BFO-based firefly algorithm for multi-objective optimal allocation of generation by integrating renewable energy sources

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Abstract: Among the rapid evolution of modernisation of alternative energy, the electric power system can be made out of a few Renewable Energy Resources (RES). This paper presents a modern and proficient technique for clearing up the ELD issue. To resolve this issue we have amalgamated two meta-heuristic optimisation algorithms, e.g., the Bacterial Foraging Optimisation (BFO) algorithm and the Firefly Optimisation Algorithm (FA) by incorporating both the renewable energies, such as solar and wind power. The quality of the proposed methodology is tried and approved on the standard IEEE 3, 6 and the 10-unit systems by solving some cases as the fuel cost minimisation, whole generation cost minimisation, emission minimisation, and at the same time the system transmission loss. The attained results are contrasted and the MOPSO and the hybrid BOA algorithms. The results show that the proposed methodology gives an accurate solution for some category of objective functions.

Keywords: ELD; economic load dispatch; solar energy; wind power; fuel and total generation cost; BFO; bacterial foraging optimisation; firefly optimisation algorithm.

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1 Introduction

The power system is an electrical system to deliver, transmit, and distribute electrical power as one located in the various utilities to supply power (Ralhan et al., 2018). The updated power system is winding up increasingly more complex in its structure that makes breakdown in the electrical system (Fang et al., 2018). The principal target of the execution of the smart grid is circled the electrical power from the mass sources to minute apparatuses (Olivella-Rosell et al., 2018) and expanding the utilisation of electric energy utilising smart grid advances, which gives expanded reliability and power quality (He et al., 2018). Microgrids (MG) have seemed to be an excellent choice for adjustable power systems if there should arise an occurrence of cataclysmic occasions, i.e., typhoons, storms and seismic tremors (Manur et al., 2018). The thought MG has been described for perfect and practical task to supply adjacent load (Mehdizadeh et al., 2018). It represents a confident model of prospect electric power systems that self-sufficiently synchronise distributed renewable energy source (e.g., solar

PVs), controlled generation unit (e.g., gas generators), and the outside grid to fulfil time-differing energy demand of a nearby network (Zhang et al., 2018).

ELD is the procedure for reason for the output power produced by the segment or segments to supply the specific load in a way that will diminish the overall expense of fuel. ELD issue has become a critical task in the operation and planning of power system (Ali and Abd Elazim, 2018). The primary concern of ELD is to design the committed generators so that complete fuel cost is least satisfying the required load demand under set equality and inequality constraints (Mandal et al., 2018). In a power system, the ELD issue is managed by orchestrating a lot of generating units' outputs in an accurate order to diminish the expense of the working fuel and to coordinate the power system load demand (Al-Betar et al., 2018). ELD problem has been solved by specialised computer software.

Extraordinary advancement in power application requires an enormous amount of power generation (Gouthamkumar et al., 2015). By reason of deficient accessibility of ordinary energy sources, the need for Renewable Energy Sources (RES) has been expanded day by day. Current power system exist an assortment of power creating units utilising RES (Bhadoria et al., 2018) with a combination of RES in the power system can supply for better acknowledgment of the general energy generation proficiency, as the impacts of their intrinsic recurrences are decreased (Lorestani and Ardehali, 2018) RES in the energy generation faces many challenges to the System Operators (SO) mainly caused by the vulnerability atmosphere (Bakirtzis et al., 2018) without joining of renewable energy sources in the power system that takes a great deal of danger in the earth.

Miscellaneous procedures were incorporated to control economic dispatch in the power system. Singh and Dhillon (2019) proposed a hybrid algorithm called Ameliorated Gray Wolf Optimisation (AGWO) algorithm to clarify the classic optimisation issues with unimodal, spasmodic or multimodal target capacities with equilibrium of exploration and exploitation aspects. Xiong and Shi (2018) handled a hybrid method named BBOSB by joining Biogeography-Based Optimisation (BBO) with Brainstorm Optimisation (BSO). Pandey et al. (2018) examined the Improved Fireworks Algorithm-Chaotic Sequence Operator (IFWA-CSO) algorithm to solve complex economic dispatch issue of power systems considering several realistic constraints, e.g., valve-point loading impact, ramp rate limits, denied operating zones, and so on. Kumar and Dhillon (2018) proposed the Artificial Algae Algorithm (AAA) hybridised with Simplex Search Method (SSM) and a new hybrid algorithm known as Hybrid Artificial Algae Algorithm (HAAA). Kumar et al. (2018) approached new optimisation on the population-based meta-heuristics algorithm, known as Whale Optimisation Algorithm (WOA) for controlled ELD issues. Prakash et al. (2018) proposed a meta-heuristic algorithm named as Quasi-Oppositional Self-Learning Teacher-Learner-Based-Optimisation (QOSLTLBO) for solving non-convex ELD problem.

The remaining article is as follows. Section 2 considers some of the current works related to the ELD issue. Section 3 explains some of the theoretical learning about solar as well as wind energy. The issue formulation, which comprises the four proposed targets and the optimisation under equality and inequality constraints is discussed in Section 4. Section 5 presents simulation results and discourse on solution quality. Conclusions are summarised in Section 6.

2 Related work

Cardozo et al. (2018) presented a novel technique of security limitation in the economic dispatch issue. This method represents the various accumulations of the dynamic parameters of the reserve units in the optimal allocation of the recurrence containment reserve. The approach may permit the extension of renewable, yet non-synchronous, sources while guaranteeing the power system security and generation plans generally great.

Xie et al. (2018) proposed an Analytical Target Cascading (ATC) theory and it was developed to decouple the dispatching of DNs and MGs by demonstrating the tie-line stream as a pseudo generator/stack, so that Micro Grids (MGs) and Distribution Network (DNs) could separately utilise their separate resources to enhance their task and economic advantages.

Wang and Singh (2008) talked about a bi-objective economic dispatch issue considering wind penetration was designed, which treats operational expenditures and security impacts as clashing targets. Distinctive fuzzy enrolment tasks were utilised to imitate the dispatcher's viewpoint toward the wind power infiltration. An adjusted Multi-Target Particle Swarm Optimisation (MOPSO) algorithm was adopted to build up a power dispatch conspire which was capable to accomplish cooperation among economic and security necessities.

Li and Xiong proposed new method for a novel cascade integrated solar consolidated cycle system, named ISCC-DSG&ET, in which a parabolic trough solar field with Direct Steam Generation (DSG) innovation and an Evacuated Cylinder (ET) solar field are at the same time integrated into a natural gas-fired combined cycle power system in a cascade way to make full utilisation of their advantages at various temperature levels.

Liang et al. (2018) proposed a multi-target hybrid bat algorithm to solve the consolidated economic/emanation dispatch issue with power stream restrictions in the proposed algorithm the author utilised a controlled non dominated arrangement method and an altered swarming distance arrangement method was introduced to attain a uniformly circulated Pareto optimal front.

3 Renewable energy

In this investigation, just solar and wind power are contemplated for renewable sources (Pazheri et al., 2012). Wind power is generated by the wind turbine and solar power can be created either by solar panels or by solar thermal plants or by both.

