frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 07 September 2022
DOI 10.3389/fenrg.2022.972069

Static and dynamic environmental economic dispatch using tournament selection based ant lion optimization algorithm

H. Vennila[1], Nimay Chandra Giri[2,3], Manoj Kumar Nallapaneni[4], Pampa Sinha[5], Mohit Bajaj[6,7], Mohamad Abou Houran[8] and Salah Kamel[9]*

[1]Department of EEE, Noorul Islam Centre for Higher Education, Kumarakovil, India, [2]Department of Electronics and Communication Engineering, Centurion University of Technology and Management, Jatni, Odisha, India, [3]Centre for Renewable Energy and Environment, Centurion University of Technology and Management, Jatni, Odisha, India, [4]School of Energy and Environment, City University of Hong Kong, Kowloon, Hong Kong SAR, China, [5]School of Electrical Engineering, KIIT University, Bhubaneswar, India, [6]Department of Electrical Engineering, Graphic Era (Deemed to be University), Dehradun, India, [7]Department of Electrical Engineering, National Institute of Technology, Delhi, India, [8]School of Electrical Engineering, Xi'an Jiaotong University, Xi'an, China, [9]Electrical Engineering Department, Faculty of Energy Engineering, Aswan University, Aswan, Egypt

The static and dynamic economic dispatch problems are solved by creating an enhanced version of ant lion optimisation (ALO), namely a tournament selection-based ant lion optimisation (TALO) method. The proposed algorithm is presented to solve the combined economic and emission dispatch (CEED) problem with considering the generator constraints such as ramp rate limits, valvepoint effects, prohibited operating zones and transmission loss. The proposed algorithm's efficiency was tested using a 5-unit generating system in MATLAB R2021a during a 24-hour time span. When compared to previous optimization methods, the suggested TALO reduces the costs of fuel and pollution by 9.01 and 4.7 percent, respectively. Furthermore, statistical analysis supports the suggested TALO optimization superiority over other methods. It is observed that the renewable energy output can be stabilized in the future by combining a hybrid dynamic economic and emission dispatch model with thermal power units, wind turbines, solar and energy storage devices to achieve the balance between operational costs and pollutant emissions.

KEYWORDS

ant lion optimizer, tournament selection ant lion optimization, combined static and dynamic economic emission dispatch, valve point loading, optimization

Check for updates

OPEN ACCESS

EDITED BY
Sudhakar Babu Thanikanti,
Chaitanya Bharathi Institute of Technology, India

REVIEWED BY
Adel Oubelaid,
Université de Bejaia, Algeria
Kitmo,
University of Ngaoundéré, Cameroon

*CORRESPONDENCE
Salah Kamel,
skamel@aswu.edu.eg

SPECIALTY SECTION
This article was submitted to Advanced Clean Fuel Technologies, a section of the journal Frontiers in Energy Research

RECEIVED 17 June 2022
ACCEPTED 30 June 2022
PUBLISHED 07 September 2022

CITATION
Vennila H, Giri NC, Nallapaneni MK, Sinha P, Bajaj M, Abou Houran M and Kamel S (2022), Static and dynamic environmental economic dispatch using tournament selection based ant lion optimization algorithm.
Front. Energy Res. 10:972069.
doi: 10.3389/fenrg.2022.972069

COPYRIGHT
© 2022 Vennila, Giri, Nallapaneni, Sinha, Bajaj, Abou Houran and Kamel. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

1 Introduction

In today's environment, the most efficient and effective operation of an electric power system is critical. In recent years, all utilities have become increasingly reliant on operating their systems at the lowest possible cost while satisfying consumer demand in order to generate income (Basu, 2011). Because of the large growth in demand for the power system, the limited availability of generating systems, and supply and fuel cost constraints, all committed units should provide energy at the lowest possible cost to fulfill demand (Giri and Mohanty, 2020). The energy delivered by committed units is not continuous in Economic Dispatch Problems. It is permitted to generate within specified parameters in order to meet particular demands with the least quantity of fuel possible. The traditional method alone is not possible to deliver energy at low cost. Aside from fuel cost targets, Emission dispatch is a temporary solution that should be maximized. The majority of electricity is generated by fossil fueled thermal power plants which results in environmental pollutants such as CO_2, SO_2 and NO_x. SO_2 and other sulfur oxides can contribute to acid rain which can harm sensitive ecosystems. As a result, the combined economic and emission dispatch (CEED) is considered as a multi-objective optimization problem. By taking into consideration diverse objective functions, a variety of traditional and cutting-edge solutions have been used to tackle economic power dispatch challenges (Benasla et al., 2014). Various traditional techniques such as lambda iterative technique, gradient-based technique, Newton-based method, modified group search optimization (MGSO) (Daryani and Zare, 2018), Dynamic economic dispatch problems: PSO approach (Ab Ghani et al., 2017). A new modified artificial bee colony algorithm (Secui, 2015b), particle swarm optimization and genetic algorithm techniques (Hussain et al., 2019), chaotic improved harmony search algorithm Several optimization strategies and procedures have been utilized to solve the dynamic economic dispatch (DED) problem with complex objective functions or constraints since the topic was proposed in the 1980s (Rezaie et al., 2019). Literature survey shows to solve this problem using conventional algorithms (Kamli and Amraee, 2017), Dynamic economic dispatch using hybrid meta heuristics (Santra et al., 2020) and Simulated Annealing method (Bouddou et al., 2020) for non-smooth or non-convex cost functions, the majority of these strategies are ineffective. To solve the DED problem, a variety of heuristic optimization methods have been used, including Ant based optimization (Secui, 2015a; Vennila and Rajesh, 2022), Dragon fly based optimization (Chandrasekaran et al., 2021), Hybrid HB-SA algorithm (Vennila et al., 2013), differential evolution techniques (Li et al., 2022; Zou and Gong, 2022), harmony search algorithm (Rezaie et al., 2019), and bee swarm based optimization algorithm (Hussain et al., 2019). With some limits in the cost function curves, many of these strategies have been proved to be effective in tackling the DED problem. These techniques solve the DED based on a population of individuals, each of whom represents a potential solution (Wang et al., 2016). The original population is then evolved by applying a group of operators to the traditional methods in order to replace them with new ones. Mirjalili recently developed Ant Lion Optimization (ALO), a breakthrough nature-inspired approach (Pan et al., 2022). The ALO approach was used to tackle the CEED problem, which took into account restrictions on ramp rate, Effects of valve points, forbidden transmission loss, operational zones (Song et al., 2015). The effectiveness of the proposed method was demonstrated on a six- and ten-unit generation system, respectively.

