Economic dispatch by optimization techniques

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ABSTRACT

The current paper offers the solution strategy for the economic dispatch problem in electric power system implementing ant lion optimization algorithm (ALOA) and bat algorithm (BA) techniques. In the power network, the economic dispatch (ED) is a short-term calculation of the optimum performance of several electricity generations or a plan of outputs of all usable power generation units from the energy produced to fulfill the necessary demand, although equivalent and unequal specifications need to be achieved at minimal fuel and carbon pollution costs. In this paper, two recent meta-heuristic approaches are introduced, the BA and ALOA. A rigorous stochastically developmental computing strategy focused on the action and intellect of ant lions is an ALOA. The ALOA imitates ant lions' hunting process. The introduction of a numerical description of its biological actions for the solution of ED in the power framework. These algorithms are applied to two systems: a small scale three generator system and a large scale six generator. Results show were compared on the metrics of convergence rate, cost, and average run time that the ALOA and BA are suitable for economic dispatch studies which is clear in the comparison set with other algorithms. Both of these algorithms are tested on IEEE-30 bus reliability test system.

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1. INTRODUCTION

In the economic system, economic dispatch has a fundamental role in assuring reliability and security in the electric power system. The process of obtaining the optimal operation in the electrical power systems is a difficult task that many have sought to find a solution to, due to the increase in the size of the system and the number of variables and limitations of each issue as well as depends on the nature of the goal to be reduced according to fixed conditions, so became the trend to use optimization inspired by nature. The key purpose of the economic dispatch is to deploy the load economically and physically inside the units concurrently. For e.g., variables influencing running costs, such as load distance generator, fuel size, load flexibility and lack of transmission lines. So, it's possible to define economic dispatch (ED) concerned by short-term operational decisions which use the targets scheduling the power outputs of generating unit to satisfy demand at the lowest cost at minimum cost to meet customers electricity requirements reliably and other system constraints must be satisfied. The economic dispatch is one of the importance and basis factor in the planning studies of any project, including the generating plants and also to assure reliability and security stage for system. Many scholars have given a great deal of attention to how various numerical optimization algorithms may be used as solutions for economic dispatch problems in recent years using traditional approaches or in today's environment because they have a clear potential to identify the best global answer.

The classical optimization strategies of Wood *et al.* [1] for solution of the economic dispatch load problem were introduced. That is the lambda iteration method, gradient method, and dynamic programming (DP) process. The presentations of Chowdhury and Rahrnan [2] include a summary of documentation and studies on different economic dispatch aspects. Artificial intelligence has a major role in power systems economic load dispatch [3]. Lee and Sode-Yome [4] In order to speed up the integration of the neural network device Hopfield, design two separate methods of slope change and bias modification process. The modern Hopfield model for solving economic dispatch problems is implemented in Su and Lin [5] by specifying the energy feature, overall fuel costs and transmission line losses is specified. Lin *et al.* [6] proposes a new algorithm through the combination of evolutionary programming (EP), tabu quest (TS) and quadratic programming (QP). Altun and Yalcinoz [7] for successful application to solve the ED dilemma, issues related to the execution of soft computing solutions are highlighted: Soft computing solutions, like TS, genetic algorithms (GA). The relationship between cost generation and quantity of power given is represented by Sahay *et al*. [8] in a polynomial equation and is solved by using a genetic algorithm and virtual algorithm using a mathematical technique which are worth seeking the best solution. The dynamic economic dispatch problem (DED) defined by Niknam *et al.* [9] was a modified adaptive particulate swarm optimization algorithm (MAPSO) which takes into consideration both valve point impact and ramp rate limits. Abbas *et al.* [10] hybrid particulate swarm optimization (PSO) forms used for economic dispatch with limited issue submitted with full information. Combined with other optimization methods, the way PSO solve the premature question of convergence to guarantee an optimum overall response and strengthened convergence characteristics. Chen *et al.* [11] Introduce the enhanced particulate swarm optimization (BLPSO) for solving the issues of ED concerning multiple inequalities and equity limitations such as balance of resources, ramp-rate limits, and restricted operational areas. Dixit *et al*. [12] has presented mathematically model by artificial bee colony algorithm technique for addressing fiscal, pollution combined problems with the distribution of emissions through a single equal target. Rao *et al.* [13] and Ma *et al.* [14] provide a multi-target optimum economic dispatch method for electric power systems with the bees algorithm. Basu and Chowdhury [15] proposes an algorithm for cuckoo hunt to solve both convex and non-convex issues of the economic dispatch of generators fired with fossil fuels in view of transmission damages, multiple fuels, valve loading points and forbidden operational areas. Zakaria *et al.* [16] Provided with the optimum control dispatch, bacterial foraging optimization (BFO) is used for sound control device load management. Reddy and Vaisakh [17] proposed method of novel optimization based on a hybrid SHF algorithm, the SDE algorithm incorporating the advantages of a ShHFL algorithm and differential assessment. Touma [18] has proposed an original technique for solving the economic dispatch problem, called the whale optimization algorithm process. Reddy and Reddy [19] proposes a flower pollination algorithm (FPA) to explain dynamic economic load dispatch (DELD) problem with valve-point effects and piecewise fuel options. Nassar *et al.* [20] have proposed the lightning search algorithm (LSA) to solve the ED problem with regard to consideration system constraints. Kamari *et al.* [21] process the optimal generator allocation by using moth flame optimizer (MFO) to explain ED issue in power system.

