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Constrained Static/Dynamic Economic Emission Load Dispatch Using Elephant Herd Optimization

Rajagopal Peesapati [1], Yogesh Kumar Nayak [2], Swati K. Warungase [3] and Surender Reddy Salkuti [4,*]

[1] Department of Electrical and Electronics Engineering, Raghu Engineering College, Visakhapatnam 531162, India; rajgopal.peesapati@raghuenggcollege.in
[2] Department of Electrical Engineering, Government Engineering College, Keonjhar 758002, India; yogeshnayak_fee@gcekjr.ac.in
[3] Department of Electrical Engineering, K K Wagh Institute of Engineering Education and Research, Nashik 422011, India; swarungasethete@gmail.com
[4] Department of Railroad and Electrical Engineering, Woosong University, Daejeon 34606, Republic of Korea
* Correspondence: surender@wsu.ac.kr

Abstract: The rapid growth in greenhouse gases (GHGs), the lack of electricity production, and an ever-increasing demand for electrical energy requires an optimal reduction in coal-fired thermal generating units (CFTGU) with the aim of minimizing fuel costs and emissions. Previous approaches have been unable to deal with such problems due to the non-convexity of realistic scenarios and confined optimum convergence. Instead, meta-heuristic techniques have gained more attention in order to deal with such constrained static/dynamic economic emission load dispatch (ELD/DEELD) problems, due to their flexibility and derivative-free structures. Hence, in this work, the elephant herd optimization (EHO) technique is proposed in order to solve constrained non-convex static and dynamic ELD problems in the power system. The proposed EHO algorithm is a nature-inspired technique that utilizes a new separation method and elitism strategy in order to retain the diversity of the population and to ensure that the fittest individuals are retained in the next generation. The current approach can be implemented to minimize both the fuel and emission cost functions of the CFTGUs subject to power balance constraints, active power generation limits, and ramp rate limits in the system. Three test systems involving 6, 10, and 40 units were utilized to demonstrate the effectiveness and practical feasibility of the proposed algorithm. Numerical results indicate that the proposed EHO algorithm exhibits better performance in most of the test cases as compared to recent existing algorithms when applied to the static and dynamic ELD issue, demonstrating its superiority and practicability.

Keywords: energy management; economic load dispatch; artificial intelligence; elephant herd optimization

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1. Introduction

1.1. Overview

One of the key issues with the power dispatch system is the ELD, which aims to schedule the active power of the CFTGU as efficiently as possible while adhering to certain equality and inequality constraints. The efficient allocation of generators leads to minimizing electricity costs for the end consumer, which is achieved via the effective solution methodology [1]. Various approaches have frequently been applied to the ELD problem in the past, such as genetic algorithms (GA), sequential quadratic programming (SQP) and evolutionary programming (EP) [2,3]. These approaches are fast and require derivatives of their fitness function, but cannot successfully solve large and complex problems such as ELD with VPE and ramp rate limits, as the Hessian or Gradient matrix is too difficult to form [4,5]. Additionally, EPs involve long computational times while handling composite constraints. In view of this, quantum bits can be incorporated into EP to overcome composite constraints and to avoid local minima in the solution [6]. Likewise, in the recent past, algorithms such as an improved genetic algorithm with multiplier updating (IGAMU) [7], self-tuning hybrid differential algorithm (HDE) [8], anti-predatory particle swarm optimization (AP-PSO) [9], and EP with mutations (MEP) [10] have gained importance in solving the ELD problem. Further, algorithms such as PSO [11], evolutionary strategy optimization (ESO) [12] artificial bee colony (ABC) algorithm [13], hybrid quantum mechanics-inspired PSO (Q-PSO) [14], biogeography optimization (BBO) [15], and hybrid differential evolution with BBO [16] have been utilized to solve the complex ELD problem considering valve point effects (VPE) and transmission losses (TL). Even though these techniques are the most fitting choices for nonlinear optimization, they inherently suffer from lower convergence rates, tendencies toward local minima, and are highly sensitive to the control parameters.