3.1 Solar energy

The utmost solar power $P_s(W)$ supplied by a solar panel is corresponding to solar irradiation $i_s\left(W/m^2\right)$ and is given as:

$$P_s = P_p \frac{i_s}{1000W/m^2}\left[1-\theta(T-25)\right] \quad (1)$$

where P_p is the panel power rating and θ is the drift in panel output due to temperature per $°C$. The estimated solar power implemented by solar thermal plant is also proportional to i_s and is given as:

$$P_s = \xi_c A_c S \quad (2)$$

where ξ_c is the collector efficiency and A_c is the collector area in m^2.

3.2 Wind energy

The mechanical power produced by a wind turbine $P_w(W)$ can be written as:

$$P_w = \frac{1}{2} a_c \rho \mu S_w^3 \quad (3)$$

where a_c is the aerodynamic coefficient of the wind turbine which rely on the turbine and the wind speeds, ρ is the air density, μ is the surface swept in m^2 and S_w is the wind speed in m/s. So as to restrain the modify in the useful power delivered under varying wind speed, the system is designed so that the output power is persistent for a particular range of wind speeds. Also, wind turbines are planned to develop a nominal power P_n with a nominal wind speed S_n. Wind speeds higher than S_n cause mechanical overloading of the turbine.

To evade this congestion as well as to control the variance in the power output, the output power versus wind speed characteristic has précised in Table 1. Here, S_1, S_2 and $S_3\left(S_{min} < S_1 < S_2 < S_3 < S_n < S_{max}\right)$, are diverse wind speed levels available per day and P_{w_1}, P_{w_2} and P_{w_3} are the corresponding power outputs.

Table 1 Wind power variation with wind speed

Wind speed $S_w m/s$	*Wind power* $P_n(W)$
$S_w \le S_{\min}$	0
$S_{\min} S_w S_n$	Useful power
$S_1 \le S_w S_2$	P_{w_1}
$S_2 \le S_w S_3$	P_{w_2}
$S_3 \le S_w S_n$	P_{w_3}
$S_n \le S_w \le S_{\max}$	P_n
$S_w \ge S_{\max}$	0

4 Proposed BFO-based firefly algorithm for multi-objective ELD problem

The main objective of ELD is to decrease the generation cost so that the system load demand is met while satisfying various restraints.

4.1 Problem formulation

The main goal of customary ELD is to tighten the fuel cost, the outpouring of pollutant gases in spite of the overall generation cost as extracting most excessive power from the inexhaustible sources. Afterwards, the target functions should incorporate fuel cost, total generation cost, in addition to the emanation functions.

4.1.1 Objective functions

i) *Minimisation of fuel cost:* The target of conventional ELD issue is to discover the best allowance of generating powers in a power system. The power balance necessity, as well as the spawning power limitations for all units, should be satisfied. In other words, the ELD issue is to find the most favourable arrangement of power generations which limit the total fuel cost (Younes et al., 2014) while gratifying the power balance equality limitations and several inequality limitations on the system. The total fuel cost work is formulated as:

$$f_c(P_G) = \sum_{i=1}^{N_G} f_{c_i}\left(P_{G_i}\right) \quad (4)$$

where the term $f_{c_i}\left(P_{G_i}\right)$ can be expressed as follows:

$$f_{c_i}\left(P_{G_i}\right) = x_i P_{G_i}^2 + y_i P_{G_i} + z_i \quad (5)$$

where $f_c\left(P_{G_i}\right)$ is the total production cost; $f_{c_i}\left(P_{G_i}\right)$ is the fuel cost function of unit i; x_i, y_i and z_i are the fuel cost coefficients of unit *i*; P_{G_i} is the real power output of unit *i* in MW.

ii) *Minimisation of the impacts of emitted pollutants:* The primary outflows in thermal plants are SO_2 and NO_x. The surge of SO_2depends upon fuel utilisation and can be represented by a function that has the same form as the fuel cost function. Numerous components, for example, the temperature of the heater as well as the air content decide the emanation dimensions of NO_x. In general, the emission $f_e\left(P_{g_i}\right)$ in ton/h of SO_2 and NO_x pollutants is a function of generator output power and can be expressed as:

$$f_e\left(P_{G_i}\right) = \sum_{i=1}^{N_G}\left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 + \delta_i e^{\tau_i P_{G_i}}\right) \quad (6)$$

where α_i, β_i, γ_i, δ_i and τ_i are the emission coefficients of the *i*-th generating unit. P_{G_i} is the real power output of the *i*-th generator and N_G is the number of generators.

iii) *Minimisation of total generation cost:* The ELD problem reduces the total cost as given by Abu-Mouti and El-Hawary (2012),

$$f_T = \sum_{i=1}^{N_G} f_i \left(P_{G_i} \right) \tag{7}$$

where f_T is the total generation cost.

4.1.2 Constraints

i) *Equality constraints*: Any power system wants to balance the generator output with the demand and also compensate for the losses (Rathinam and Phukan, 2012). For power stability, an equality constraint ought to be satisfied. The generated power ought to be the same as the total load demand added to the total line misfortunes. It is unreasonable to avoid the system's transmission misfortunes so the B-coefficient formula is normally used to express it. Accordingly, the arithmetical formulation representing the equality constraints of the issue considered is as per the following:

$$\sum_{i=1}^{n} P_{G_i} = P_{d_i} + P_{l_i} \tag{8}$$

where P_{G_i} represents the current power generation of *i*-th unit, P_{d_i} denotes the power demand of *i*-th unit, and P_{l_i} is the net Power loss of *i*-th unit. Integration of the Renewable Source (RS) changes the equality constraints function to be as follows:

$$\sum_{i=1}^{n} P_{G_i} = P_{d_i} + P_{l_i} - \sum_{RS=1}^{m} \varphi_{RS} P_{RS_i} \tag{9}$$

where φ_{RS} represents the multiplier which is set to an acceptable amount of active power injected by RS which is set to 1, and P_{RS_i} represents the estimated real power from RS $\forall\, RS \in \{1, 2, ..., m\}$.

ii) *Inequality constraints*: The inequality constraints of the ELD problem are the unit's ramp-rate limits, i.e., the upper ramp rate $\left(U_{r_i} \right)$ (MW/time period) and the down ramp rate $\left(D_{r_i} \right)$ (MW/time period). At the point when the generator yield surpasses as far as possible, the generator affected over-voltage and insulation damage. Overload leads to a low voltage condition in generators, in the constant operation is causing load shedding issues. So, rely upon the upper and lower states of generator yield, the optimisation algorithm is tuned to turn into a constrained optimisation issue which can be considered as pursues

$$P_{G_i} - P_{G_i}^0 \le U_{r_i} \tag{10}$$

$$P_{G_i}^0 - P_{G_i} \le D_{r_i} \tag{11}$$

where $P_{G_i}^0$ is the previous operating point of the *i*-th generator. These upper as well as the lower limits are selected by inequality constraints as shown in equation (12).

$$P_{G_i,\min} \le P_{G_i} \le P_{G_i,\max} \tag{12}$$

where $P_{G_i,\min}$ represents the minimum generator output and $P_{G_i,\max}$ denotes the maximum generator output.

iii) *Ramp rate limit*: According to the operating increases and operating decreases of the generators are ramp rate limit (Singh and Kumar, 2013) the constraints are described in equations (13) and (14).

