i-th variable maximum at t^{th} iteration;

4.1.3 Trapping in Pits of Antlion

Ants traverse a hyper-sphere defined by vectors c and d around a selected ant lion, influenced by ant lion traps. To mathematically model this assumption, the following equations are proposed:

$$c_i^t = Antlion_j^t + c^t \tag{14}$$

$$d_i^t = Antlion_j^t + d^t \tag{15}$$

Where:
c^t: is the minimum of all variables at t^{th} iteration;
d^t: indicates the vector including the maximum of all variables at t-th iteration;
c^t_i: is the minimum of all variables for i^{th} ant,
d^t_i: is the maximum of all variables for i^{th} ant
$Antlion^t_j$: the position of the selected j^{th} ant lion at t^{th} iteration.

4.1.4 Building Trap

A roulette wheel is employed to select ant lions based on their fitness during optimization to model their hunting capability. Ants are assumed to be trapped in a single selected ant lion. This mechanism provides higher chances for more fit ant lions to capture ants.

4.1.5 Sliding Ants Towards Antlion

Once the ant lions realize that an ant is in the trap, they pull sand outward toward the center of the pit. This behavior slides down the trapped ant attempting to escape. To mathematically model this behavior, the radius of the hyper-sphere for ant random walks is adaptively decreased. The following equations are proposed in this regard:

$$c^t = \frac{c^t}{I} \tag{16}$$

$$d^t = \frac{d^t}{I} \tag{17}$$

In equations (15) and (16), I is a ratio defined by:

$$I = 10^w \frac{t}{T}$$

Where T is the maximum number of iterations and w is a constant defined based on the current iteration. Essentially, the constant w can adjust the level of exploitation precision.

4.1.6 Catching Prey and Re-Building the Pit

To mimic the final step of the hunting process, it is assumed that prey capture occurs when ants become fitter (penetrate the sand) than their corresponding antlion, which is necessary to update its position to the last position of the hunted ant. This is defined by the following equation:

$$Antlion_j^t = Ant_i^t \ if \quad f\left(Ant_i^t\right) > Antlion_j^t \tag{18}$$

4.1.7 Elitism

In this algorithm, the best antlion obtained in each iteration is recorded and treated as elite. As the elite is the fittest antlion, it is assumed to influence the movements of all ants during iterations. Therefore, it is assumed that each ant randomly walks around an antlion selected by the roulette and the elite simultaneously, as follows:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{19}$$

Where Ant^t_i denotes the position of the i^{th} ant, R_A^t and R_E^t represent the random walk around the ant lion and the elite selected by the roulette at the t^{th} iteration. Figure 5 (Appendix) represents the ant lion optimizer flowchart and the all precedent steps.

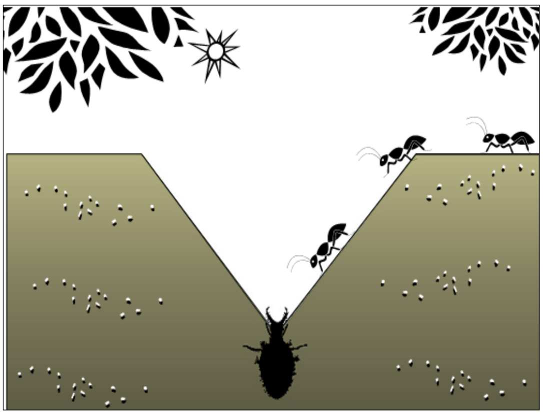

Fig. 3: Cone-shaped traps and hunting behavior of antlions, [29]

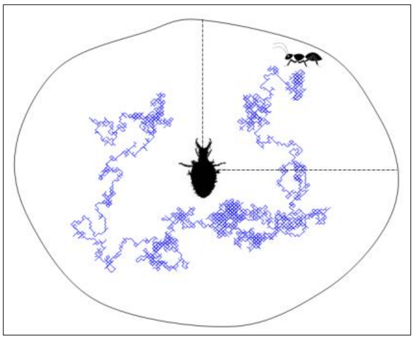

Fig. 4: An ant Random walks inside an antlion's trap, [29]

4.2 Multi-Objective Ant Lion Optimization

To make an application of Multi-Objective Ant Lion Optimization, there are two steps to choosing a solution in the archive, [28]:

First Step: the antlions are selected using the following equation from the solutions with the least populated neighborhood:

$$P_i = \frac{c}{N_i} \tag{20}$$

Where c is a constant and should be greater than 1 and N_i is the number of solutions in the vicinity of the i^{th} solution.