The methods used in the past provide reasonable solutions, but search efficiency drops and higher times for convergence are required when utilizing ELD with valve point effects [17–19]. Due to the above limitations, the hybridized techniques, such as Q-PSO [20], hybrid PSO (HPSO) [21], gravitational search algorithm (GSA) [22], enhanced multi–objective cultural algorithm (EMOCA) [23], improved orthogonal design PSO (IDPSO) [24], modified kill herd algorithm (MKHA) [25], modified crow search algorithm (MCSA) [26], a self-adapted across neighborhood search (SA-ANS) [27], flooding-based topology discovery algorithm (FBTDA) [28], JAYA with self-adaptive multi-population and levy flights (JAYA-SML) [29], JAYA with teaching learning-based optimization (JAYA-TLBO) [30], hybrid grey wolf optimization (HGWO) [31], kernel tricks (KSO) [32], an improved Q-PSO [33], emended salp swarm algorithm (ESSA) [34,35], exchange market algorithm method (EMAM) [36], peafowl optimization algorithm (POA) [37], and modified H-PSO with BAT algorithm-inspired acceleration coefficients (BAAC) [38] have been proposed in order to solve the ELD problem. The above algorithms do not always achieve the global best, but generally tend to reach near to the global optimal value [39,40]. The traditional static ELD problem seeks to minimize the generation cost of CFTGU for a certain load in a given time-period by satisfying limitations such as power balance and generation limits. Additionally, when the load demand fluctuates significantly, it becomes more challenging to solve the ELD problem due to the ramp rate constraints of the CFTGUs.

Another suitable actual power dispatch requirement is the DEELD, which uses the dynamic dispatching for a load cycle of a 24 h period. The DEELD problem has been tackled in a number of different ways to date. At first, mathematical methods such as lambda step, optimal point, participation coefficients, and gradient-based approaches have generally been utilized for the DEELD problem. However, mathematical methods have drawbacks such as excessive memory utilization and being less accurate when addressing a highly complex problem. As a result, numerous artificial intelligence techniques (AIT) have since been used to tackle the DEELD problem and produce successful dispatch outcomes. In this context, to solve the multi-objective DEELD (MO-DEELD) problem, the dynamic non-sorted biogeography-based optimization (Dy-NSBBO) algorithm is suggested in reference [41]. Similarly, the algorithms such as the multi-objective virus colony search (MO-VCS) algorithm [42], moth–flame optimization with position disturbance updating strategy (MFO-PDU) [43], improved tunicate swarm algorithm (ITSA) [44], and improved sailfish algorithm (ISFO) [45] were created in order to solve the DEELD problem in the recent past. In [46], the authors noted that the DEELD problem is more challenging address as it involves both fuel and pollution costs.

Similarly, in [47], an improved bacterial foraging algorithm (IBFA) was implemented in order to solve the DEELD problem. In [48], the DEELD problem was solved using a multi-objective BAT optimization algorithm, which considers slope rate constraints and valve point effects. In [49], the convergence performance was not confirmed when the orthogonal-PSO algorithm was implemented to solve the DEELD problem. Likewise, many works have not addressed the emissions objectives when attempting to solve the DEELD problem [50]. In sum, even though the previous algorithms have been successfully applied to the DEELD problem, various drawbacks, such as higher convergence rates, a tendency to become stuck at local optimum values, and addressing only limited objectives, can be identified as major gaps.

On the other hand, the elephant herd optimization (EHO) algorithm has a strong potential of achieving a global optimal solution, with robustness and fast convergence speed; it is a newly proposed intelligent algorithm (see [51] and [52]). It has proven its ability to achieve the global optimal solution by implementing it in various standard test functions [53]. Likewise, the EHO has proven its ability to obtain the optimal solution using lower convergence rates when subjected to the design of the optimal PI controller for the control of the grid-tied four-phase switched reluctance generator (SFG) [54]. Furthermore, the discrete EHO (DEHO)-based partial transmit sequence (PTS) method is recommended to improve the peak-to-average power ratio of universal filtered multicarrier (UFMC) signals to minimum levels. The recent literature describing the static/dynamic ELD problem and a summary of the implemented algorithms are presented in Table 1.

Table 1. Literature review describing the methodology and associated problem of interest.