While the generation increases the ramp rate limit has represented as,

$$P_{G_i} + P_{G_i}^0 \le U_{r_i} \tag{13}$$

And once the generation decreases the ramp rate limit has represented as,

$$P_{G_i}^0 - P_{G_i} \ge D_{r_i} \tag{14}$$

As soon as the generator ramp rate limits are deliberate, the operating limits in place of each unit, the output are constrained through the time-dependent ramp up/down rate at each hour as given below:

$$P_{G_i,\min} = \max\left(P_{G_i,\min}, P_{G_i}^0 - D_{r_i} \right) \tag{15}$$

$$P_{G_i,\max} = \min\left(P_{G_i,\max}, P_{G_i}^0 - U_{r_i} \right) \tag{16}$$

$$P_{G_i,\min} \le P_{G_i} \le P_{G_i,\max} \tag{17}$$

iv) *Prohibited operating zone constraints (Papageorgiou and Fraga, 2007)*: Sporadically the fuel cost will have some unequal ranges. For this matter, there are some sources, e.g., valve-point impact performance, imprudent ambiences on shafts as well as the physical restrictions in gadgets. Each generator with *R-I* denied zones has branded by *R* disjoint working sub-areas $\left(\hat{P}_{G_i,R}^L, \hat{P}_{G_i,R}^U \right)$

$$\hat{P}_{G_i,r}^L \le P_{G_i} \le \hat{P}_{G_i,R}^U,\ \forall i \in \omega, r = 1, ..., R \tag{18}$$

where $\hat{P}_{G_i,I}^L = P_{G_i,\min}$, $\hat{P}_{G_i,R}^U = P_{G_i,\max}$ and that only one of the above mutually exclusive restrictions should be gratified.

v) *Valve-point loading*: Valve-point loading distresses the input-output features of the generating units, passing on the fuel costs non-linear and non-smooth. It has been contemplated in the solution of ELD issues, yet not in the planning phase of unit commitment.

4.2 Optimisation techniques

4.2.1 Bacterial foraging optimisation algorithm

i) *BFO strategy*: Padmanabhan et al. (2011) was created by Kevin M. Passino activated by the ordinary option which will in general eliminate the animals with poor foraging strategies and favour those having fruitful foraging strategies. The foraging stratagem has basically managed by dint of four procedures specifically Chemotaxis, Swarming, Reproduction, and Elimination, in addition to Dispersal.

ii) *Chemotaxis*: Chemotaxis process is the attribute of development of bacteria in look for of nourishment and comprises of two routes namely swimming and tumbling. A bacterium is assumed as swimming if it interchanges in a pre-determined way, in addition to tumbling whether the bacterium transfers in an overall assorted pattern. Assume $\vartheta^i(p,q,r)$ represents *i*-th bacterium at *p*-th chemotactic, *q*-th reproductive and *r*-th elimination dispersal step. $si(i)$ is the size of the step taken in the random direction specified by the tumble (run length unit). At that point in computational chemotaxis, the fluctuation of the bacterium might beepitomizedas,

$$\vartheta^i(p+1,q,r) = \vartheta^i(p,q,r) + si(i)\frac{\Delta i}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{19}$$

where Δ shows a vector in the arbitrary route whose component recline in [–1, 1].The random walk of *E. coli* bacterium can be explained in two steps:

a) Swimming

b) Tumbling

Principally, the *E. coli* bacteria will move in two different paths. It will swim for a particular amount of time in one direction then it is going to tumble (change direction). Say $x(i)$ represents *i*-th bacteria and si, the step size taken within the random direction specified by the swim length. During the progress of chemotaxis, the $x(i+1)^{th}$ bacteria could likewise be assumed as

$$x(i+1) = x(i) + si(i)\frac{\Delta i}{\Delta(i)\Delta^T(i)} \tag{20}$$

iii) *Swarming*: It is constantly desired that the bacterium which has searched the best path of nourishment look for must attempt to attract other bacteria so that they reach the desired place more rapidly. Swarming makes the bacteria gather together into gatherings and consequently move a concentric pattern of gatherings with high bacterial thickness. Mathematically, swarming can be represented by

$$\begin{aligned} pen_c(\vartheta, pr(p,q,r)) = &\sum_{i=1}^{n}\left[-c_{1_{attract}}\, exp\left(-c_{3_{attract}}\sum_{fb=1}^{pr}\left(\vartheta_{fb}-\vartheta_{fb}^{i}\right)^2\right)\right] \\ &+\sum_{i=1}^{n}\left[-c_{2_{repellant}}\, exp\left(-c_{3_{repellant}}\sum_{fb=1}^{pr}\left(\vartheta_{fb}-\vartheta_{fb}^{i}\right)^2\right)\right] \end{aligned} \tag{21}$$

where pen_c is the penalty added to the original cost function. pen_c is basically the relative distances of each bacterium from the fittest bacterium. n is the number of bacterium, pr represents number of parameters to be optimised, ϑ_{fb} is the position of the fittest bacterium, $c_{1_{attract}}$, $c_{2_{repellant}}$, $c_{3_{attract}}$ and $c_{3_{repellant}}$ are dissimilar coefficients.

iv) *Reproduction*: In reproduction, populace members who have adequate nutrients will reproduce and the least healthy bacteria will pass away. The healthier half of the populace changes with the other half of the bacteria which gets disposed of, because of their poorer foraging performances. This makes the populace of bacteria constant in the development process.

The pseudo-code for the BFO algorithm has illustrated as follows.

Algorithm 1: BFO algorithm

1 Initialise the parameters D, N, st_s, st_c, st_{re}, pb_e, st_{ed}, $st(i)$, $(i = 1,2,3, ..., N)$, ϑ^i.
Where D denotes the Search space dimensions, N is the number of Bacterium, st_s: Swim steps, st_c: Chemotactic steps, st_{re}: Reproductive steps, pb_e: Probability of elimination, st_{ed}: Elimination and dispersal steps, $st(i)$: Step size, $l(i)$: Run length limit.

2 Elimination-dispersal loop $r = r+1$

3 Reproduction loop: $q = q+1$

4 Chemotaxis loop: $p = p+1$

for **i** $= 1,2,3, ..., N$ take a chemotactic step for bacterium i as follows

Compute the fitness function $fit(i, p, q, r)$.

Assign $fit_{last} = fit(i, p, q, r)$

//save the value since may find a better cost via a run.

Tumble

Generate a random vector $\Delta(i) = \mathbb{R}^D$.

Compute $\vartheta^i(p, q, r)$.

Swim

Let $ct = 0$, i.e., a counter for the swim length.

while $m < st_s$

if $fit_{last} > fit(i, p+1, q, r)$

Let $fit_{last} = fit(i, p+1, q, r)$, compute $\vartheta^i(p, q, r)$.

Then compute the new $fit(i, p+1, q, r)$.

else

Let $ct = st_s$.