In this study, the generator's power constraints are regarded as a new way for handling static and dynamic CEED problems using Tournament-based ALO methodology. CEED's purpose is to simultaneously minimise operating fuel costs and emissions while fulfilling power demand and operational limitations. Using a modified weighting factor technique, this multi-objective CEED problem is reduced to a single goal function. TALO is being investigated in order to determine the proper generator loading in power systems. The resilience of TALO is demonstrated using the results of simulations for local and valve loading effect in large-scale power systems. The Tournament based Ant Lion Optimizer (TALO), which is inspired by the way ant lions hunt, is suggested. Five unit test functions are used to benchmark the TALO algorithm.

The manuscript is structured in five sections; Section 2 presents problem formulation. The proposed algorithm for solving the problem is given in Section 3. Results and discussion are provided in Section 4, followed by conclusions in Section 5.

2 Problem formulation

The CEED's mission challenge is to lower both fuel prices and emissions while maintaining equity and disparity. Because the functions of fuel price and pollution cost are independent of one another, the problem issue is two-objective. Two-objective problems can be solved by combining two objective functions into a single one. The CEED issue is changed into a single-objective function in this work, and a price penalty component is employed to improve the process.

2.1 Economic load dispatch

In order to reduce the overall cost of generation and meet the equality and inequality restrictions, the economic load dispatch is an online mechanism for assigning generation among the available generating units.

To minimise the fuel cost, the below function is considered,

$$F(P_i) = a_i P_i^2 + b_i P_i + C_i \ \$/\mathrm{h} \tag{1}$$

2.2 Equality constraints

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

2.3 Economic load dispatch with loss

$$P_L = \sum_{I=1}^{N}\sum_{J=1}^{N} P_i\, B_{ii} + \sum_{i=1}^{n} B_{01} P_i + B_{00} \tag{3}$$

where,

P_i—The real power on the i^{th} generator of the MW unit.
P_j—The real power on the j^{th} generator of the MW unit.
B_{ij}—Power Transmission losses between the i^{th} and j^{th} generating units in MW are represented by coefficients.
P_L—Power loss in MW.

2.4 Capacity limitations

$$P_{imin} \le P_i \le P_{imax} \quad i = 1, 2 \ldots N \tag{4}$$

2.5 Valve point loading for cost-effective load dispatch

When the valve is not entirely opened, the impact of the valve point is enormous, and when the valve is fully opened, the impact is minimal (Yang et al., 2021). This behaviour can be mimicked in the characteristic curve by combining a multiple routine sinusoidal curve with a regular quadratic value feature. As a result, the generator devices' real input-output curves are non-convex. There will also be ripples in the gasoline price curve when the valve begins to establish/final and will burst off when the valve is fully opened. The objective function will become when the valve point-impact is added.

$$FC_T = \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 + |d_i sin(e_i (P_{imin} - P_i))| \tag{5}$$

Coefficients of fuel price of ith generator unit are a_i, b_i, c_i, d_i and e_i.

P_i—is the load of the i^{th} generator in MW.
N_i—is represents the total number of generators.
P_{imin}—Minimum power generation of i^{th} generator.
FC_i—displays the cost of generator fuel for the ith generator.
FC_T—indicates the total fuel cost.

2.6 Limits on ramp rates

Limitations on ramping up and down can be expressed as:

$$P_U - P_{U-1} \le UR_i \tag{6}$$

$$P_{U-1} - P_U \le DR_i \tag{7}$$

Where P (i, t) and P (i, t-1) respectively, are the present and previous real power outputs. The ramp-up and ramp-down limits of ith unit are URi and DRi. By considering both ramp rate restrictions and limits on actual power output the equation is:

$$\max\{P_{i,\,min},\ P_{i,\,t-1} - DR_i\} \le P_{i,t} \le \min\{P_{i,max},\ P_{i,t-1} + UR_i\} \tag{8}$$

2.7 Prohibited operating zones

Due to machine component constraints or worries about instability, a limited operation zone may exist for producing units. The generator's possible operating zones can be defined as follows (Wang et al., 2016; Rezaie et al., 2019):

$$P_{i,j} \in \begin{cases} P_{i,min} \le P_{i,j} \le P_{i,l}^{l} \\ P_{i,k-1}^{u} \le P_{i,t} \le P_{i,k}^{l},\ k = 2, 3, \ldots, pz \\ P_{i,pzi}^{u} \le P_{i,t} \le P_{i,max},\ i = 1, 2, .., n_{pz} \end{cases} \tag{9}$$

2.8 Dispatching of emissions

The function of emission dispatch, can be written as

$$E_T = \sum_{i=1}^{N} E_i (P_i) \sum_{i=1}^{N} \alpha_i + \beta_i P_i + \gamma_i P_i^2 \tag{10}$$

Toxic gases emitted by the energy plant must be transported to the system.