Reference	Methodology	Static ELD	Dynamic EELD
[4,5]	SQP	√	×
[7]	IGAMU	√	×
[8]	HDE	√	×
[9]	AP-PSO	√	×
[12]	ESO	√	×
[13]	ABC	√	×
[14,20]	Q-PSO	√	×
[15]	BBO	√	×
[16]	Hybrid-BBO	√	×
[21]	Hybrid-PSO	√	×
[22]	GSA	√	×
[23]	EMOCA	√	×
[24]	IDPSPO	√	×
[25]	MKHA	√	×
[26]	MCSA	√	×
[31]	HGWO	√	×
[34]	ESSA	√	×
[36]	EMAM	√	×
[41]	Dy-NSBBO	×	√
[42]	MO-VCS	×	√
[43]	MFO-PDU	×	√
[44]	ITSA	×	√
[45]	ISFO	×	√
[47]	IBFA	√	√
Proposed	EHO	√	√

1.2. Research Contributions

The major contributions of this work are as follows:

1. An artificial intelligence algorithm, namely, elephant herd optimization (EHO), is implemented in order to solve a critical engineering problem.

2. The algorithm is implemented in order to solve both the convex static and dynamic EELD problems of power systems.
3. The predictability of the proposed algorithm is evaluated by implementing the algorithm on three different systems, such as 6-, 10-, and 40-unit systems.
4. The obtained results are compared to the recent available algorithms in the literature to demonstrate the efficacy of the proposed approach.

1.3. Organization of the Present Work

Section 2 outlines the basic ELD problem formulations with various constraint scenarios. Section 3 illustrates the modeling of DEELD problem with constraints. Section 4 discusses the mathematical modeling of the EHO algorithm. Finally, Section 5 deliberates on the results, and Section 6 presents the conclusions drawn from the present work.

2. Problem Formulation for the Basic ELD Problem

2.1. Objective Function

The basic ELD problem comprises a fitness function along with various practical constraints. In the basic form, the fitness function is a quadratic function that describes the various cost functions of participating generators [20] on a hourly basis. The mathematical form of the fitness function for the BELD problem is shown below:

$$F_{BELD} = \sum F_g(P_g) = \sum a_g P_g^2 + b_g P_g + c_g \ \$/\mathrm{h} \quad \forall g \in N_g \tag{1}$$

The ELD problem consists of minimizing F_{BELD} is subject to the following constraints.

2.2. Constraints

2.2.1. Power Balance Constraints

The total power generated should be equal to the sum of the total load on the system and total transmission line network losses [25]. The mathematical form for the power balance constraint is shown below:

$$\sum_g P_g - \sum_d P_d - P_L = 0 \qquad \forall g \in N_g \text{ and } \forall d \in N_d \tag{2}$$

The transmission loss P_L may be represented using B coefficients [39]:

$$P_L = \sum_g \sum_g [P_g][B][P_g] + \sum_g B_0 P_g + B_{00} \qquad \forall g \in N_g \tag{3}$$

2.2.2. Generator Capacity Constraints

The output delivered from the generators maintained to be within their lower and upper limits, as shown below:

$$P_g^{min} \le P_g \le P_g^{max} \qquad \forall g \in N_g \tag{4}$$

2.2.3. Ramp Rate Limits Constraints

The power delivered P_g by the generator g in a period is to be maintained within certain up-ramp UR_g and down-ramp DR_g limits [34], with respect to the previous P_{g0}. This is shown below:

$$P_g - P_{g0} \le UR_g \quad \text{if } P_g \ge P_{go} \qquad \forall g \in N_g \tag{5}$$

and

$$P_{g0} - P_g \le DR_g \quad \text{if } P_g \le P_{go} \qquad \forall g \in N_g \tag{6}$$

and

$$\mathrm{Max}\left(P_g^{min}, P_{go} - DR_g\right) \le P_g \le \mathrm{Min}\left(P_g^{max}, P_{go} + UR_g\right) \quad \forall g \in N_g \tag{7}$$

The fitness function (1) is subject to real power balance constraints (2), generator capacity constraints (4), and ramp rate limit constraints (7).

3. Problem Formulation for Dynamic EELD Problem

In this section, we provide the mathematical formulations for the DEELD problem. We assume that the network has dispatchable power generators, $\forall g \in N_g$. The control variables of the DEELD problem are collected in the vector at each hour $x = [x_1, x_2, \ldots x_n]$, where $\{x \in P_g \forall g\}$ and P_g is the vector collecting the generations for all $\forall g \in N_g$. Let the function $\mathrm{f_{DEED}} : \mathbb{R} \to \mathbb{R}$ be the positive valued, differentiable, non-decreasing, and convex objective function that captures the generation cost for the DEELD problem. Let the $\partial_{P_g}(f_{DEELD})$ be the partial derivative with respective to the control variable P_g and the constraints imply that $\partial_{P_g}(f_{DEELD}) \geq 0$ for all $\forall g \in N_g$ [49]. The cost function for the DEELD problem f_{DEED} comprises a fuel cost function f_{FCF} and an emission dispatch function f_{EDF}, which are shown as follows:

3.1. Fuel Cost Function

The 24 h fuel cost function for all $\forall g \in N_g$ is represented as quadratic costs valued in USD (\$) [48]. The fuel cost function utilized in this work is shown as below:

$$f_{FCF} = \sum_{t=1}^{N_H} \sum_{g=1}^{N_g} a_g P_{g,t}^2 + b_g P_{g,t} + c_g \$ \quad \forall g \in N_g,\ \forall t \in N_H \tag{8}$$

3.2. Emission Dispatch Function

The next fitness function is the emission pollutants (f_{EDF}) in (kgs). It has a straight relationship with the output generated from the gth conventional generator. The emissions include CO_2, nitrogen oxide (NOx) and sulfur oxide (SOx), which are caused by the burning of fossil fuels [48]. The f_{EDF} can be expressed as follows:

$$f_{EDF} = \sum_{t=1}^{N_H} \sum_{g=1}^{N_g} \alpha_g P_{g,t}^2 + \beta_g P_{g,t} + \gamma_g \quad \forall g \in N_g,\ \forall t \in N_H \tag{9}$$

The above functions are minimized, as they are subject to various constraints, i.e., limits on active power generations, ramp rate limits, power balance constraints, and transmission loss constraints. The next sub-section discloses the constraints considered in this work.

3.3. Constraints

Transmission losses: The loss at any time segment tth, including B-coefficients, is given as follows:

$$P_{loss,t} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} [P_{i,t}] \times [B] \times [P_{j,t}] + \sum_{g=1}^{N_g} B_0 \times P_{g,t} + B_{00} \quad \forall g \in N_g, \forall t \in N_H \tag{10}$$

Active Power Balance Constraints: The power generated at any tth time segment is utilized to supply the demand and transmission losses at the given time segment. This is mathematically represented as follows:

$$\sum_{g=}^{N_g} P_{g,t} = P_{d,t} + P_{loss,t} \qquad \forall g \in N_g, \forall t \in N_H \tag{11}$$

Limits on active power generation: The active power generation $P_{g,t}$ at time segment t is restricted by the prescribed upper and lower limits. Figure 1 shows the pictorial representation of the maximum and minimum limits of a 6-unit system. This is mathematically represented as follows:

$$P_g^{min} \leq P_{g,t} \leq P_g^{max} \qquad \forall g \in N_g, \forall t \in N_H \tag{12}$$

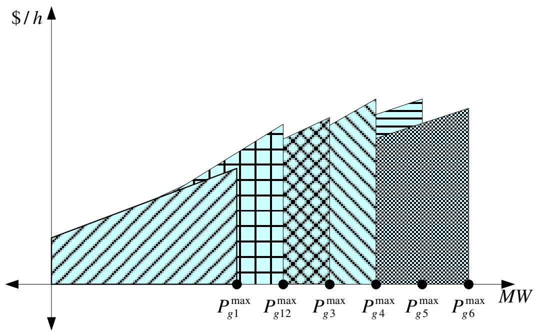

Figure 1. Thermal generator maximum and minimum limits.

Ramp Rate Limits: This is specified as follows [45]:

$$P_{g,t-1} - P_{g,t} \le UR_g \quad \text{if } P_{g,t} \ge P_{g,t-1} \quad \forall g \in N_g, \forall t \in N_H \tag{13}$$

$$P_{g,t-1} - P_{g,t} \le DR_g \quad \text{if } P_{g,t} \le P_{g,t-1} \quad \forall g \in N_g, \forall t \in N_H \tag{14}$$

$$max\left(P_g^{min}, P_{g,t-1} - DR_g\right) \le P_{g,t} \le min\left(P_g^{max}, P_{g,t-1} + UR_g\right) \ \forall g \in N_g, \forall t \in N_H \tag{15}$$

3.4. Weighted Fitness Function to Obtain the Optimal Scheduling Strategy

The weighted fitness function has been utilized in order to find the optimum fuel cost and emission dispatch of the generators. The weighted multi-objective function is discussed as follows:

$$f_T = u_1 f_{FCF} + u_2 f_{EDF} \tag{16}$$

where u_1 and u_2 are the weighting factors, set as 0.5 in this work.