Go to the next bacterium $i+1$, if $i \neq D$.

5 ***if*** $fit < st_c$, Go to Step 4. //Continue chemotaxis since the bacterium is alive.

6 **Reproduction**

For the given q and r, and for each bacterium, computes its health.

7 ***if*** $< st_{re}$, Go to Step 3.

We have reached the number of specified not reproduction steps, so we start the next generation of the chemotactic loop.

8 **Elimination-dispersal**

Eliminate and disperse each bacterium according to the probability pb_e.

if $< st_{ed}$, then go to Step 2; otherwise end.

End

v) *Elimination and dispersal*

An unexpected abrupt event may completely change the sequence and may cause the abolition and/or scattering to a new domain. They have the impact of conceivably obliterating the chemotactic progress; thus far they in like manner have the impact of assisting in chemotaxis, since dispersal may place bacteria near great nourishment sources. Removal and dispersal help in lessening the behaviour of stagnation for example being trapped in a premature solution point or local optima.

4.2.2 *Firefly (FA) optimisation algorithm*

The FA (Yang et al., 2012) is a meta-heuristic, nature-inspired optimisation algorithm which depends on the social gleaming behaviour of fireflies. It relies upon the swarm lead, e.g., fish, creepy crawlies or bird schooling in nature. It is to make sure a lot easier both in idea and execution. Its major advantage is that it utilises mainly real random numbers, and it is based on global communication among the swarming particles called as fireflies. The FA has three explicit admired principles that rely upon a part of the foremost sporadic attributes of authentic fireflies. Those attributes are as per the following

- All fireflies are unisex and they will move towards progressively gorgeous and brighter ones apart from their sex.
- The level of pleasant appearance of a firefly is proportional to its brightness which reduces as the separation from the other firefly augments. This is because of the way that the air ingests light. If there is anything brighter or more attractive firefly than a particular one, it will around then move arbitrarily.
- The brightness or light force of a firefly is calculated by the value of the target function of a given issue. For maximisation issues, the light force is proportional to the value of the objective work.

The pseudo code for the proposed FA has illustrated as follows.

Algorithm 2: Firefly optimisation algorithm

Objective function $(ps), ps = (ps_1, ps_2, \ldots, ps_D)^T$.

Initialise a population of fireflies $ps_i\ (i = 1, 2, \ldots, n)$.

Define light absorption coefficient η.

while $(t < MaxGeneration)$

for $i = 1 : n$ all n fireflies

for $j = 1 : i$ all n fireflies

Light intensity l_i at ps_i is determined by $F(ps_i)$.

if $(l_j > l_i)$

Interchange the firefly *i* on the way to *y* in all *D* dimensions.

end if

Attractiveness varies with distance d via $exp\left[-\eta d^2\right]$.

Evaluate new solutions and update light intensity.

endfor j.

endfor i.

Rank the fireflies and find the current best

end while

Post process results and visualisation.

i) *Attractiveness*: In the firefly algorithm, the layout of the attractiveness function of a firefly is given by the following monotonically decreasing function

$$\beta(d) = \beta_0 * exp\left(-\eta d_{ij}^m\right) \text{ With } m \geq 1 \tag{22}$$

where d is the distance between any two fireflies, β_0 is the initial attractiveness at $d = 0$, and γ is an absorption coefficient which controls the decrease of the light intensity (*l*).

ii) *Distance*: The distance between any two fireflies i and j at positions ps_i and ps_j respectively can be authenticated as a Cartesian or Euclidean distance as follows:

$$d_{ij} = ps_j - ps_i = \sqrt{\sum_{k=1}^{d}\left(ps_{j,k} - ps_{i,k}\right)^2} \tag{23}$$

where $ps_{i,k}$ is the *k*-th component of the spatial coordinate ps_i for the *i*-th firefly D is the number of dimensions, for $D = 2$.

$$d_{ij} = \sqrt{\left(ps_j - ps_i\right)^2 + \left(ps_j - ps_i\right)^2} \tag{24}$$

Though, depending on the characteristic of a problem, the calculation of distance d is also genuine using other distance matrix, such as Mahalanobi or Manhattan distance.

iii) *Movement*: The movement of a firefly i which is fascinated by means of a progressively striking, i.e., brighter firefly j has specified as

$$ps_i = ps_i + \beta_0 * exp\left(-\eta d_{ij}^2\right) * \left(ps_j - ps_i\right) + \omega * \left(r\text{and} - \frac{1}{2}\right) \tag{25}$$

where the underlying term represents the present position of a firefly, the second term is utilised for considering a firefly's allure to light force seen by neighbouring fireflies and the third term has connected for the arbitrary movement of a firefly if there are no more brighter ones. The coefficient ω is a randomisation parameter dictated by the issue of interest, rand is a random number generator consistently conveyed in the space [0, 1].

4.2.3 *Bacterial foraging-based firefly optimisation algorithm (BFO-FA)*

This segment presents a hybrid strategy comprising of BFO and FA algorithms. The two fundamental phases tangled in the improvement of the proposed algorithm are:

1. Global search through the FA operator pursued by
2. Local search over the BFO (chemotaxis) which alters the solution.

The incorporation of BFO and FA has several advantages over the advantages of the separation of the two algorithms. Some of them are

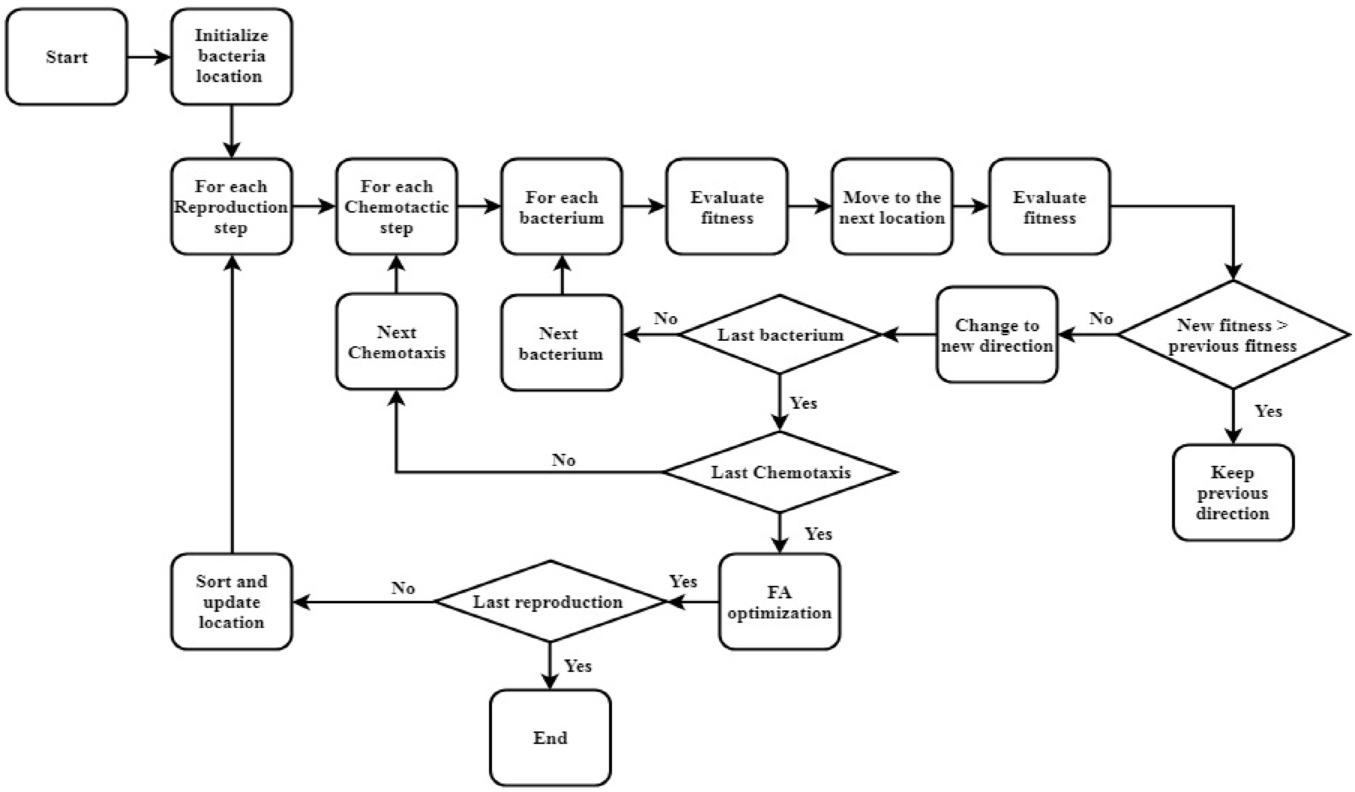
- The algorithm is not being imprisoned into the local least.
- Increased convergence speed.