As a result, the mixed emission feature is as follows:

$$E_T = \sum_{i=1}^{N} \alpha_i + \beta_i P_i + \gamma_i P_i^2 + \epsilon_i \exp(\vartheta_i P_i) \tag{11}$$

P_i denotes the ith unit's generating power in megawatts (MW).

N The number of generating units is denoted by this symbol.
E_T denotes the system's total emission in tones per hour.

2.9 Combined economic and emission dispatch

The combined economic and emission dispatch (CEED) problem is used to minimise fuel costs and emissions concurrently by adhering to a variety of real-world equality and inequality constraints.

Combined Economic and Emission function is given as.

$$C_T = FC_T + Pf*E_T \tag{12}$$

3 Algorithm for ant lion optimization

3.1 Inspiration

The ALO a set of guidelines, based on a description of the way an ant-lion takes its prey by digging sand pit traps in the sand and trapping it. The pit's dimension is proportional to the moon's mild. The ant-lion minimise the size of its pit with the help of its prey (Pan et al., 2022).

3.2 Mathematical model of the ant-lion algorithm

The versioning of random ant walks is the first stage in the set of rules.
X_1 (t) = 0; cs1 (2r1 (t_1−1),cs1 (2r1 (t_2−1),. . ..cs1 (2r1 (t_n−1).
The total of all random walks is referred to as 'cs1.'
The total number of iterations executed is denoted by n'.

r1 (t) is a initial-rate characteristic described and r (t) is the principal feature for the same, and t' portrays an ant's random and unique step.

$$M_{Ant} = \begin{vmatrix} An_{1,1}\ An_{1,2} \ldots\ldots\ An_{1,d} \\ An_{2,1}\ An_{2,2} \ldots\ldots\ An_{2,d} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ An_{n,1}\ An_{n,2} \ldots\ldots\ An_{n,d} \end{vmatrix}$$

Because of the possibility of being stuck by an ant lion, ant fitness is taken into consideration. This health must also be correctly expressed in a matrix.

$$M_{Ant} = \begin{vmatrix} \int An_{1,1}\ An_{1,2} \ldots\ldots\ An_{1,d} \\ \int An_{2,1}\ An_{2,2} \ldots\ldots\ An_{2,d} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \int An_{n,1}\ An_{n,2} \ldots\ldots\ An_{n,d} \end{vmatrix}$$

Ant lions are also thought to be hiding in the area, in addition to ant behaviour. As seen in the picture below, their function becomes still another key requirement.

$$M_{Antlion} = \begin{vmatrix} AnL_{1,1}\ AnL_{1,2} \ldots\ldots\ AnL_{1,d} \\ AnL_{2,1}\ AnL_{2,2} \ldots\ldots\ AnL_{2,d} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ AnL_{n,1}\ AnL_{n,2} \ldots\ldots\ AnL_{n,d} \end{vmatrix}$$

For better use-case resolution, an ant lion fitness component should be considered. Because of the matrix that represents each ant lion's fitness functions, MOAL is handled.

$$M_{Ant} = \begin{vmatrix} \int AnL_{1,1}\ AnL_{1,2} \ldots\ldots AnL_{1,d} \\ \int AnL_{2,1} AnL_{2,2} \ldots\ldots AnL_{2,d} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \int AnL_{n,1}\ AnL_{n,2} \ldots\ldots AnL_{n,d} \end{vmatrix}$$

Any additional requirement is to maintain the random stroll within the designated location. A mix-max normalisation method is used to test this.

$$X_i^t = \frac{X_i^t - a \times (d_i - C_i^t)}{d_i^t - a_i} + C_i$$

Where,

a_i—denotes the smallest of the variable I walks, and
bi—denotes the highest of the variable I walks.
The smallest of the ith variable at the tth iteration is shown by C_i^t it.
d_i^t—the greatest value of the ith variable at the tth iteration.

$$C_i^t = Antlion_j^t + C^t$$
$$d_i^t = Antlion_j^t + d^t$$

Ant lions may construct snare that are commensurate to their objective function levels (instant). They compelled to move in a disorganized level. When the ant lions are attentive that the ants are being held captive, they sling sand from the cone-shaped hole's centre to the floor, diminishing the ants' chances of escaping. By gradually decreasing the width of the ants' search radius, the derivative model of this behavior can be overfed. The following equations are used to compensate.

$$C^t = C_t/_i$$
$$d^t = d_t/_i$$

With ants finishing the middle of the pit and an ant lion seizing it with its jaws, the hunt comes to an end. After this stopping condition, the ant lions drive the ants nearer to the pit's centre, where they are destroyed. For the purposes of analyzing the whole use case scenario, we'll assume that after an ant-lion take its prey, it gets much fitter than an ant-lion of that generation. To augment its chances of gathering morel ants, the ant lion was supposed to return to its current site while observing ants. The following equation is presented for the same.

$$Antlion_j^t = Ant_i^t \; if \; \left(Ant_i^t\right) > \int\left(Antlion_j^t\right)$$

Ant lion tj denotes the position of the jth ant lion at the tth new release, whereas Ant ti denotes the placement of the ith ant lion at the tth new release.