2. RESEARCH METHOD

The aim of the ED issue (fuel cost objective) is to reduce the overall generation cost in order to meet the demand for energy taking into consideration the generator limits and satisfying all the constraints, be they equal or unequal.

2.1. Fuel expense generation device goal

Minimizing total generation cost, mathematically by (1):

$$C_i(P_i) = \sum_{i=1}^{N} C_i = \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 \quad (1)$$

where $ai, bi,$ and ci are charge factors of the ith manufacturing unit. Pi is ith generator output. N is number of generators.

2.2. Equality and inequality constraints

- Power stability equality constraint: an equitable requirement should be met with the balance of force. The total power produced is the same as the total demand for charge plus the total loss of thread [22].

$$\sum_{i=1}^{N} P_i = P_D + P_L \quad (2)$$

– Generation output inequality constraint: The output of each generator is supposed to be between minimal and maximum limits [23]. For each generator, the corresponding inequality limit is

$$P_{i(\min)} \leq P_i \leq P_{i(\max)} \quad i = 1, \ldots.., N \tag{3}$$

note that the framework losses are approximated by:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j \tag{4}$$

where P_L is the transmission power losses, MW. P_D is the power demand, MW. B_{ij} are called the loss coefficients.

2.3. Ant lion optimization algorithm (ALOA)

A new heuristic meta-algorithm proposed in [24], [25] is ant lion optimizer (ALO). The ant lions hunting system in nature is imitated by the ALOA. Two major stages, larva, and adult are part of the development cycle for ant lion. The ant lions hunting system in nature is imitated by the ALOA. The quest for the right cure for real-life issues is conducted through five key stages of hunting prey including the random walk of insects, constructing traps, trapping of insects in cages, capturing of bearings, and restoration. In a circle track, a lion larva creeps a pit shaped like a cone into sand and throws out sands and its big head. The larva is hiding under the cone floor and waiting to see insects caught in the pit after digging the trap. The cone edge is smooth and insects quickly slip under the net. When the ant lion thinks that a beast is in the room, it attempts to apprehend him. It is then removed and ingested beneath the dirt. After the food has been consumed, the ants push the remains out of the pit and clear the pit for the next chase. The importance of trap size and two aspects is another curious behavior that can be seen in ant-lions lifestyle: the hunger degree and moon form. Ant lions are more active, and/or when their moon is full, as they catch bigger traps. Two species, ants and ant lions are used in the ALOA. As described before, the ants are search officers in decision rooms, and the ant lions are able to locate, capture and strike their positions in order to make them more equipped with D variables to improve their role, N ants and M ant lions have been saved and used by the following matrices throughout their optimization phase and development:

$$Ant's\ Location = \begin{bmatrix} A_{11} & A_{12} & \ldots & A_{1D} \\ A_{21} & A_{22} & \ldots & A_{2D} \\ \ldots & \ldots & \ldots & \ldots \\ A_{N1} & A_{N2} & \ldots & A_{ND} \end{bmatrix} \tag{5}$$

$$Antlion's\ Location = \begin{bmatrix} Al_{11} & Al_{12} & \ldots & Al_{1D} \\ Al_{21} & Al_{22} & \ldots & Al_{2D} \\ \ldots & \ldots & \ldots & \ldots \\ Al_{M1} & Al_{M2} & \ldots & Al_{MD} \end{bmatrix} \tag{6}$$

where Ai,j s the value of matrix the j[th] dimension's value of i-th ant. $Al_{i,j}$ is the value of matrix the j[th] dimension's value of i[th] ant lion. N is the number of ants. M is the number of ant lions. D is the number of decision variables. The fitness (objective) function of the respective ages and ant lions is used during the optimization process and all ants have been equipped with the following matrix:

$$f_A = \begin{bmatrix} f(|A_{11} & A_{12} & \ldots & A_{1D}|) \\ f(|A_{21} & A_{22} & \ldots & A_{2D}|) \\ & \ldots & & \\ & \ldots & & \\ f(|A_{N1} & A_{N2} & \ldots & A_{ND}|) \end{bmatrix} \tag{7}$$

$$f_{Al} = \begin{bmatrix} f(|Al_{11} & Al_{12} & \ldots & Al_{1D}|) \\ f(|Al_{21} & Al_{22} & \ldots & Al_{2D}|) \\ & \ldots & & \\ & \ldots & & \\ f(|Al_{M1} & Al_{M2} & \ldots & Al_{MD}|) \end{bmatrix} \tag{8}$$

where fA is the health matrix for any ant spot, f describes the goal function for any ant lion spot, and fAl is a fitness matrix.

2.3.1. Random walk of ants

The ALOA simulates the ant lion trapping process. In order to model these encounters, ants have to cross the room to look for food as ants travel spontaneously in nature and ants may follow and become more equipped with traps. For the movement of insects, a random footpath is chosen:

$$X_h^t = \frac{\left(X_h^k - a_h\right)*\left(d_h - C_h^k\right)}{\left(d_h^k - a_h\right)} + C_h \tag{9}$$

where:
ah is the minimal random walking value of hth variables.
dh is the largest random walk value of hth variables.
chk is the minimal value of hth variables at kth iteration.
dhk is the cumulative value of hth variables at kth iteration.