In this hybrid incorporation, FA quickly earns a near-ideal solution which is then followed by the local search of BFO that regulates the solution and contributes an ideal solution of high exactness. FA has high convergence speed while BFO has the shortcoming of having a very poor convergence speed but has the ability of not being trapped in the local optima.

Figure 1 signifies the flow diagram of the proposed BFO-FA optimisation algorithm for reducing the ELD problem. After a specified number of entire swims, the resulting solution is stored in the descending order. A detailed portrayal of the total algorithm can be followed in Algorithm 3. In all the wrapper algorithms used, BFO-FA solves optimisation problems using the techniques of development and has risen as a promising one.

Figure 1 represents the flow diagram of the proposed BFO-FA optimisation algorithm for minimising the ELD problem.

Figure 1 Proposed flow diagram



Algorithm 3: Proposed BFO-FA algorithm

1 Set the parameters, D, N, st_s, st_c, st_{re}, pb_e, st_{ed}, $st(i)$, ps_i, η, l_i.

2 Start Elimination-dispersal loop

3 ***for*** every Reproduction, perform the following

4 ***for*** every Chemotaxis, perform the following

Calculate the fitness function fit of the initial population.

Set $fit_{last} - fit$. Hold this value. We can find a better cost value via a swim.

Tumble: Create a random vector delta (Δ) from -1 to 1.

Move: Let move the bacterium to a position with the step size $st(i)$ using the below equation and the equation (20) called Tumble.

Calculate $del = \left[r\text{and}(1,1) - 0,5 \right] \times 2$ (26)

Again **Swim**

Let $ct = 0$

While $m < st_s$ (not climbed too much)

$ct = ct + 1$;

if $fit(i) > fit_{last}$ (if present fitness is better than the previous),

Let $fit_{last} = fit(i)$ and use fit_{last} to calculate the new fit.

Calculate equation (20)

else add a new random number and calculate new $fit(i)$.

Let $m = st_s$;

end

5 Updation (FA algorithm)

for $ps_i \; (i = 1, 2, \ldots, n)$

Initialise the light absorption coefficient η.

Calculate the light intensity by $F(ps_i)$.

Update the movement of the *i*-th firefly using equation (25).

Estimate the new solutions and update the light intensity.

6 The bacteria with the lowest fit_{health} (final fitness) values will die and the left over bacteria with the finest fitness values are split into two bacteria thus making populattheion of the bacteria constant.

End

5 Simulation results

The proposed BFO based FA is applied for economic load dispatch issue. The intensity of the above-examined system tried with 3, 6 and 10 unit generating systems. The proposed technique is executed in MATLAB Software. In this work, the ideal portion of the generation has suggested that contemplates the combination of wind and solar resources together with random states of solar and wind power. The generation cost for this proposed allotment system has been determined in an hourly manner. The corresponding data of the hourly calculated generation are appeared Table 2.

The planned power system network comprises 3 cases decreased total generation; fuel cost also diminished the transmission loss and emitted pollution. In this proposed method the result is match up with MOPSO (Wang and Singh, 2008), and Hybrid BOA (Liang et al., 2018) algorithms. The proposed methodology has validated in three IEEE systems, such as,

i) IEEE 3-generating unit systems,

ii) IEEE 6-generating unit systems, and

iii) IEEE 10-generating unit systems.

i) *Three generating unit system*: A three-unit power system is a tiny system consists of three generators and meeting a load demand of 300 MW and includes generating cost, fuel cost.

Table 2 Hourly generated data

Time	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*
G_{s1}	0	0	0	0	0	0	0	0	0	0	4	4	4	4	4	4	4	4	4	4	4	4	4	4
G_{s2}	6	6	6	6	6	6	4	4	4	4	2	2	2	2	4	4	6	8	9	1	10	10	10	10
G_{s3}	5	7	2	4	1	6	8	6	9	2	10	10	4	7	8	8	8	9	9	9	2	3	3	5
G_{s4}	5	5	5	5	5	5	5	2	2	2	2	4	2	5	5	6	1	6	6	1	1	1	1	1
G_{s5}	0	0	0	0	0	0	3	3	3	3	3	6	6	6	6	6	7	7	7	9	9	9	9	9
G_{w1}	5	5	5	5	5	5	5	5	5	5	8	8	9	5	4	2	7	7	7	3	2	5	5	6
G_{w2}	4	7	5	8	5	3	9	10	5	2	10	10	4	6	8	9	7	9	10	10	10	10	10	10
G_{w3}	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2
G_{w4}	3	4	3	3	3	3	3	5	4	2	6	4	7	5	3	2	1	5	4	4	4	4	4	4
G_{w5}	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Figure 3 Three-generator unit system

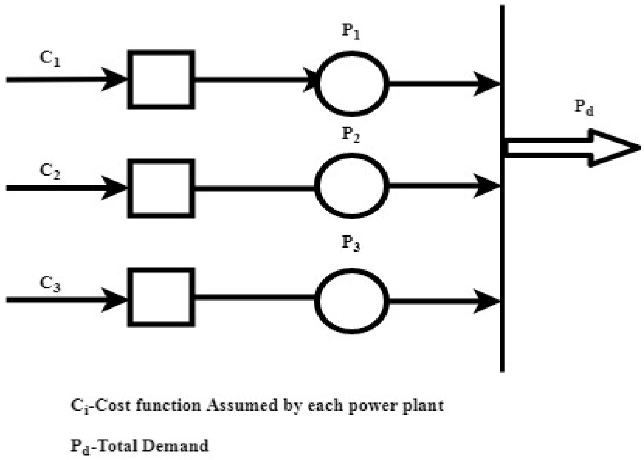


Figure 2 shows the line depiction of the three unit systems. The data of the 3-generator units and coefficients are given in Table 3.