Many algorithms have an elitism feature that allows them to preserve their most favorable output at any point during implementation. The gorgeous ant lion spotted below the new release was reclaimed in the database and is now regarded as a good result. Because the elite ant lion is viewed as the best, it will influence the actions and movements of all ants in succeeding cycles. This assumes that the chosen ant lion ringed every ant walk at random.

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

Where R_A^t denotes an ant movement all over the ant lion described by the roulette wheel at the tth iteration's place.

3.3 Tournament selection based ant lion optimization algorithm

The ALO algorithms haphazardly walk model, mechanism of hunting, selection technique, and other features were updated in this study. The random walking mechanism in the earliest ALO program generates the ant's shambling route using the iteration count maximum. In terms of the algorithm's execution time, this method is ineffective. As a result, by lowering the size of the random walk, the first ALO algorithm breakthrough was achieved. It was chosen as the number of iterations that can be done in a given amount of time. As a result, the ALO algorithm's long running time has been significantly reduced. During the stage of sliding ants towards the ant lion's trap, a certain rate of slippage is used to shift the ants toward the ant lion's trap. We were able to improve the ants' movement by adding sand to the ant lion's pit. The following formulae are used to calculate it.

$$\left.\begin{array}{l} C_i^t = Antlion_i^t + C^t \\ d_i^t = Antlion_i^t + d^t \end{array}\right\} if\, 0.75 < opt < 1 \tag{13}$$

$$\left.\begin{array}{l} C_i^t = Antlion_i^t - C^t \\ d_i^t = Antlion_i^t - d^t \end{array}\right\} if\; 0.5 < opt < 0.75 \tag{14}$$

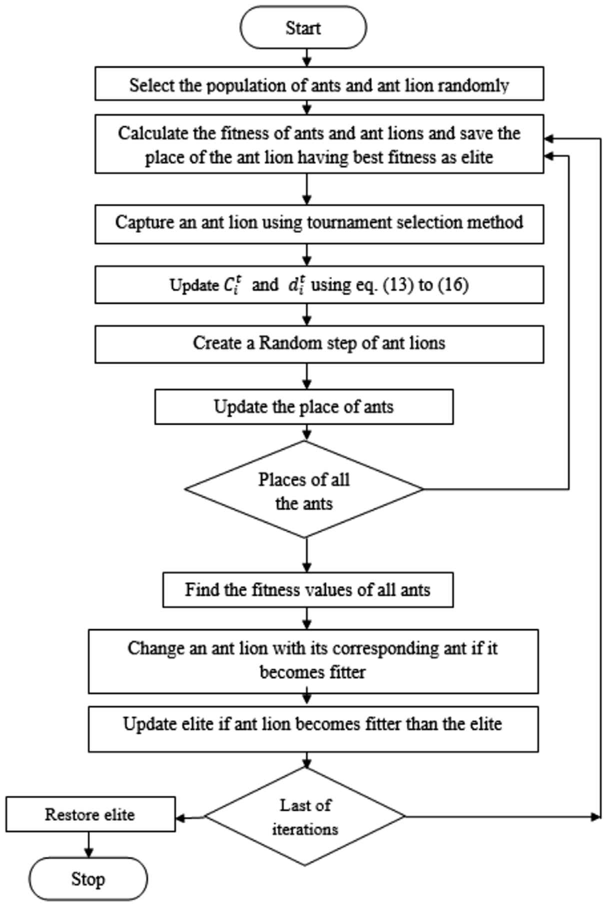

FIGURE 1
Tournament Selection Based Ant Lion Optimization.

$$\left.\begin{array}{l} C_i^t = -Antlion_i^t + C^t \\ d_i^t = -Antlion_i^t + d^t \end{array}\right\} if\; 0.25 < opt < 0.5 \tag{15}$$

$$\left.\begin{array}{l} C_i^t = -Antlion_i^t - C^t \\ d_i^t = -Antlion_i^t - d^t \end{array}\right\} if\; opt < 0.25 \tag{16}$$

Where opt denotes a variable chosen randomly. The rates of change have been upgraded, which has enhanced the precision and quickness of the hunting mechanism. The new mechanism for updating compares Ants' cost values and ant lion's cost for each ant couple. If the ant lion's cost is less than the ant lion's cost, the ant lion's location is shifted to the ant location. Another new feature involves ants who depart the position. When the ant's place is outside of the search space, unlike the original ALO algorithm, they return to it. This method assures that the ants take up places in the search space at random.

$$Ant_i^t = b_{low} + rand1 \times \left(b_{up} - b_{low}\right), \tag{17}$$
$$if\, Ant_i^t > b_{up} or\; Ant_i^t < b_{low}$$

Where rand1 represents a random number between (Ab Ghani et al., 2017) b_{low} indicates the lower bound and b_{up} is the upper

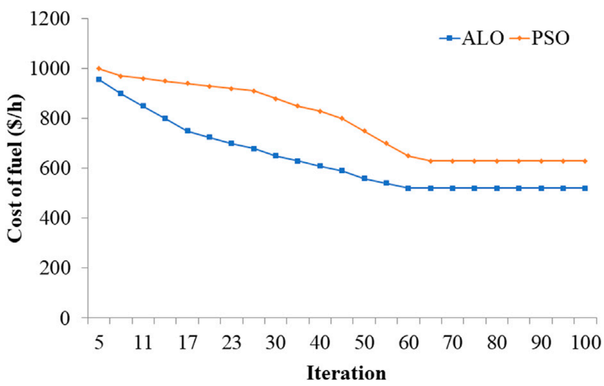

FIGURE 2
Characteristics of convergence for 5 generators system using ALO.