Constraint Handling

The power balance constraints, including the real power generations, load demand, and charging/discharging, are handled by including a penalty factor to the objective function (17) as shown below:

$$Pf_T = u_1 f_{FCF} + u_2 f_{EDF} + \lambda_1 \left[\sum_{g=1}^{N_g} P_{g,t} - P_{d,t} - P_{loss,t}\right] + \lambda_2 \sum_{g=1}^{N_{gb}} \Delta P_g^2 + \lambda_3 \sum_{rg=1}^{N_{rb}} \Delta P_{rg}^2 \tag{17}$$

where

$$\Delta P_g = \begin{cases} P_g^{min} - P_{g,t} \ \ if \ P_{g,t} \le P_g^{min} \\ P_g^{max} - P_{g,t} \ \ if P_{g,t} \ge P_g^{max} \end{cases} \tag{18}$$

$$\Delta P_{rg} = \begin{cases} P_{g,t-1} - P_g \le UR_g \quad if P_g \le P_g^{min} \\ P_{g,t-1} - P_g \le DR_g \quad if P_g \ge P_g^{max} \end{cases} \tag{19}$$

The fitness function (17) is subjected to real power balance constraints (10), limits on active power generation (11), and ramp rate limits specified in (13)–(15).

4. Elephant Herd Optimization

In 2015, Wang et al. [51] created the EHO algorithm, taking inspiration from the social behaviors of elephant herds observed in nature. Even though elephants demonstrate intelligent behavior in real life, the EHO algorithm was created using the following idealized rules. The elephant population is divided into clans containing a constant number of elephants in each clan. One elephant in each tribe guides the others as they look for food and water. Additionally, as generations pass, some elephants of a particular age leave their clan to live independently in distant areas far from the family group they belong to. On this basis, the basic EHO algorithm is designed to have two main phases, namely clan updating and separation.

Clan Updating Operator

As previously stated, each of the elephants is led by a matriarch in their respective clan. Thus, matriarch authority ci influences the next position of each elephant in the clan ci. For instance, elephant j in clan ci is updated as follows:

$$x_{new,ci,j} = x_{ci,j} + \alpha \times \left(x_{best,ci} - x_{ci,j}\right) \times r \tag{20}$$

Here, uniform conveyance is utilized. No group's fittest elephant can be replenished by Equation (18). For the finest elephant, the clan is updated as shown below:

$$x_{new,ci,j} = \beta \times x_{centre,ci} \tag{21}$$

We can observe a new individual, $x_{new,ci,j}$, in Equation (19), which is produced by the data obtained by all the elephants in the clan ci. $x_{centre,ci}$ for the d^{th} aspect may be calculated as follows:

$$x_{centre,ci,d} = \frac{1}{n_{ci}} \times ci \sum\nolimits_{j=1}^{n_{ci}} x_{ci,j,d} \tag{22}$$

The center of clan ci,$x_{centre,ci,d}$ can be determined through the D estimations using Equation (20). Using the process above, the group refreshing administrator can be uncovered. When they reach puberty, the male elephants in each clan will depart from their group and live independently. When handling improvement-related concerns, an administrator can serve as an example of this isolating cycle. Let us assume that the elephants with the worst health will act as the isolating administrator at every age in order to improve the search capability of the EHO strategy. This mechanism is shown in Equation (21).

$$x_{worst,ci} = x_{min} + (x_{max} - x_{min} + 1) \times rand \tag{23}$$

The pseudo-codes for the clan updating operator and separating operator are shown in Figure 2 below.

Pseudo code for clan updating operator

Begin

for ci = 1 to n_{ci} do, for j = 1 to n_j do

    Update $x_{ci,j}$ and generate according to Equation (15).

if $x_{ci,j} = x_{best,ci}$ then

    Update $x_{ci,j}$ and generate $x_{new,ci,j}$ according to Equation (16)

end if, end for j, end for ci,

end

Pseudo code for separating operator

Begin

for ci = 1 to n_{ci} do

        Replace the worst elephant individual in clan ci by Equation (20).

end for ci

end

Figure 2. Pseudo-codes for the EHO algorithm.

5. Case Study

5.1. Description of Systems

In this study, the EHO algorithm is used to minimize the total fuel cost for both static and dynamic ELD problems of the power system. The results are evaluated on three different test systems to assess the effectiveness of the proposed approach. Concisely, the flow chart in Figure 3 illustrates the internal mechanism of the proposed algorithm along with process of achieving results.