Table 3 Generator cost coefficients for the 3-generator unit system

Unit	$P_{G_i,\min}$	$P_{G_i,\max}$	x_i	y_i	z_i
1	50	250	0.00525	8.663	328.13
2	5	150	0.00609	10.04	136.91
3	15	100	0.00592	9.76	59.16

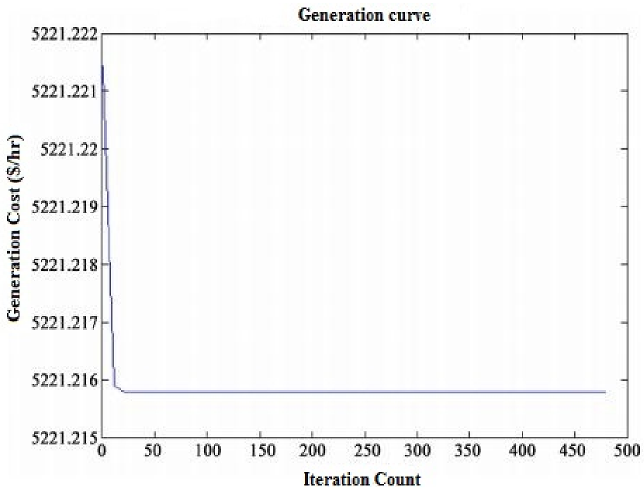
From the above table, we can recognise that each coefficient has its own unique value along with $P_{G_i,\min}$, and $P_{G_i,\max}$. The Table 4 shows the better suited algorithm for the ELD problem for the various loads for the system under consideration.

The optimal generation curve for the 3-generating systems has demonstrated in the following Figure 3.

Table 4 Comparison of the power output of 3-generator system

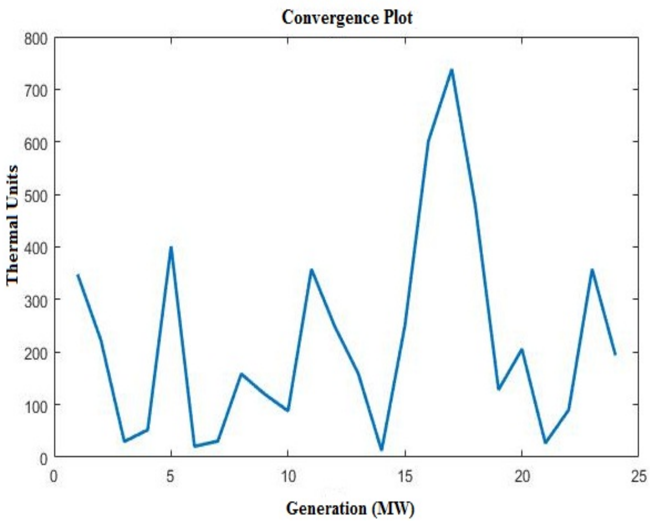
Different algorithms	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{l_i} *(MW)*	$f_c(P_G)$ $(\$/h)$
MOPSO (Wang and Singh, 2008)	193.82	74.78	15.00	8.61	3333.14
Hybrid BOA (Liang et al., 2018)	189.31	79.13	15.00	8.44	3332.69
Proposed FA-BFO	185.40	82.96	15.00	8.36	3331.42

Figure 3 Optimal generation curve for 3-generator unit



The cost convergence plot is expressed as follows. Figure4 shows the cost convergence of BFO-FA algorithm for various numbers of generations.

Figure 4 Cost convergence plot for 3-generating unit



It is clearly shown from the Figure that the solution is converted to a high-quality solution at the early iterations.

ii) *Six generating unit systems*: The 6-generating unit system consists of six generators and meeting a load demand of 1263 MW and includes transmission loss, POZ, and ramp-rate limits.

Figure 5 shows the line illustration of the 6-generating unit system. The data of the 6-generator units and coefficients are given in Table 5.

Figure 5 Six-generating unit system

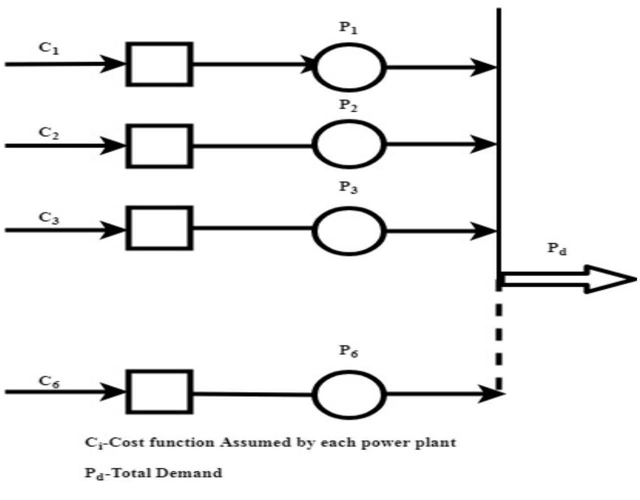


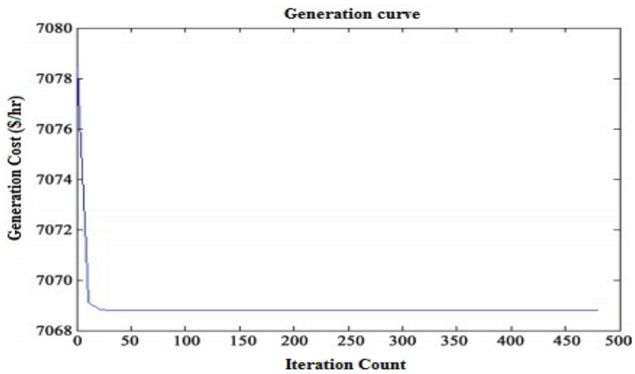
Table 5 Generator cost coefficients for the 6-generator unit system

Unit	$P_{G_i,\min}$	$P_{G_i,\max}$	x_i	y_i	z_i
1	100	500	0.007	7	240
2	50	200	0.005	10	200
3	80	300	0.009	8.5	220
4	50	150	0.009	11	200
5	50	200	0.008	10.5	220
6	50	120	0.0075	12	150

From the above table, we can recognise that each coefficient has its own distinctive value along with $P_{G_i,\min}$, and $P_{G_i,\max}$. Table 6 shows the better suited algorithm for the ELD problem for the various loads for the system under consideration.

The optimal generation curve for the 6-generator systems has illustrated in the following Figure 6.