TABLE 1 ALO and PSO were used to optimise the cost of a five-generator system.

Generators	ALO	PSO
P1	47.0512	45.7654
P2	45.1675	46.8007
P3	46.2571	48.4312
P4	48.2645	46.9782
P6	49.1302	48.9532
Emission(ton/h)	**0.21542**	**0.21105**
Cost of Fuel ($/h)	**520.505**	**639.248**

To highlight fuel and emission cost.

TABLE 2 Data of the 5 unit system.

Quantities	P1	P2	P3	P4	P5
ai ($/(MW2h)	0.0080	0.0030	0.0012	0.0010	0.0015
bi ($/MWh)	2.0	1.8	2.1	2.0	1.8
ci ($/h)	25	60	100	120	40
ei ($/h)	100	140	160	180	200
fi (rad/MW)	0.042	0.040	0.038	0.037	0.035
αi (lb/MW2h)	0.0180	0.0150	0.0105	0.0080	0.0120
βi (lb/MWh)	−0.805	−0.555	−1.355	−0.600	−0.555
γi (lb/h)	80	50	60	45	30
ηi (lb/h)	0.6550	0.5773	0.4968	0.4860	0.5035
δi (1/MW)	0.02846	0.02446	0.02270	0.01948	0.02075
Pi, min (MW)	10	10	10	10	10
Pi, max (MW)	75	125	175	250	300
URi (MW/h)	30	30	40	50	50
DRi (MW/h)	30	30	40	50	50
POZs-1	[25, 30]	[45, 50]	[60, 70]	[95, 110]	[80, 100]
POZs-2	[55, 60]	[80, 90]	[125, 140]	[160, 180]	[175, 200]

TABLE 3 Obtaining an hourly based plan from DED (wt1 = 1, wt2 = 0).

Hour	P1	P2	P3	P4	P5	PLoss
1	24.8513	97.5298	29.0100	219.8059	51.0100	4.2070
2	50.2510	97.5298	29.0500	207.8058	49.0100	4.5166
3	74.0100	21.9569	31.4348	208.8283	137.9302	5.3002
4	64.1616	97.5296	111.6535	208.8058	51.0100	5.1805
5	74.0100	115.5426	112.4874	208.8365	52.0214	7.5777
6	51.2143	97.5322	111.6635	123.9179	228.5096	8.8574
7	74.5549	97.5327	113.6835	210.8258	138.7698	8.3267
8	42.7230	68.3959	113.6839	208.8258	226.5296	9.1272
9	39.0168	99.5298	125.2645	208.8058	227.5296	10.1465
10	25.0553	99.5708	113.6836	250.9099	228.5296	10.7891
11	18.0429	97.5571	176.0100	208.8258	228.5296	10.9254
12	36.5402	101.6153	175.0100	209.8258	228.5296	11.4809
13	65.0210	98.5298	112.6832	208.8258	229.5296	10.5695
14	66.5703	20.0100	175.9899	208.8258	228.5296	9.9255
15	12.6682	98.5739	111.6706	208.8258	228.5296	9.2680
16	73.9894	20.0120	175.9897	86.6327	228.5296	7.1514
17	12.9225	22.1882	174.0000	124.9180	228.5296	6.5482
18	55.0692	98.5298	111.6634	209.8258	138.7298	6.8579
19	39.8528	98.5555	175.9696	208.8058	138.7498	8.9535
20	65.2097	97.3213	111.6625	208.8058	227.5096	9.5688
21	54.3204	21.0700	174.0100	208.8158	228.5296	9.5358
22	52.0175	98.5299	111.6535	207.8058	137.7548	7.7565
23	55.8795	99.5300	111.6724	123.9879	137.7898	5.7805
24	10.0100	20.0114	112.6828	40.0100	285.4657	5.0970

Cost = 42,417.3552 $, Emission = 21,538.5964 lb, Loss = 190.5072 MW

bound of the search location. The selection approach is used by meta-heuristic algorithms to pick better people from a group. Roulette wheel, tournament, truncation, linear ranking, and selection based on exponential ranking are only a few examples. The most effective way for overcoming reduction concerns is tournament selection. This method involves holding a tournament among people chosen at random, with the tournament champion being the person with best cost-benefit ratio. The tournament size, often called the tour, is an important part of this technique. Only two people were allowed to join the excursion. The tournament method divides the population into two groups at random, with the size of each group determined by dividing the population by the tournament size, as given in Figure 1.

4 Results and discussion

4.1 Five generator test systems with ant lion optimizer

To provide the findings, the unit with ALO was completed with the same old quantities and general demand as 2.83 p.u. The

TABLE 4 Obtaining an hourly based plan from DEED (wt1 = wt2 = 0.5).