2.3.2. Trapping in ant lion’s pits

The following equations are applied to describe the concept of ant lion's pits mathematically.

$$C_h^k = Ant\ lion_j^k + c^k \tag{10}$$

$$d_h^k = Ant\ lion_j^k + d^k \tag{11}$$

where:
$c\ k$ at kth iteration is the minimum of all factors.
$d\ k$ is the limit of all kth iteration variables
Chk is the minimum of a hth ant vector
$dhk\ i$s the largest of all hth ant variables and Ant lion$_j^k$ is the location of the preferred jth ant lion in kth

2.3.3. Building ant lion’s trap

A roulette wheel is applied to ant lions. It is utilizing for selecting ant lions based depending on its health and fitness during optimization process. The fitter ant lions are also likely to be caught ants through this method.

2.3.4. Sliding the ants into the trap

Amexes was targeted at the lions of the species. Ant lions will create traps according to their fitness, and ants may spontaneously shift. The ant lion tries to push the sands outside to the middle of the pit as soon as it lands in the pit. This behavior causes the ant to crawl into the middle of the trap. Ant lions fire sands in the middle of the fell as soon as they know an ant is in the pit. The area of random walks of the ants is expressed in this regard as the following:

$$c^k = \frac{c^k}{I} \tag{12}$$

$$d^k = \frac{d^k}{I} \tag{13}$$

$$I = 10^W * \frac{k}{T} \tag{14}$$

where:
k is the present amount of iteration,
T is the cumulative amount of iteration,
W is dependent constant on amount of iteration (w=2 t>0.1 T, w=3 t>0.5 T, w=four t>0.75 T, w=5 t > 0.9 T and w=6 t > 0.95 T).
c^k at kth iteration is the minimum of all factors.
d^k is the limit of all kth iteration variables.
I is the proportion.

2.3.5. Catching prey and re-building the pit

The last step in hunting is to take the ant and place it in the mouth of the ant and in the mouth of an ant king, the ant's body becomes. Following this step, it is presumed that the ant is arrested when the ant is stronger than the corresponding ant lion for the modeling of this process in the ALOA. Ant lion must then improve his place with the last hunted ant so that the odds of capturing the next ant are improved. The killing method and restoration of the trap improve the likelihood of capturing fresh beasts. In this context, the following equation is proposed:

$$Antlion_j^k = Ant_h^k \ [if\ f(Ant_h^k) \geq f(Antlion_j^k)] \tag{15}$$

where k is the current iteration, $Antlion_j^k$ is the position of selected j[th] ant lion at k[th] iteration, and Ant_h^k is the position of h[th] ant at k[th] iteration.

2.3.6. Elitism

Elitism is an essential component of evolutionary algorithms that enables them to retain the best solution at any time throughout the optimization process. The strongest ant lion ever met is held in the ALO equation, as the elite and the fittest ant lion. The two random walks around the chosen ant lion roulette wheel and the elite are known as the following for the generation of new positions of ant:

$$Ant_h^k = \frac{R_A^k + R_E^k}{2} \tag{16}$$

where R_A^k is the random walks around the selected ant lion by using the roulette wheel at k[th] iteration, R_E^k is the random walks around the selected ant lion by using the around elite at k[th] iteration, and Ant_h^k is the position of h[th] ant for k[th] iteration

2.4. Bat algorithms (BA)

The new bat algorithm has been developed with Yang in 2010 [26] and is focused on the echolocation behavior of bats for the identification, identification of food or shelter, the avoidance of obstacles, as well as the placement of their roosting splits inside the dark. Echo position of bats serves like a kind of bats sonar for bats, who typically send out fast and noisy bursts of high-pitched noises. These signals then bounce off artifacts in the area and display echoes. The time-lapse between echo and emission assists a bat to explore and pursue. Bats will therefore work out how far from an entity.

2.4.1. Echolocation of microbats

And most species of microbats are tiny and poorly formed. They even have strong scent and sound senses. Echolocation of bats is a form of vision. You should radiate a rough sound pulse and tun for the re-echo which is rebounded by the components. Their pulses vary in properties, depending on the species and can be corresponded to their chasing methods. Most bats use small, repeating synchronized signals for clearing up about an octave, and any pulse is a few thousandths of a second in the frequency range of 25-150 kHz (up to about 8-10 m/s). Normally, the speeds of heartbeat outflow may be increased to approximately 200 pulses every Second, when it is on its prey to load approximately 10 to 20 such strong blows per second. The wavelength μ of the ultrasonic sound overflows with continuous recurrence f is Ţ=v/f since the air sound level is around 340 m/s [21].

2.4.2. Bat motion

Of course, we use robotic bats. We may decide how their x_i and velocity v_i locations are being modified in a d-dimensional search field. The latest x_{i0} and v_{i0} solutions are given for phase t:

$$f_i = f_{min} + (f_{max} - f_{min}) * \beta \tag{17}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_0) * f_i \tag{18}$$

where β directly from an even distribution. β directly from a random variable. x_0 is the greatest place in the world. Depending on the mystery dilemma domain level, for the overwhelming majority of applications, f_{min}=0 and f_{max}=100. At the outset, any bat is assigned haphazardly to an on-going recurrence (f_{min}, f_{max}). If a solution is chosen from among the best-established solutions, the random walk will produce a new solution locally for each bat:

$$X_{new} = X_{old} + E.A^t \tag{19}$$

where E is the random number, E $\in$[-1,1] and A^t is the normal commotion of the considerable number of bats as of now step.