Figure 6 Optimal generation curve for 6-generating units

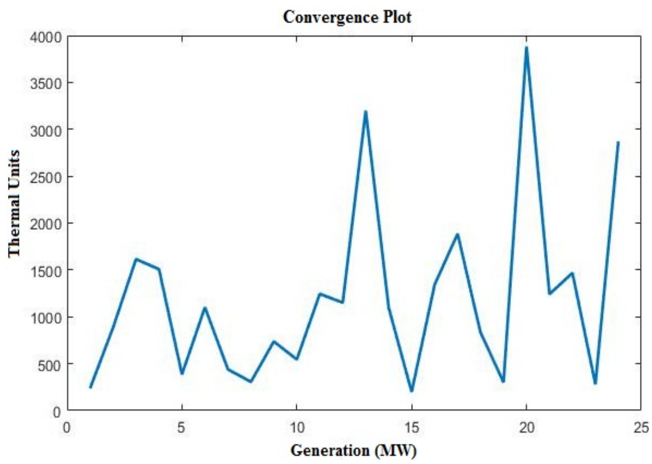


The cost convergence plot has expressed as follows. Figure 7 shows the cost convergence of BFO-FA algorithm for various numbers of generations.

Table 6 Comparison of the power output of 6-generator system

Different algorithms	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{l_i} *(MW)*	$f_c(P_G)$ ($\$/h$)
MOPSO (Wang and Singh, 2008)	30.26	20.687	256.48	778.97	3.9545
Hybrid BOA (Liang et al., 2018)	28.29	10.96	230.06	757.43	3.6912
Proposed FA-BFO	17.62	9.6	212.73	717.00	3.4569

Figure 7 Cost convergence plot for 6-generator unit



It was visibly shown from the Figure that the solution is converted to a high-quality solution at the early iterations.

iii) *Ten unit system*: The 10-generating units considered are having different characteristic. Their cost function characteristics are given by the equations. The data of the 10-generating units and coefficients are given in Table 7.

Table7 Generator cost coefficients for the 10-generator unit system

		$P_{G_i,\max}$	x_i	y_i	z_i
1	12	73	0.0051	2.2034	3.3804
2	36	93	0.0040	1.9104	3.4760
3	42	143	0.0039	1.8518	3.8539
4	18	700	0.0038	1.6966	4.6159
5	30	93	0.0021	1.8015	4.0396
6	100	350	0.0026	1.5354	3.8305
7	100	248	0.0029	1.2643	3.6327
8	40	190	0.0015	1.2130	3.8270
9	70	590	0.0013	1.1954	3.2521
10	40	113	0.0014	1.1285	3.3987

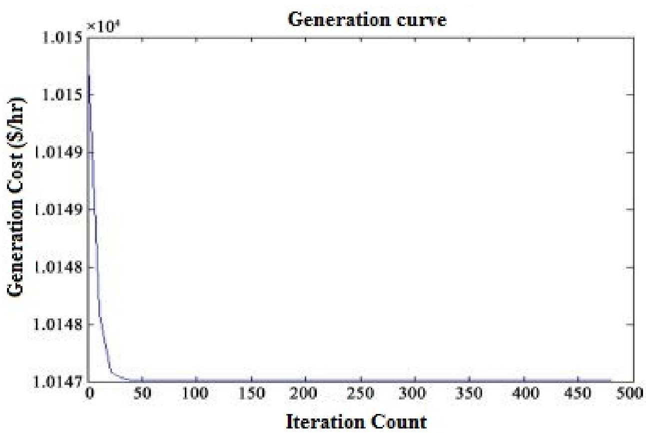
From the above table, we can identify that each coefficient has its particular value along with $P_{G_i,\min}$, and $P_{G_i,\max}$. The Table 8 shows the better suited algorithm for the ELD problem for the different various loads for the system under consideration.

Table 8 Comparison of the power output of the 6-generator system

Different Algorithms	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{G_1} *(MW)*	P_{l_i} *(MW)*	$f_c(P_G)$ $(\$/h)$
MOPSO (Wang and Singh, 2008)	120.78	225.74	1.9104	1.59945	4.2034
Hybrid BOA (Liang et al., 2018)	118.96	118.68	1.8518	1176.7	3.5354
Proposed FA-BFO	98.58	125.36	1.6966	1021.9	3.1285

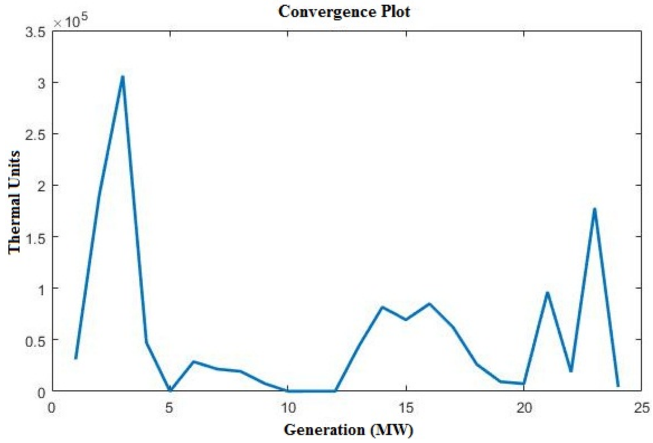
The optimal generation curve for the 10-generator systems has displayed in the following Figure 8.

Figure 8 Optimal generation curve for 10-generator unit



The cost convergence plot has expressed as follows. Figure 9 shows the cost convergence of BFO-FA algorithm for various numbers of generations.

Figure 9 Cost convergence plot for 10-generator unit



It was clearly shown from the figure that the solution is converted to a high-quality solution at the early iterations.

5.1 Case studies

Our proposed methodology consists of three cases which are explained as follows.

Case 1: Diminish generating cost and fuel cost

This case treats to confine the generation cost. The generator cost coefficients, generation limits of three unit frameworks, 6-unit frameworks, and ten unit frameworks are given below. ELD solution for 3, 6 and 10 unit frameworks is solved using BFO-based firefly algorithm. So it absorbs less amount of energy and this energy is produced from renewable energy sources so the spending amount fuel is less contrasted with the other framework

Case 2: Shrink environmental pollution

To diminish environmental corrosion because of outpouring from fossil fuels in power plants, the number of pollutants ought to rely upon the output power from the generating power plant, for example, the non-renewable energy sources previously mentioned. Be that as it may, for comparison purposes, the total ton/h diffusion *E* (*PG*) of these pollutants can be determined as

$$E(PG)=\sum_{a=1}^{n}10^{-2}\left(\alpha_a+\beta_a P_{Ga}+\gamma_a P_{Ga}^2\right)+\delta_a\exp\left(\epsilon_a P_{Ga}\right) \quad (27)$$

where, β_a, γ_a and ϵ_a are coefficients of the generator discharge characteristics. But, in this proposal source energy is from the renewable sources so it is not destructive for the environment.

Case 3: Decrease transmission loss

In this framework, just 3-, 6- and 10-generator units are used. So the number of the connection terminals is countable so there is no more loss in the transmission and distribution system. At the point when transmission distance is very small and load density is very high so the transmission loss is neglected.