Second Step: when the archive is complete, the solutions with the most inhabited neighborhoods are deleted to make space for new solutions. This is done by utilizing the following equation:

$$P_i = \frac{N_i}{c} \tag{21}$$

In Figure 6, the MOALO algorithm Pseudo codes can be represented with the conditions of the algorithm.

```
while the end condition is not met
    for every ant
        Select a random antlion from the archive
        Select the elite using the Roulette wheel from the archive
        Update c and d using equations Eqs. (16) and (17)
        Create a random walk and normalize it using Eq. (11) and Eq. (13)
        Update the position of the ant using (19)
    end for
    Calculate the objective values of all ants
    Update the archive
    if the archive is full
        Delete some solutions using the Roulette wheel and Eq. (21) from the archive
        to accommodate new solutions.
    end
return while
return archive
```

Fig. 6: The MOALO algorithm Pseudo codes, [28]

5 Results and Discussions

In this paper, research has tested the Multi-Objective Ant Lion Optimizer for Congestion Management, so this approach is presented to mitigate congestion in IEEE 30 bus and modified IEEE 30 bus systems. The two networks contain 41 transmission lines and 30 buses, 6 generator units, [31]. The load in each system is 283.4 MW, with a total active and reactive power of 126.2 MVar. Values of scheduled generators and bid price of Gencos for congestion cost calculation are considered from reference, [18].

5.1 IEEE 30 Bus System

A. Case Study I: Bus 2 Carrying 250% More Load with Line (3–4) Breakdown

In this case, we test the performance of our proposed method by making a Breakdown of lines3–4, with an increase of 250% in the load on bus 2. After that, we run the power and load flow for each branch. We note that the power flow in lines1-2 becomes 191.8133 MVA when the line limit of this line is 130 MVA. The overload in lines1-2 appears in this case, so the goal is to reduce the load flow to the line limit with consideration of the main goal "Congestion management cost minimization". After the application of the proposed method, the load flow in line 1-2 was reduced to 129.9992 MVA. Table 1 presents the effectiveness of (MOALO) by comparing it with other optimization techniques like WOA, ERWCA, and ABC. The power flows in lines before and after congestion management are shown in Figure 7.

The congestion management cost is reduced to 1462.9869 $/h. We note that the total generation (MW) is 346.6535 MW and the losses are 9.2035 MW. Table 2 (Appendix) and Figure 8 present the comparison of results between the proposed method (MOALO) and other optimization techniques WOA, ERWCA, and ABC, and the real-power changing in MW are presented by Figure 9. In Figure 10, we note that the voltage magnitude respected the lower and the upper voltage.

Table 1. Congestion in line 1–2 with a comparison between different optimization techniques

Congested Line (1-2)	Line limit(MW)	Power flow after outage (MW)	Violation(MW)	Power flow after CM
MOALO	130	194.6769	64.6777	129.9992
ERWCA, [19]	130	196.638	66.638	129.205
ABC, [32]	130	196.32	66.32	128.59