2.4.3. Variations of loudness and pulse rates

Inverse proportion to the size of the target is the pulse emission limit. The noise normally reduces as a bat discovers that its food and pulse emission intensity rise and, in the meantime, it reduces as bats swim to the food. The loudness and pulse emission intensity are variable in our tests, while a method is changed [22]. The bat continues to the desired solution:

$$A_i^{t+1} = \alpha A_i^t \tag{20}$$

$$r_i^{t+1} = r_i^t[1 - e^{\gamma t}] \tag{21}$$

where A_i is the loudness of pulse emission, r_i is the rate of pulse emission and α and γ are constants.

3. APPLICATION OF ALOA AND BA TO SOLVE THE ECONOMIC DISPATCH PROBLEM

3.1. Application of ALOA to solve the economic dispatch problem

The definition of the ALOA proposed is:

- Stage-1: economic shipping input details [output unit total, B matrix, up and down unit cap, drivetrain coefficient failure and load demand] including reading power supply, load, and transmission lines.
- Stage-2: run the load flow for evaluating the control flow and having device resource losses.
- Stage-3: update population parameters; arbitrarily devise ants and ant lions, taking into consideration the lower and top parameters of the species.
- Stage-4: the values of health for ants and ant lions are determined.
- Stage-5: recognize and position as elite the finest lions' solutions.
- Stage-6: use the roulette wheel for picking the ant lion.
- Stage-7: modify the parameters d and c to the middle of the ant-lion tap with (10) and (11).
- Stage-8: random walks and the ant lion and ant solutions are calibrated with (9), (2), and (9).
- Stage-9: change the location of ant lions with (13) [24].
- Stage-10: swap the ant lion with the larvae. The replacement procedure has been revised. The replacement ant lion is fitter to pursue the right answer than the top.
- Stage-11: recommend the right path forward. Optimum printing of fuel and production economic dispatch.

3.2. Application of bat algorithm to solve the economic dispatch problem

A definition of the proposed bat algorithm is as:

- Stage-1: economic shipping input details [output unit total, *B* matrix, up and down unit cap, drivetrain coefficient failure and load demand including reading power supply, load, and transmission lines.
- Stage-2: run the load flow for evaluating the control flow and having device resource losses.
- Stage-3: build the initial random solutions and receive their fitness values (1) and determine the best fitness value and the best solution.
- Stage-4: original random bat location x_i and fitness estimation, Ci and Pi generation where $i=1, ... n$, r_i and noisy nett original pulse rate, produce pulse frequency fi
- Stage-5: upgrading level f_i (17), (18) and (19) respectively, v_i^t and distance xit.
- Stage-6: create the X_{new} approach (19), accompanied by unfairness tests (2), and (3)
- Stage-7: test the current approach, change the A_i^{t+1} loudness rating and r_i^{t+1} pulse emission rating to decide the right health benefit and approach.
- Stage-8: Iterate stage 5 to 7 until the stop criteria is given
- Stage-9: The strongest strategy analysis. Optimum printing of fuel and production economic dispatch.

4. ALGORITHM VALIDATION

Two optimization techniques presented in the section, which is the ant lion optimization and the bat algorithm methods are implemented. The application is achieved on three standard test systems of three, six generating units. The outcomes of these different systems and the response of the two algorithms which is compared to other approaches.

4.1. The three generating units test system

The necessary data required in ED [25], [27]. The units generating limits are presented in Table 1. Also, the averaged B-coefficients for the power demands under study are presented in Table 2.

Table 1. Fuel cost function parameters

Unit No.	Fuel Cost Coefficients			Generation Limits	
	A ($/MW)	b ($/MWh)	C ($/h)	P_{min} (MW)	P_{max} (MW)
1	0.03546	38.30553	1243.531	35	210
2	0.02111	36.32782	1658.5696	130	325
3	0.01799	38.27041	1356.6592	125	315

Table 2. The B-coefficients

B-coefficients=		
0.000071	0.000030	0.000025
0.000030	0.000069	0.000032
0.000025	0.000032	0.000080

4.1.1. Ant lion optimization algorithm (ALOA)

The test device contains 3-generation systems with differing demands of 300-700 MW. The ALOA approach is being applied for economic dispatches. Table 3 reports the division of the groups.

Table 3. Economic dispatch results, 3-unit system using ALOA method

Load	P1	P2	P3	PL	Total cost (fuel cost)
400	82.0783	174.9937	150.4959	7.56812	20812.2934
500	105.8799	212.7279	193.3064	11.9143	25465.4690
600	130.0210	250.84619	236.4367	17.3040	30333.9856
700	154.5139	289.3596	279.8944	23.7680	35424.391

Note: load P1, P2 and P2 for MW- total cost for $/h

4.1.2. Bat algorithm (BA)

In this scenario, the BA is devised to deal with complex equations as bats have a good ability to forage in order to survive, and the ant lion method simulates the evolution of a group of lions, which divide into groups and share information in order to obtain the shortest and best path. Table 4 shows the results obtained for economic dispatch using BA method. The results of Table 4 is close to these of Table 3, particularly at the 400-700 MW load level. The ant lion optimization and bat algorithm methods are first used to find the optimal economic dispatch of a well-documented systems. Three standard systems were considered [11], [27]–[29]. Table 5 shows the here used ALOA and BA methods results along with other optimization algorithms for comparison to validate the effectiveness of the introduced methods and verify the validity of the ant lion optimization and bat algorithm adopted in this work. Table 5 presents a sample comparison result selected from literature and those obtained in this work for 400 to 700MW load case. The results concerned are P1, P2, P3, PL and total cost (fuel cost) as those are the new considered factors here. The results resemblance is quite evident between these obtained in this work and those documented in the literature as noted. This scenario is the first, as there will be another investigation that will apply other techniques such as a genetic algorithm [30], [31].