5.2 Comparative study

Table 9 Total generation of different test cases

Different algorithms	Different test cases		
	3-generating unit	6-generating unit	10-generating unit
MOPSO (Wang and Singh, 2008)	3463.37	1012.44	1117.13
Hybrid BOA (Liang et al., 2018)	3205.99	905.54	984.94
Proposed FA-BFO	2549.23	735.07	829.92

The outcome of the proposed FA-BFO algorithm has compared with those obtained by modified multi-objective Particle Swarm Optimisation (MOPSO) algorithm (Wang and Singh, 2008), and hybrid bat optimisation (Liang et al., 2018) algorithm. The total generation cost for the three types of generating units for different optimisation algorithms has listed in Table 9.

The above table demonstrates that this proposed BFO-FA algorithm has low generation cast in all the three different test cases compared with the other optimisation algorithms. The fuel cost for the three types of generating units for different optimisation algorithms has listed in Table 10.

Table 10 Fuel cost of different test cases

Different algorithms	Different test cases		
	3-generating unit	6-generating unit	10-generating unit
MOPSO (Wang and Singh, 2008)	625.18	574.41	774.38
Hybrid BOA (Liang et al., 2018)	574.03	481.74	626.24
Proposed FA-BFO	488.50	323.81	481.72

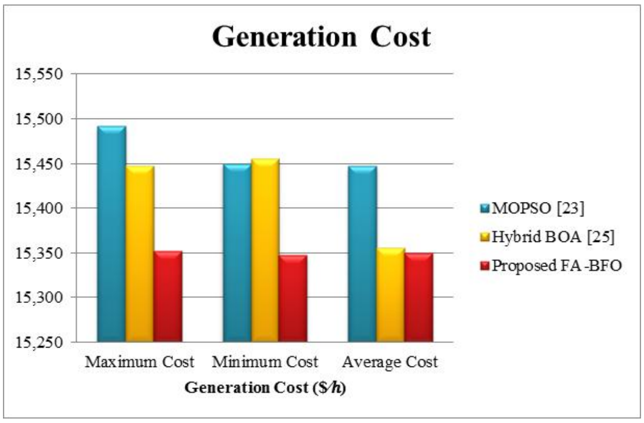
The above table shows that this proposed BFO-FA algorithm has low fuel cost in all the three different test cases compared with the other optimisation algorithms. The different generation cost values of different optimisation algorithms have displayed in Table 11 for the 3-unit system.

Table 11 Comparison of cost among different optimisation algorithms for 3-generator unit

Different algorithms	*Generation cost* $(\$ / h)$		
	Maximum cost	*Minimum cost*	*Average cost*
MOPSO (Wang and Singh, 2008)	15.492	15.450	15.447
Hybrid BOA (Liang et al., 2018)	15.447	15.455	15.356
Proposed FA-BFO	15.352	15.348	15.350

Based on the above table, the comparison graph has constructed, which is shown in Figure 10.

Figure 10 Comparison of generation cost for the 3-unit system



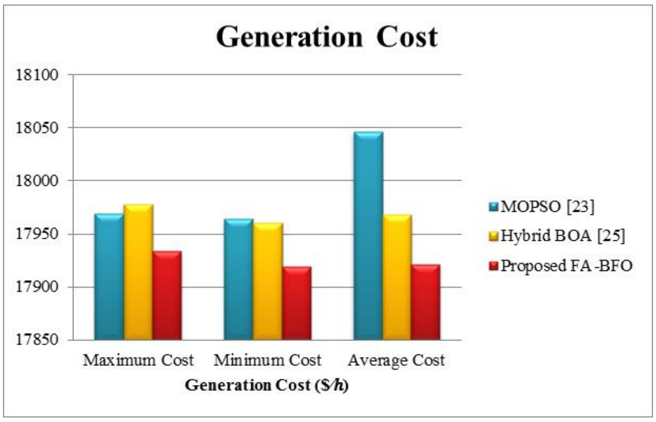
From the above figure, we can conclude that the proposed FA-BFO algorithm has least generation cost compare with other optimisation techniques**.** For the 6-unit system, the comparison of the maximum, minimum and the average cost has displayed in Table 12.

Table 12 Comparison of cost among different optimisation algorithms for 6-generating unit

Different algorithms	*Generation cost* $(\$ / h)$		
	Maximum cost	*Minimum cost*	*Average cost*
MOPSO (Wang and Singh, 2008)	17969.09	17963.89	18046.38
Hybrid BOA (Liang et al., 2018)	17978.14	17960.37	17967.94
Proposed FA-BFO	17933.61	17918.73	17921.12

Based on the above table, the comparison graph has constructed, which is shown in Figure 11.

Figure 11 Comparison of generation cost for the 6-unit system



From the above figure, we can consummate that the proposed FA-BFO algorithm has minimum generation cost than the other optimisation techniques for the 10-unit system.

The different generation cost values of different optimisation algorithms are shown in Table 13 for the 10-unit system.

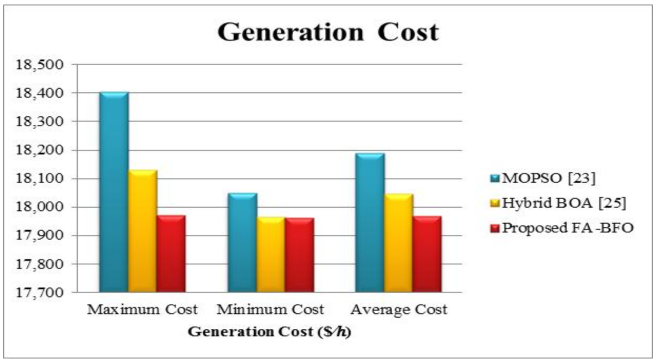
From the above figure, we can achieve that the proposed FA-BFO algorithm has least generation cost than the other optimisation techniques. Hence from the above outcomes, it is clarify that the MPSO algorithm leads to satisfactory results with faster convergence and better accuracy when compared to the conventional method and the PSO algorithm.

Table 13 Comparison of cost among different optimisation algorithms for 10-generator unit

Different algorithms	*Generation cost* ($/h)		
	Maximum cost	*Minimum cost*	*Average cost*
MOPSO (Wang and Singh, 2008)	15.492	15.450	15.447
Hybrid BOA (Liang et al., 2018)	15.447	15.455	15.356
Proposed FA-BFO	15.352	15.348	15.350

Based on the above table, the comparison graph has constructed, which is shown in Figure 12.

Figure 12 Comparison of generation cost for the 10-unit system



6 Conclusion

In this examination, we presented a method allowing the solution of the issue of the ELD of an electrical network by integrating the RES, for example, solar and the wind energy sources. We propose a hybrid optimisation method which has two meta-heuristic algorithms, for example, the BFO and FA. This method is utilised to solve the ELD issue including minimisation of fuel as well as the total generation cost, pollutant discharges, and simultaneously the network transmission loss. The issue is addressed by thinking about the infusion of wind as well as the solar power into the electric network. The results demonstrate that the proposed methodology has provided naturally to improve the multi-target work and to solve the above-mentioned objectives. Numerical testing demonstrates that the hybrid algorithm combines quicker to a considerably more appropriate solution for a variety of benchmark test functions. From the promising results, the proposed BFO-FA method has the potential to be applied in the dynamic ELD issues in future publications.

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