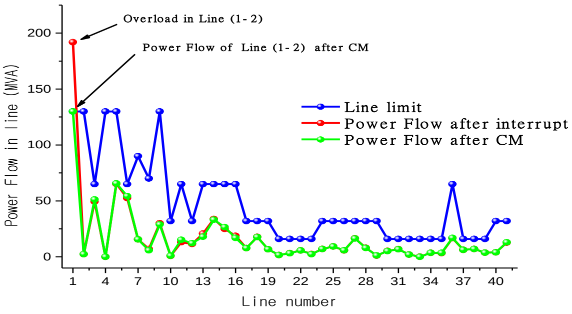

Fig. 7: Power flow in lines before and after congestion management

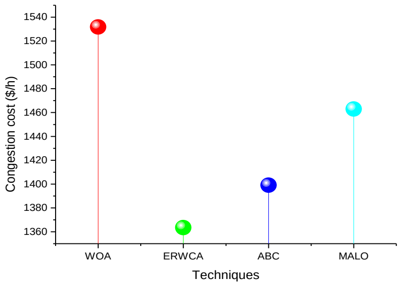

Fig. 8: Congestion cost comparison

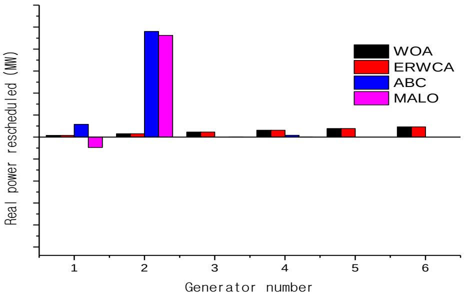

Fig. 9: Real-power change in MW

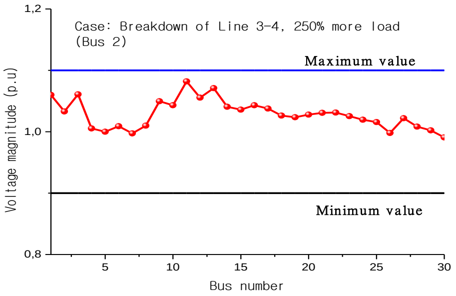

Fig. 10: Voltage magnitude in p.u

B. Case Study II: Load raising in Bus 19 by 130% with Interrupting the Line (1-3)

In this case, the line 1-3 is interrupted and raises the load at bus 19 by 130%. The power and load flow for each branch in this case was changed. In Table 3, we note that the power flow in lines1-2 becomes 173.6757 MVA when the line limit of this line is 130 MVA. The overload in lines1-2 appears too in this case. By using the proposed method, the load flow in lines1-2 was reduced to 129.9933 MVA with 43.6824 MW as a violation.

Table 3. Congestion in line 1–2 with a comparison with ABC

Congested Line (1-2)	Line limit (MW)	Power flow after outage (MW)	Violation (MW)	Power flow after CM
MOALO	130	173.6757	43.6824	129.9933
ABC [32]	130	155.66	25.66	129.95

Table 4. Congestion cost comparison obtained by MOALO and ABC

Generator number	Load raising in bus 19 by 130% with Interrupting the line (1-3)		
		ΔP	
	MOALO	ABC [32]	MOALO
P1	129.9995	8.5174	-8.5905
P2	82.0034	24.3320	24.4434
P3	24.5596	0	-0.0004
P4	35.0000	0	0
P5	17.9360	0	0.0260
P6	16.9473	0	0.0173
Total generation (MW)	306.4457	32.8494	33.0776
Congestion Cost ($/h)		656.032	669.7831
Total load (MW)	295.7500	/	/
Transmission loss (MW)	10.6957	/	/

The congestion management cost is reduced to 669.7831 $/h. We note that the total generation (MW) is 306.4457 MW and the losses are 10.6957 MW. Table 4 presents the comparison of results between the proposed method (MOALO) and ABC.

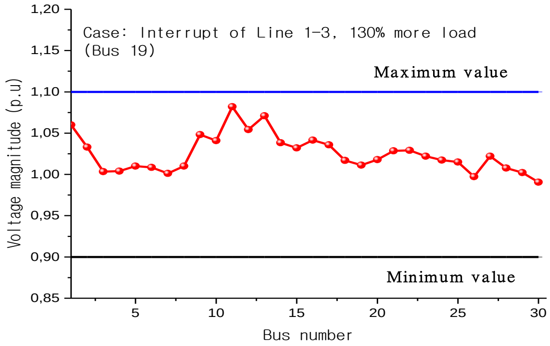

Fig. 11: Voltage magnitude in p.u

To illustrate the extent to which the model applied in this paper respects the line limits, Table 5 helps us to know this respect by seeing what happens in all the lines for the 2 cases, where we notice that line 1-2 are the only one on overload, and the applied model, with the proposed method, was able to return the load to the limit of 130 MVA. In Figure 11, we note that the voltage magnitude respected the lower and the upper voltage.