Hour	P1	P2	P3	P4	P5	PLoss
1	57.2025	68.7561	111.6725	122.9179	52.0600	3.5600
2	57.5473	91.8584	111.6835	125.9179	51.0100	4.0271
3	75.0200	76.8269	130.9277	125.9179	71.9778	4.6704
4	75.8200	92.1440	111.6535	123.9179	132.2662	5.7215
5	75.9989	97.1625	126.0047	123.9069	136.3588	6.4548
6	74.0100	97.5449	156.2911	146.0603	138.7497	7.5259
7	74.0400	97.5642	131.7728	191.3324	138.5629	8.1854
8	74.0100	111.0965	129.4108	208.7740	137.7496	9.0900
9	74.0700	98.7530	174.0100	219.1973	138.9648	9.9041
10	75.0100	114.3718	175.9996	208.9698	141.0283	10.3684
11	75.0100	117.5650	175.0050	218.9204	141.3634	10.8608
12	75.0600	107.3605	175.0600	237.0487	154.1514	10.4806
13	75.0400	108.0182	175.0500	209.8150	142.5395	10.3527
14	75.0700	104.0928	172.8935	205.2614	138.7687	9.9563
15	75.0800	98.5480	142.8635	206.8783	139.7769	8.9867
16	74.9989	95.3535	152.9118	124.9179	138.7889	6.9521
17	75.0200	98.5576	123.9806	128.1728	138.7697	6.4607
18	75.0400	98.5498	175.4817	128.8644	138.7694	7.6263
19	75.0300	98.2879	161.3830	188.5271	138.7076	8.8665
20	75.0400	115.1752	174.6723	208.7539	138.7688	10.3512
21	75.0100	98.5144	171.4055	203.9153	138.7785	9.5176
22	75.0400	98.5676	114.9718	186.4855	137.7587	7.6646
23	73.5632	96.6749	111.6835	123.9279	127.9583	5.7978
24	75.9199	97.3178	111.6541	125.9179	57.5545	4.5322
Cost = 45,233.3166 \$, Emission = 16,502.1423 lb, Loss = 184.1553 MW						

TABLE 5 Obtaining an hourly based plan from PDED (wt1 = 0, wt2 = 1).

Hour	P1	P2	P3	P4	P5	PLoss
1	53.6586	57.2556	117.5416	109.5871	73.3440	3.4730
2	58.0572	61.3719	120.8409	116.9736	77.6118	3.8754
3	63.5562	68.0700	131.2107	128.7605	86.0739	4.6513
4	73.1507	77.4377	142.5427	146.8116	97.8810	5.7836
5	73.9899	82.3254	146.2223	152.9148	105.9685	6.4209
6	75.0200	91.9599	159.4648	171.2398	117.9850	7.6594
7	75.0050	94.1664	163.1854	176.1623	121.5652	8.1093
8	74.0500	93.8916	167.7968	191.1270	135.0921	8.8565
9	75.0500	84.7658	173.9828	211.8998	152.2454	9.7728
10	75.0500	98.8718	172.6187	213.1151	151.7157	11.3243
11	75.0500	110.2914	175.9876	214.4327	153.1192	11.8298
12	75.0520	123.9303	175.9868	218.0773	161.4453	1.4747
13	75.5400	117.6821	164.7824	215.3778	144.5734	11.3847
14	75.0650	106.6570	175.7876	201.5936	141.8776	9.9168
15	75.0690	112.5616	163.4252	181.0786	132.8550	8.8933
16	75.0650	86.8110	152.9206	160.2842	108.8281	6.5549
17	75.0290	82.2531	146.2524	152.9151	104.0231	6.5408
18	75.0570	93.9873	156.1894	173.8854	118.6624	7.6536
19	75.0320	95.9859	172.2849	187.1710	132.3793	8.7522
20	75.0560	122.3432	173.8755	192.8565	151.2763	9.3336
21	75.1020	111.1516	172.5618	190.3585	136.5516	9.6334
22	75.1040	92.8875	155.7195	167.6137	117.3578	7.4685
23	71.7135	76.9252	141.9281	145.9211	97.2594	5.7374
24	62.8533	65.0722	128.7358	125.2168	85.5263	4.4153
Cost = 50,925.1736 \$, Emission = 15,595.6567 lb, Loss = 184.1825 MW						

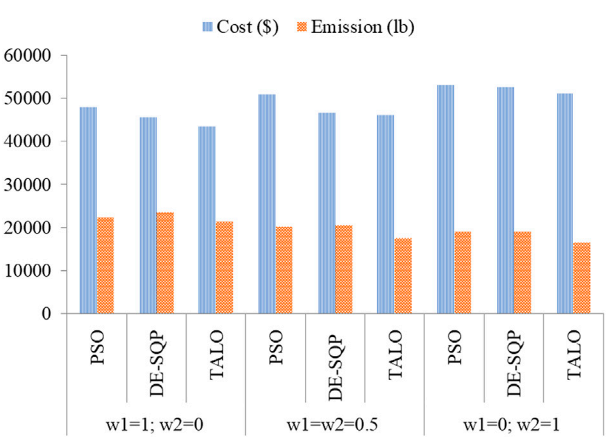

FIGURE 3
Graphical representation vs optimisation techniques.

TABLE 6 5-Unit system comparison results.