Table 4. Economic dispatch results, 3-unit system using BA method

Load	P1	P2	P3	PL	Total cost (fuel cost)
400	82.07835	174.9937	150.4960	7.5681254	20812.2934
500	105.8799	212.7279	193.3064	11.9143	25465.4690
600	130.0210	250.8462	236.4367	17.3040	30333.9856
700	152.8146	291.0264	279.9525	23.7936	35424.4149

Note: load P1, P2 and P2 for MW- total cost for $/h

Table 5. Comparing ALOA and BA methods to other optimization algorithms for 3 generator system

pD	Performance	ALO	BA	GA [28]	PSO [28]	TS [29]	ABC [12]	CSA [32]
400	P1 (MW)	82.0783	82.0783	102.617	102.612	104.0372	102.5422	
	P2 (MW)	174.9937	174.9937	153.825	153.809	150.0000	153.7333	
	P3 (MW)	150.4959	150.4960	151.011	150.991	153.3721	151.1370	
	PL (MW)	7.56812	7.56812	7.41324	7.41173	7.4093	7.568	
	Total cost (fuel cost) $/h	20812.2934	20812.2934	20840.1	20818.3	20845	20838	20812.3
500	P1 (MW)	105.8799	105.8799	128.997	128.984	181.4774	128.8241	
	P2 (MW)	212.7279	212.7279	192.683	192.645	150.0000	192.5837	
	P3 (MW)	193.3064	193.3064	190.11	190.063	180.0000	190.2859	
	PL (MW)	11.9143	11.9143	11.6964	11.6919	11.4774	11.6937	
	Total cost (fuel cost) $/h	25465.4690	25465.4690	25499.4	25495	25774	25495	25465.5
600	P1 (MW)	130.0210	130.0210	155.714	155.711	228.8856	NONE	
	P2 (MW)	250.84619	250.8462	231.895	231.859	178.8856		
	P3 (MW)	236.4367	236.4367	229.479	229.428	208.8856		
	PL (MW)	17.3040	17.3040	17.0039	16.9987	16.6568		
	Total cost (fuel cost) $/h	30333.9856	30333.9856	30372.3	30368.2	30837		30334.0
700	P1 (MW)	154.5139	152.8146	182.783	182.806	264.2929	182.6011	
	P2 (MW)	289.3596	291.0264	271.478	271.463	214.2929	271.2813	
	P3 (MW)	279.8944	279.9525	269.132	269.039	244.2929	269.4840	
	PL (MW)	23.7680	23.7936	23.365	23.3626	22.8788	23.3664	
	Total cost (fuel cost) $/h	35424.391	35424.4149	35466	35464.6	36037	35464	35424.4

4.2. The six generating units test system

The method mentioned is extended to the IEEE test network, which consists of 30 buses, 6 thermal generator units 41, as shown in Figure 1. Table 6 show the fuel cost and Table 7 presents the averaged B-coefficients. Also, in Table 8 show the units generating limits are presented with the system data contained in Table 9 and Table 10 (see in appendix).

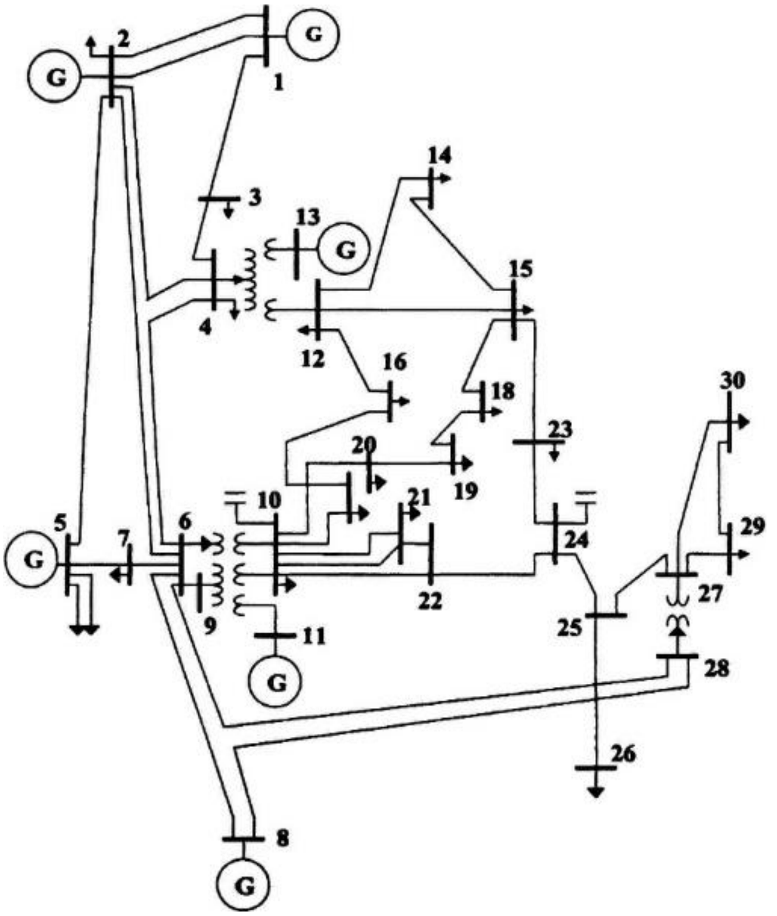

Figure 1. Single line diagram of IEEE 30-bus test system

Table 6. Fuel cost function parameters

Unit No.				Generation Limits	
	a($/MWh)	b($/MWh)	c ($/h)	P_{min}	P_{max}
1	0.00375	2.00	Zero	50	200
2	0.01750	1.75		20	80
3	0.06250	1.00		15	50
4	0.00834	3.25		10	35
5	0.02500	3.00		10	30
6	0.02500	3.00		12	40