Table 5. Power flow in lines before and after congestion management

CASE 1: Bus 2 carrying 250% more load with line (3–4) breakdown			CASE 2: Load raising in bus 19 by 130% with Interrupting the line (1-3)		
Limit	Before	After	Limit	Before	After
130	**191.8133**	129.9992	130	**200.481**	129.9933
130	2.4028	2.4028	130	0	0
65	49.4587	51.2304	65	54.0414	57.3636
130	0	0	130	2.4	2.4
130	65.3021	65.6827	130	66.4951	68.8908
65	52.5477	54.3147	65	56.751	60.1205
90	15.5892	15.6215	90	14.1717	14.3667
70	6.9808	5.857	70	4.6034	2.8418
130	30.0576	28.9089	130	27.6341	25.8562
32	0.8527	0.9704	32	0.6168	0.7428
65	13.0855	15.2051	65	15.3515	18.9799
32	11.5571	12.2075	32	13.3637	14.5367
65	20.8007	17.9554	65	23.6001	18.8492
65	33.8861	33.1605	65	38.9516	37.8291
65	24.9612	26.6055	65	28.2778	31.2377
65	18.7839	16.9328	65	20.6921	16.9831
32	7.8581	7.8306	32	8.8361	8.7251
32	17.8685	17.7535	32	21.6098	21.2305
32	6.8185	6.7542	32	7.3239	7.0652
16	1.5833	1.5562	16	2.5423	2.4344
16	3.2693	3.2055	16	3.7657	3.5124
16	5.7271	5.7043	16	10.9148	10.7838
16	2.4911	2.4686	16	7.5893	7.4628
32	7.0131	7.0355	32	14.2972	14.422
32	9.3164	9.3394	32	16.8289	16.9563
32	5.756	5.8197	32	5.261	5.5135
32	16.4923	16.3943	32	16.4041	16.2049
32	8.0785	8.0146	32	8.0213	7.8912
32	1.1243	1.2215	32	1.2143	1.4101
16	5.3006	5.1834	16	4.7074	4.3675
16	6.8975	6.7369	16	6.7495	6.4255
16	2.0667	1.9504	16	1.4772	1.1416
16	0.1994	0.075	16	0.5366	1.189
16	3.5448	3.5448	16	3.5456	3.5449
16	3.3477	3.6225	16	4.0875	4.7402
65	16.6441	16.9207	65	17.3944	18.0478
16	6.1903	6.1903	16	6.1927	6.1903
16	7.0925	7.0925	16	7.0955	7.0925
16	3.7038	3.7038	16	3.7046	3.7038
32	3.9424	4.0288	32	4.0782	4.2558
32	12.7394	12.931	32	13.3583	13.8364

5.2 Modified IEEE 30 Bus System

A. Case Study I: Outage of line (1-2)

In this case, the congestion is created in the test system with line outages1-2. Due to the line outage, the congestion occurs in lines 1–7 and 7–8. Before the congestion management, we note an overload in lines 1–7 and 7–8, when the load flows are 151.6661 MVA and 140.0123 MVA respectively. After the application of the proposed method, the load flow in lines1–7 was reduced to 129.9524 MVA, the load flow in line 7–8 was reduced to 120.7572MVA, and Figure 12 presents the line flow of each line before and after congestion management.