Weight	Techniques	Fuel cost (\$)	Emission (lb)
wt1 = 1; wt2 = 0	PSO (Hussain et al., 2019)	47,852	22,405
	DE-SQP (Shehata and Elaiw, 2015)	45,590	23,567
	TALO	42,417.3552	21,538.5964
wt1 = wt2 = 0.5	PSO (Hussain et al., 2019)	50,893	20,163
	DE-SQP (Shehata and Elaiw, 2015)	46,625	20,527
	TALO	45,233.3166	16,502.1423
wt1 = 0; wt2 = 1	PSO (Hussain et al., 2019)	53,086	19,094
	DE-SQP (Shehata and Elaiw, 2015)	52,611	18,955
	TALO	50,925.1736	15,595.6567

results, which included generation value and pollution cost, were well-optimized, with excellent convergence characteristics. These are listed in the table below.

The simulation results received from the ALO for the best solution to the power demand of 2.83 p.u are shown in Table 1, which shows the simulation results acquired from the ALO for the best solution to the power demand of 2.83 p.u and the convergence characteristics are shown in Figure 2. Table 1 compares ALO and various optimization algorithms when compared to existing population-based optimization techniques in the literature, the suggested algorithm performs the best.

The recommended approach's effectiveness is demonstrated using a 5-unit generation system with rugged fuel cost and emission functions. The need for the system has been distributed into 24 intervals, ranging from 414 to 751.47 MW, with a total of 468.0899 MW. Transmission losses are calculated using the B-loss coefficients formula. The simulation parameters are as follows: Maximum generation is 100, and the population size is 40. Table 2 shows the selected data of the 5 unit system and Tables 3, 4, 5 show the optimum solutions for dynamic economic dispatch (DED), dynamic economic emission dispatches (DEED), and pure dynamic emission dispatch (PDED), respectively.

The hourly generation time, cost, and emission obtained from the DED issue are shown in Table 3. The generating schedule is updated every hour. The cost, and emission obtained from the PDED problem are shown in Table 5. Tables 3, 5 show that the cost of DED is 42,417.3552 $, but that it rises to 509,251.1736 $ under PDED, and that the emission derived from DED is 21,538.5964 lb, but that it drops to 15,595.6567 lb under PDED. Table 4 displays the DEED problem's hourly generation schedule, cost, and emission. It can be observed that the cost is 45,233.3166 dollars, which is more than 42,417.3552 dollars but lower than 50,925.1736 dollars and the emission is 16,502.1423 pounds, which is lower than 21,538.5964 pounds but higher than 15,595.6567 pounds.

Table 6 compares the effectiveness of the suggested solution to alternative approach for the DEED problem with various weighting factors. Both the fuel price and the emission cost are lower than other mechanism published in the article. The graphical representation of various optimisations techniques is shown in Figure 3.

5 Conclusion

This work describes the tournament selection-based ALO algorithm (TALO), which was used to solve a static and dynamic combined economic and emission dispatch (CEED) problem using MATLAB R2021a. The simulation results received from the ALO for the best solution of static economic and emission dispatch problem to the power demand of 2.83 p.u is obtained. The TALO algorithm was compared to the PSO and DE-SQP algorithms. The comparison reveals that the suggested TALO method may compete in terms of performance with meta-heuristic algorithms. The proposed TALO method outperforms the original ALO algorithm on all metrics. When the suggested TALO algorithm adjustments are compared to alternative optimization methodologies, the outcome clearly show that the proposed TALO algorithm clearly outperforms the competition. The significant findings are:

1) The generation cost for dynamic economic and emission dispatch problems was reduced by 18.51 percent utilizing TALO, and the emission of harmful pollutants into the atmosphere was reduced by 1.8 percent.
2) Among the two methods discussed in the literature, the method that was suggested had the least gap in Economic and Emission values, indicating that it produces a better-compromised solution than the other two. Because the suggested TALO reduces the generating cost and the amount of emitted pollutants by 9.01 percent and 4.7 percent, respectively.

This research based on the economic and emission dispatch approach can be extended by solving large dynamic and multimodal test systems including renewable energy. The combined economic and emission dispatch problem with wind power penetration also aims to achieve optimal scheduling of power generators to minimize the fuel cost and emission generated by thermal generators while simultaneously satisfying all the equality and inequality constraints so that wind energy becomes a part of energy mix and supplies a portion of the power demand. Renewable energy power generation technology has an important impact on reducing pollutant emissions and promoting sustainable development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

HV: Conceptualisation, Methodology, Formal analysis, Writing–Original Draft; NC: Conceptualisation, Data Curation, Writing–Original Draft; NM: Validation, Resources, Writing–Review and Editing, Visualization; PS: Supervision; MB: Validation, Writing–Review and Editing; MA: Supervision; SK: Funding acquisition. All authors reviewed the results and approved the final version of the manuscript.