Table 7. B-coefficients

B-coefficients=					
0.000218	0.000103	0.000009	-0.00010	0.000002	0.000027
0.000103	0.000181	0.000004	-0.000015	0.000002	0.000030
0.000009	0.000004	0.000417	-0.000131	-0.000153	-0.000107
-0.00010	-0.000015	-0.000131	0.000221	0.000094	0.000050
0.000002	0.000002	-0.000153	0.000094	0.000243	-0.00000
0.000027	0.000030	-0.000107	0.000050	-0.00000	0.000358

Table 8. Power flow solution by Newton-Raphson method

Bus	Voltage	Angle	Load		Generation		
No.	Mag.	Degree	MW	Mvar	MW	Mvar	Mvar
1	1	1.06	0	0	0	0	0
2	2	1.043	-5.4969	21.7	12.7	40	0
3	0	1.0215	-8.004	2.4	1.2	0	0
4	0	1.0129	-9.6615	7.6	1.6	0	0
5	2	1.01	-14.381	94.2	19	0	0
6	0	1.0121	-11.398	0	0	0	0
7	0	1.0034	-13.15	22.8	10.9	0	0
8	2	1.01	-12.115	30	30	0	0
9	0	1.051	-14.434	0	0	0	0
10	0	1.0444	-16.024	5.8	2	0	0
11	2	1.082	-14.434	0	0	0	0
12	0	1.0574	-15.302	11.2	7.5	0	0
13	2	1.071	-15.302	0	0	0	0
14	0	1.0424	-16.191	6.2	1.6	0	0
15	0	1.0378	-16.278	8.2	2.5	0	0
16	0	1.0447	-15.88	3.5	1.8	0	0
17	0	1.0391	-16.188	9	5.8	0	0
18	0	1.0279	-16.884	3.2	0.9	0	0
19	0	1.0253	-17.052	9.5	3.4	0	0
20	0	1.0293	-16.852	2.2	0.7	0	0
21	0	1.0321	-16.468	17.5	11.2	0	0
22	0	1.0327	-16.455	0	0	0	0
23	0	1.0272	-16.662	3.2	1.6	0	0
24	0	1.0216	-16.83	8.7	6.7	0	0
25	0	1.0189	-16.424	0	0	0	0
26	0	1.0012	-16.842	3.5	2.3	0	0
27	0	1.0257	-15.912	0	0	0	0
28	0	1.0107	-12.057	0	0	0	0
29	0	1.0059	-17.136	2.4	0.9	0	0
30	0	0.9945	-18.015	10.6	1.9	0	0
Total				283.4	126.2	300.998	125.144

A load flow program using Newton-Raphson method was written to find the nodal voltages and phase angles and hence the power injection at all the buses and power flows through interconnecting power channels. Table 8 shows power flow solution for the test system using the Newton-Raphson program. In Table 8 the close results resemblance between ALOA and BA is very clear with another optimization as PSO, GA, whale optimization algorithm (WOA), cuckoo search algorithm (CSA) and firefly algorithm (FFA) for the same load level when p_d=283.4 MW.

The obtained results in Table 11 for ED using ALOA or BA, explain the significant reduction in the losses. This means that the ED may perform another task (losses reduction) as well as its main task. Table 11 gives a sample of comparison results obtained and those obtained and presented in the Table 11 other optimization algorithms results match from the result it is clearer that the proposed methods in this work show the capability of being robust and reliable ones compared to other algorithms. Tables 12 and 13 show power flow solution for the test system using the Newton-Raphson program after ALOA and BA methods for P_D=283.4. Regarding the comparison between the BA and ALOA results in our study for this system, we can get that the ant lion optimization is superior to that of bat algorithm.

Table 11. ALOA and BA methods results along with other optimization algorithms

pD	Performance	ALOA	BA	WOA [18]	GA [33]	PSO [34]	CSA [35]	FFA [35]
283.4	P1 (MW)	173.7835	173.78866				120.41	149.52
	P2 (MW)	47.2827	47.2838				20.57	48.65
	P3 (MW)	20.5462	20.5465				50.00	23.41
	P4(MW)	26.4363	26.4390				35.00	22.26
	P5 (MW)	11.5409	11.5417				24.97	19.88
	P6 (MW)	12.0000	12.0000				40.00	27.23
	PL (MW)	8.1895	8.189937				7.54	7.54
	Total cost (fuel cost) $/h	798.9175	798.95344				819.81	973.01
350	P1 (MW)	199.9999	199.9999		NONE			
	P2 (MW)	59.8850	55.6802					
	P3 (MW)	24.7492	23.4771					
	P4(MW)	35	35					
	P5 (MW)	21.5781	30					
	P6 (MW)	20.0724	16.8859					
	PL (MW)	11.2849	11.0434					
	Total cost (fuel cost) $/h	1051.22094	1053.8739					
400	P1 (MW)	200	199.9999		NONE			
	P2 (MW)	80	79.8067					
	P3 (MW)	31.9075	31.3746					
	P4(MW)	35	35					
	P5 (MW)	30	29.9999					
	P6 (MW)	36.3985	37.13710					
	PL (MW)	13.3061	13.3185					
	Total cost (fuel cost) $/h	1276.3219	1276.3758					