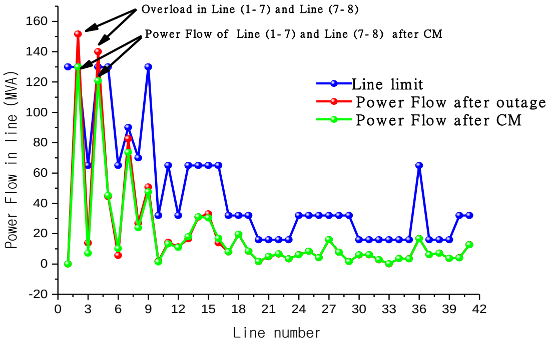

Fig. 12: Power flow in lines before and after congestion management

In Table 6 (Appendix), it can be observed that the congestion management cost is reduced to 460.9779 $/h when the total generation rescheduled (MW) is 23.0235 MW. To show the effectiveness of the proposed method (MOALO), the results are compared with some reported techniques like (SA), (RSM), (PSO), (FA) and (SBO) and presented in Figure 13 and Figure 14. By comparing results, we can see in Figure 8 and Table 6 (Appendix) that (MOALO) method can give an optimal solution relatively, especially with (SA), (RSM), (PSO), and (FA) techniques. In this case, we note also that the voltage magnitude respected the lower and the upper voltage which presented in Figure 15.

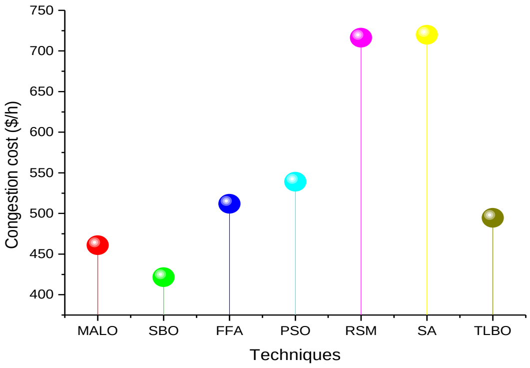

Fig. 13: Congestion cost comparison

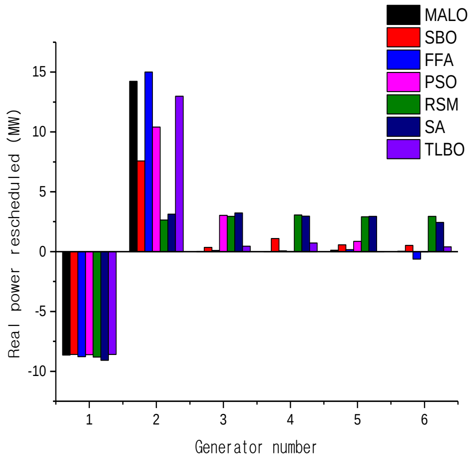

Fig. 14: Real-power change in MW obtained by different optimization techniques

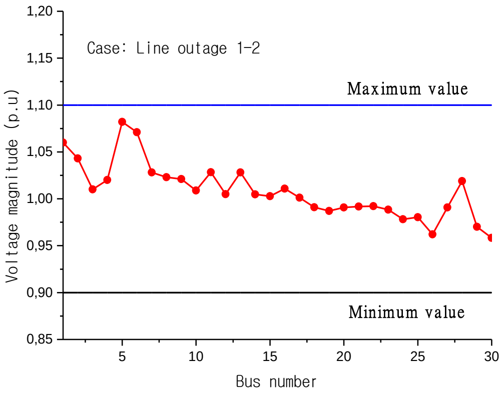

Fig.15: Voltage magnitude in p.u

B. Case Study II: Outage of the Line (1-7) with the Load Increasing 50% in All Buses

In this case, the congestion management is done by considering outages in lines1-7 with load increases of 50% at all buses. This outage and load increase to make an overload in lines 1–2, 2–8, and 2–9 with power flow of 233.0995 MW, 73.7180 MW, and 77.0975 MW respectively. By using the proposed method (MOALO) with respect to line limits, the power flow becomes 130 MW, 64.6581 MW, and 64.9999 MW when the violation is presented in Table 7 and Figure 16.