Acknowledgments

HV and NG acknowledges the support extended by Noorul Islam Centre for Higher Education, Tamil Nadu, India and

Centurion University of Technology and Management, Odisha, India.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Ab Ghani, M. R., Hussein, S. T., Amin, N. H. M., Jano, Z., and Sutikno, T. (2017). Dynamic economic dispatch problems: PSO approach. *TELKOMNIKA Telecommun. Comput. Electron. Control)* 15 (1), 48. doi:10.12928/telkomnika.v15i1.4618

Assiri, A. S., Hussien, A. G., and Amin, M. (2020). Ant lion optimization: Variants, hybrids, and applications. *IEEE Access* 8, 77746–77764. doi:10.1109/access.2020.2990338

Basu, M. (2011). Artificial immune system for dynamic economic dispatch. *Int. J. Electr. Power & Energy Syst.* 33 (1), 131–136. doi:10.1016/j.ijepes.2010.06.019

Benasla, L., Belmadani, A., and Rahli, M. (2014). Spiral optimization algorithm for solving combined economic and emission dispatch. *Int. J. Electr. Power & Energy Syst.* 62, 163–174. doi:10.1016/j.ijepes.2014.04.037

Bouddou, R., Benhamida, F., Zine, I., Zeggai, A., and Belgacem, M. (2020). Solving bid-based dynamic economic dispatch in competitive electricity market using improved simulated annealing algorithm. *Math. Problems Eng.* 07 (04), 621–630. doi:10.18280/mmep.070415

Chandrasekaran, G., Karthikeyan, P. R., Kumar, N. S., and Kumarasamy, V. (2021). Test scheduling of system-on-chip using dragonfly and ant lion optimization algorithms. *J. Intelligent Fuzzy Syst.* 40 (3), 4905–4917. doi:10.3233/jifs-201691

Daryani, N., and Zare, K. (2018). Multiobjective power and emission dispatch using modified group search optimization method. *Ain Shams Eng. J.* 9 (3), 319–328. doi:10.1016/j.asej.2016.03.001

Giri, N. C., and Mohanty, R. C. (2020). Performance evaluation of one MW on-grid SPV power generation plant in odisha, India. *Indian J. Nat. Sci.* 10 (58), 18084–18091.

Hussain, S., Al-Hitmi, M., Khaliq, S., Hussain, A., and Asghar Saqib, M. (2019). Implementation and comparison of particle swarm optimization and genetic algorithm techniques in combined economic emission dispatch of an independent power plant. *Energies* 12, 2037. doi:10.3390/en12112037

Kamli, S., and Amraee, T. (2017). Blackout prediction in interconnected electric energy systems considering generation re-dispatch and energy curtailment. *Appl. Energy* 187, 50–61. doi:10.1016/j.apenergy.2016.11.040

Li, L. L., Lou, J. L., Tseng, M. L., Lim, M. K., and Tan, R. R. (2022). A hybrid dynamic economic environmental dispatch model for balancing operating costs and pollutant emissions in renewable energy: A novel improved mayfly algorithm. *Expert Syst. Appl.* 203, 117411. doi:10.1016/j.eswa.2022.117411

Pan, S., Jian, J., and Yang, L. (2022). Solution to dynamic economic dispatch with prohibited operating zones via MILP. *Math. Biosci. Eng.* 19 (7), 6455–6468. doi:10.3934/mbe.2022303

Rezaie, H., Kazemi-Rahbar, M. H., Vahidi, B., and Rastegar, H. (2019). Solution of combined economic and emission dispatch problem using a novel chaotic improved harmony search algorithm. *J. Comput. Des. Eng.* 6 (3), 447–467. doi:10.1016/j.jcde.2018.08.001

Santra, D., Mukherjee, A., Sarker, K., and Mondal, S. (2020). Dynamic economic dispatch using hybrid metaheuristics. *J. Electr. Syst. Inf. Technol.* 7 (3). doi:10.1186/s43067-020-0011-2

Secui, D. (2015). A method based on the ant colony optimization algorithm for dynamic economic dispatch with valve point effects. *Int. Trans. Electr. Energy Syst.* 25 (2), 262–287. doi:10.1002/etep.1841

Secui, D. C. (2015). A new modified artificial bee colony algorithm for the economic dispatch problem. *Energy Convers. Manag.* 89, 43–62. doi:10.1016/j.enconman.2014.09.034

Shehata, M., and Elaiw, A. M. (2015). Hybrid DE-SQP for solving dynamic economic emission dispatch with prohibited operating zones. *Int. j. sci. eng. Res.* 6 (10), 1136–1141.

Song, H. M., Sulaiman, M. H., and Mohamed, M. R. (2015). An application of flower pollination algorithm to solve combined economic emission dispatch by considering valve-point loading effect. *Int. Rev. Model. Simulations* 8 (4), 427. doi:10.15866/iremos.v8i4.6182

Vennila, H., and Rajesh, R. (2022). *Chapter 46, ant lion optimization for solving combined economic and emission dispatch problems*. Springer Science and Business Media LLC.

Vennila, H., Ruban Deva Prakash, T., and Rajesh, R. (2013). A solution to the combined economic and emission dispatch using Hybrid HB-SA algorithm on Large scale power system. *Int. Rev. Model. Simulations* 6 (4), 1256–1263.

Wang, G. G., Gandomi, A. H., Zhao, X., and Eric Chu, H. C. (2016). Hybridizing harmony search algorithm with cuckoo search for global numerical optimization. *Soft Comput.* 20 (1), 273–285. doi:10.1007/s00500-014-1502-7

Yang, W., Peng, Z., Yang, Z., Guo, Y., and Chenc, X. (2021). An enhanced exploratory whale optimization algorithm for dynamic economic dispatch. *Energy Rep.* 7, 7015–7029. doi:10.1016/j.egyr.2021.10.067

Zou, D., and Gong, D. (2022). Differential evolution based on migrating variables for the combined heat and power dynamic economic dispatch. *Energy* 238 (Part A), 121664. doi:10.1016/j.energy.2021.121664