Table 12. Power flow solution after ALOA method

Bus No.	Voltage Mag.	Angle Degree	Load MW	Load Mvar	Generation MW	Generation Mvar	Mvar
1	1.06	0	0	0	174.929	-1.11077	0
2	1.043	-3.54263	21.7	12.7	47.2827	29.75173	0
3	1.025495	-5.42431	2.4	1.2	0	0	0
4	1.017223	-6.51335	7.6	1.6	0	0	0
5	1.01	-10.2442	94.2	19	20.5462	26.51513	0
6	1.014812	-7.61117	0	0	0	0	0
7	1.005073	-9.21871	22.8	10.9	0	0	0
8	1.01	-7.6966	30	30	26.4363	15.28295	0
9	1.052985	-9.6926	0	0	0	0	0
10	1.046735	-11.4437	5.8	2	0	0	19
11	1.082	-8.48532	0	0	11.5409	15.21475	0
12	1.059957	-10.6732	11.2	7.5	0	0	0
13	1.071	-9.82523	0	0	12	8.536679	0
14	1.045045	-11.5717	6.2	1.6	0	0	0
15	1.040271	-11.6718	8.2	2.5	0	0	0
16	1.047161	-11.2702	3.5	1.8	0	0	0
17	1.041545	-11.5978	9	5.8	0	0	0
18	1.030423	-12.283	3.2	0.9	0	0	0
19	1.027725	-12.4557	9.5	3.4	0	0	0
20	1.031696	-12.2598	2.2	0.7	0	0	0
21	1.034474	-11.9015	17.5	11.2	0	0	0
22	1.035041	-11.8927	0	0	0	0	0
23	1.029588	-12.1015	3.2	1.6	0	0	0
24	1.023741	-12.3328	8.7	6.7	0	0	4.3
25	1.020445	-12.1293	0	0	0	0	0
26	1.002823	-12.5464	3.5	2.3	0	0	0
27	1.026977	-11.7448	0	0	0	0	0
28	1.012862	-8.09991	0	0	0	0	0
29	1.007218	-12.9656	2.4	0.9	0	0	0
30	0.995789	-13.8417	10.6	1.9	0	0	0
Total			283.4	126.2	292.735	94.19	23.3

Table 13. Power flow solution after BA method

Bus No.	Voltage Mag.	Angle Degree	Load MW	Load Mvar	Generation MW	Generation Mvar	Mvar
1	1.06	0	0	0	174.9238	-1.10964	0
2	1.043	-3.54251	21.7	12.7	47.2838	29.75066	0
3	1.025496	-5.42415	2.4	1.2	0	0	0
4	1.017223	-6.51316	7.6	1.6	0	0	0
5	1.01	-10.244	94.2	19	20.5465	26.51497	0
6	1.014812	-7.61094	0	0	0	0	0
7	1.005073	-9.21849	22.8	10.9	0	0	0
8	1.01	-7.6963	30	30	26.439	15.28183	0
9	1.052986	-9.69231	0	0	0	0	0
10	1.046735	-11.4435	5.8	2	0	0	19
11	1.082	-8.48495	0	0	11.5417	15.21471	0
12	1.059957	-10.673	11.2	7.5	0	0	0
13	1.071	-9.825	0	0	12	8.536656	0
14	1.045045	-11.5715	6.2	1.6	0	0	0
15	1.040271	-11.6716	8.2	2.5	0	0	0
16	1.047161	-11.27	3.5	1.8	0	0	0
17	1.041546	-11.5976	9	5.8	0	0	0
18	1.030423	-12.2827	3.2	0.9	0	0	0
19	1.027725	-12.4555	9.5	3.4	0	0	0
20	1.031697	-12.2596	2.2	0.7	0	0	0
21	1.034474	-11.9012	17.5	11.2	0	0	0
22	1.035041	-11.8924	0	0	0	0	0
23	1.029588	-12.1013	3.2	1.6	0	0	0
24	1.023742	-12.3325	8.7	6.7	0	0	4.3
25	1.020445	-12.1291	0	0	0	0	0
26	1.002824	-12.5462	3.5	2.3	0	0	0
27	1.026977	-11.7445	0	0	0	0	0
28	1.012862	-8.09966	0	0	0	0	0
29	1.007218	-12.9654	2.4	0.9	0	0	0
30	0.995789	-13.8415	10.6	1.9	0	0	0
Total			283.4	126.2	292.735	94.189	23.3

5. CONCLUSION

ED targets scheduling the power outputs of generating unit to satisfy demand at the lowest cost where load balance and other system constraints must be satisfied. This adds to the country's economic development. BA and ALOA methods produced optimal or near optimal solutions. There has been load variation effect on the obtained results using the certain algorithms. The ED may cause losses reduction as a main objective. This fact was explained clearly from the simulated results for cases studied. There is a noticeable variation in the dispatch of generating units as a result of cost computation in the objective function. Many optimization algorithms are set to resolve economic dispatch optimization problem. In our study, BA, and ALOA succeeded in solving constrained economic dispatch problem subjected to equality and non-equality constraints. The effectiveness of the advanced methods is demonstrated on different systems with 3, 6 generators. The obtained results for the introduced algorithms are compared with each other and to other conventional and recent meat-heuristic techniques. Computational results reveal that proposed methods are promising in terms of fuel cost. So the final conclusion when comparison is set between the two proposed algorithms is that the ALOA has been more robust and effective than the BA in solving economic dispatch problem, although it is worth mentioning that the differences between the results of both algorithms is not big because the ALOA has features, including less computational time, high accuracy of solution, stable convergence features, and sound performance. The variations in each algorithm’s parameters causes parameters selection affects the obtained solution directly, so the obtained results may vary according to that.