Table 7.Congestion in line 1–7

Congested Line	Line limit (MW)	Power flow after outage(MW)	Violation (MW)	Power flow after CM
1-2	130	233.0995	103.0995	130
2-8	65	73.7180	9.0599	64.6581
2-9	65	77.0975	12.0976	64.9999

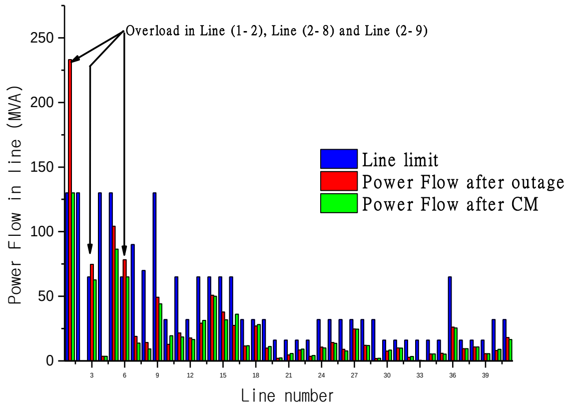

Fig. 16: Power flow in lines before and after congestion management

In Table 8 (Appendix), the cost of congestion management is reduced to 5463.4589$/h, when the total generation rescheduled (MW) is 166.9565 MW.

6 Conclusion

A new algorithm named Multi-Objective Ant Lion Optimizer (MOALO) has been proposed in this paper to solve the congestion management (CM) optimization problem. To investigate the superiority of (MOALO), the algorithm has been implemented on standard benchmark functions and two power system-related test problems (30 IEEE bus system and modified 30 IEEE bus system). The obtained results reveal that the proposed algorithm has fast convergence behavior, improved solution accuracy, and a near-global solution as compared to other contending algorithms. The analysis of initial contingency is carried out to find the severe outage case and the power flow results for the test cases are tabulated. And also, (MOALO) algorithm is used for obtaining minimum valves of generator power outputs after rescheduling, which also minimizes re-dispatch cost. The congestion management cost is reduced in 4 different scenarios and in 2 cases, (MOALO) results are better than one other optimization method like (ABC), (PSO) and (SA).

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APPENDIX

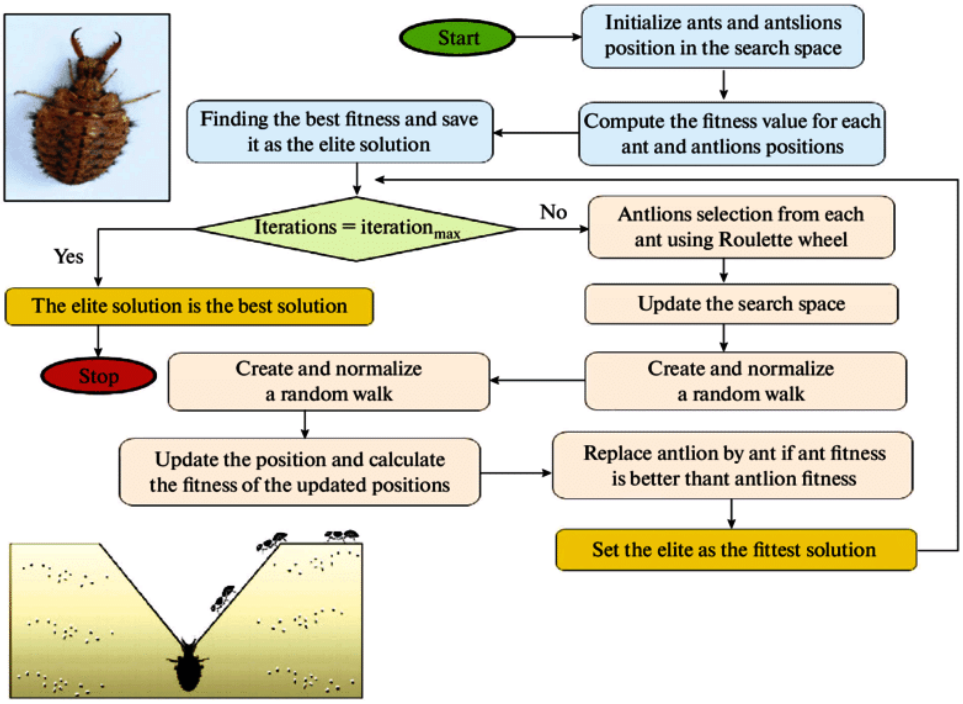

Fig. 5: Ant lion optimizer Flowchart, [30]

Table 2. Congestion cost comparison obtained by different optimization techniques

Generator number	Bus 2 carrying 250% more load with line 3–4 breakdown						
				ΔP			
	WOA [22]	ERWCA [22]	MOALO	WOA [22]	ERWCA [22]	ABC [32]	MOALO
P_1	131.6831	134.3103	132.403	− 6.8569	− 4.2297	7.5301	−6.1866
P_2	118.921	117.7261	117.681	+61.4214	+ 60.1661	62.4590	+60.1208
P_3	26.5509	24.5643	24.564	+ 1.9909	+ 0.0043	0	+0.0039
P_4	35.42957	35.1031	34.998	+ 0.42957	+ 0.1031	1.0270	−0.0018
P_5	17.49149	17.9312	17.914	−0.43851	+ 0.0012	0	+ 0.0042
P_6	16.93624	17.3790	19.093	+ 0.02624	+ 0.4690	0	+ 2.1630
Total generation (MW)	347.0123	347.0140	346.6535	71.17252	64.9734	71.0161	68.4803
Congestion Cost ($/h)				1531.7876	1363.5172	1399.1	1462.9869
Total load (MW)	337.650	337.4500	337.4500				
Transmission loss (MW)	9.3623	9.3640	9.2035				

Table 6. Congestion cost comparison obtained by different optimization techniques

		Techniques					
	MOALO	SBO[19]	FFA[20]	PSO[18]	RSM[18]	SA[18]	TLBO[21]
Total congestion cost ($/h)	460.9779	421.58	511.8737	538.95	716.25	719.861	494.66
Power flow (MW) on previously congested line 1–7	129.9524	130	129.812	129.97	129.78	129.51	130
Power flow (MW) on previously congested line 7–8	120.7572	123.54	120.617	120.78	120.60	120.35	120.78
ΔP_{G1}	-8.6377	−8.59617	−8.7783	−8.6123	−8.8086	−9.0763	−8.5876
ΔP_{G2}	14.2272	7.57019	+15.0008	+10.4059	+2.6473	+3.1332	+12.9855
ΔP_{G3}	0.0097	0.35246	+0.1068	+3.0344	+2.9537	+3.2345	+0.4598
ΔP_{G4}	-0.0060	1.09699	+0.0653	+0.0170	+3.0632	+2.9681	+0.7289
ΔP_{G5}	0.1185	0.56891	+0.1734	+0.8547	+2.9136	+2.9540	−0.0093
ΔP_{G6}	0.0246	0.52286	−0.6180	−0.0122	+2.9522	+2.4437	+0.3988
Total generation rescheduled (MW)	23.0235	18.70758	24.7425	22.936	23.339	23.809	23.169

Table 8. Congestion cost comparison obtained by different optimization techniques

		Techniques				
	MOALO	SBO[19]	FFA[20]	PSO[18]	RSM[18]	SA[18]
Total congestion cost ($/h)	5463,4589	5238.93	5304.40	5335.5	5988.05	6068.7
Power flow (MW) on previously congested line 1–2	130	130	130	129.7	129.91	129.78
Power flow (MW) on previously congested line 2–8	64.6581	61.46	62.713	61.1	52.36	51.47
Power flow (MW) on previously congested line 2–9	64.9999	64.39	64.979	64.67	55.43	54.04
ΔP_{G1}	-8,5903	−9.00148	−8.5798	NR	NR	NR
ΔP_{G2}	64,8440	62.90304	+75.9954	NR	NR	NR
ΔP_{G3}	22,3536	34.24745	+0.0575	NR	NR	NR
ΔP_{G4}	50,0284	2.05959	+42.9944	NR	NR	NR
ΔP_{G5}	20,6494	29.45485	+23.8325	NR	NR	NR
ΔP_{G6}	-0,4908	23.47373	+16.5144	NR	NR	NR
Total generation rescheduled (MW)	166.9565	161.14013	167.974	168.03	164.55	164.53

Contribution of Individual Authors to the Creation of a Scientific Article (Ghost writing Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.

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