APPENDIX

Table 9. Bus data of the 30-bus network

Bus No.	Bus code	|V| p.u.	Ang Deg	Load Max	Load Min	Gen Mvar	Gen MW	Gen Mvar Mvar	Gen Mvar MW	Injected Mvar
1	1	1.06	0	0	0	0	0	0	0	0
2	2	1.043	-5.49687	21.7	12.7	40	0	-40	50	0
3	0	1.022	-8.0040	2.4	1.2	0	0	0	0	0
4	0	1.013	-9.6614	7.6	1.6	0	0	0	0	0
5	2	1.01	-14.3812	94.2	19	0	0	-40	40	0

Table 9. Bus data of the 30-bus network *(continue)*

Bus	Bus	|V|	Ang	Load		Gen		Gen Mvar		Injected
No.	code	p.u.	Deg	Max	Min	Mvar	MW	Mvar	MW	Mvar
6	0	1.012	-11.3979	0	0	0	0	0	0	0
7	0	1.003	-13.14950	22.8	10.9	0	0	0	0	0
8	2	1.01	-12.1153	30	30	0	0	-10	60	0
9	0	1.051	-14.4338	0	0	0	0	0	0	0
10	0	1.044	-16.0241	5.8	2	0	0	-6	24	19
11	2	1.082	-14.4338	0	0	0	0	0	0	0
12	0	1.057	-15.3024	11.2	7.5	0	0	0	0	0
13	2	1.071	-15.3024	0	0	0	0	-6	24	0
14	0	1.042	-16.1913	6.2	1.6	0	0	0	0	0
15	0	1.038	-16.2782	8.2	2.5	0	0	0	0	0
16	0	1.045	-15.8804	3.5	1.8	0	0	0	0	0
17	0	1.039	-16.18829	9	5.8	0	0	0	0	0
18	0	1.028	-16.8835	3.2	0.9	0	0	0	0	0
19	0	1.025	-17.0519	9.5	3.4	0	0	0	0	0
20	0	1.029	-16.8522	2.2	0.7	0	0	0	0	0
21	0	1.032	-16.4684	17.5	11.2	0	0	0	0	0
22	0	1.033	-16.4546	0	0	0	0	0	0	0
23	0	1.027	-16.6623	3.2	1.6	0	0	0	0	0
24	0	1.022	-16.8301	8.7	6.7	0	0	0	0	4.3
25	0	1.019	-16.4238	0	0	0	0	0	0	0
26	0	1.001	-16.8422	3.5	2.3	0	0	0	0	0
27	0	1.026	-15.9124	0	0	0	0	0	0	0
28	0	1.011	-12.0574	0	0	0	0	0	0	0
29	0	1.006	-17.1363	2.4	0.9	0	0	0	0	0
30	0	0.995	-18.0146	10.6	1.9	0	0	0	0	0

Table 10. Line data of the 30-bus network

Bus No.	Bus No.	R1	X1	B/2	Tap at bus
1	2	0.0192	0.0575	0.0264	1
1	3	0.0452	0.1852	0.0204	1
2	4	0.057	0.1737	0.0184	1
3	4	0.0132	0.0379	0.0042	1
2	5	0.0472	0.1983	0.0209	1
2	6	0.0581	0.1763	0.0187	1
4	6	0.0119	0.0414	0.0045	1
5	7	0.046	0.116	0.0102	1
6	7	0.0267	0.082	0.0085	1
6	8	0.012	0.042	0.0045	1
6	9	0	0.208	0	0.978
6	10	0	0.556	0	0.969
9	11	0	0.208	0	1
9	10	0	0.11	0	1
4	12	0	0.256	0	0.932
12	13	0	0.14	0	1
12	14	0.1231	0.2559	0	1
12	15	0.0662	0.1304	0	1
12	16	0.0945	0.1987	0	1
14	15	0.221	0.1997	0	1
16	17	0.0824	0.1923	0	1
15	18	0.1073	0.2185	0	1
18	19	0.0639	0.1292	0	1
19	20	0.034	0.068	0	1
10	20	0.0936	0.209	0	1
10	17	0.0324	0.0845	0	1
10	21	0.0348	0.0749	0	1
10	22	0.0727	0.1499	0	1
21	22	0.0116	0.0236	0	1
15	23	0.1	0.202	0	1
22	24	0.115	0.179	0	1
23	24	0.132	0.27	0	1
24	25	0.1885	0.3292	0	1
25	26	0.2544	0.38	0	1
25	27	0.1093	0.2087	0	1
28	27	0	0.396	0	0.968
27	29	0.2198	0.4153	0	1
27	30	0.3202	0.6027	0	1
29	30	0.2399	0.4533	0	1
8	28	0.0636	0.2	0.0214	1
6	28	0.0169	0.0599	0.065	1

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