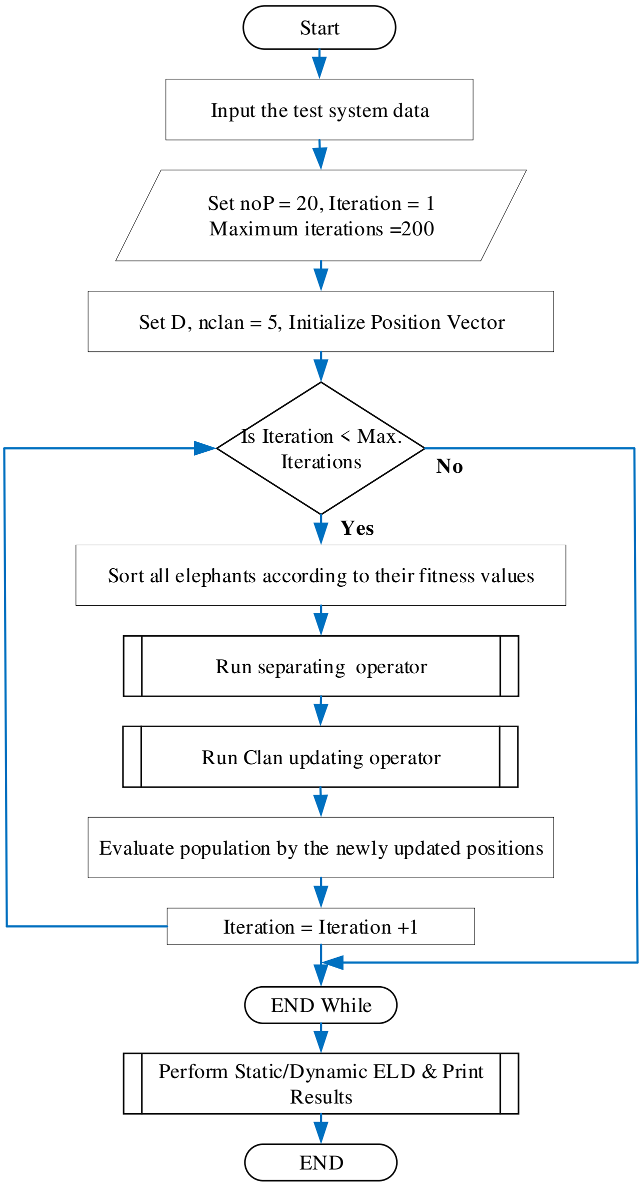

Figure 3. Flow chart for proposed EHO algorithm for ELD/DEELD problems.

5.1.1. Test System 1

Test system 1 utilized in the present study is a six-unit system. The details such as generator cost coefficients, generator limits, and the loss matrix of the test system 1 are shown in Table 2 below, which are taken from reference [25].

Table 2. Data for the six-unit system.

i	P_{gi}^{max}	P_{gi}^{min}	a_{gi}	b_{gi}	c_{gi}	B_{1i}	B_{2i}	B_{3i}	B_{4i}	B_{5i}	B_{6i}
1	500	100	0.007	7	240	0.002022	−0.000286	−0.000534	−0.000565	−0.000454	−0.000103
2	200	50	0.0095	10	200	−0.000286	0.003243	0.000016	−0.000307	−0.000422	−0.000147
3	300	80	0.009	8.5	220	−0.000533	0.000016	0.002805	0.000831	0.000023	−0.000270
4	150	50	0.009	11	200	−0.000565	−0.000307	0.000831	0.001129	0.000113	−0.000295
5	200	50	0.008	10.5	220	−0.000454	−0.000422	0.000023	0.000113	0.000460	−0.000153
6	120	50	0.0075	12	190	0.000103	−0.000147	−0.000270	−0.000295	−0.000153	0.000898

5.1.2. Test System 2

Similarly, in this study, test system 2 is a 40-unit system. The details related to this system are taken from references [30,32].

5.1.3. Test System 3

Similarly, in this study, test system 3 is a 10-unit system. The details related to this system are taken from reference [50].

5.2. Parameter Setting and System Configurations

The proposed EHO algorithm for solving static/dynamic ELD problems was implemented using MATLAB on a 64-bit laptop with a 2.60 GHz CPU and 8 GB RAM. Meanwhile, to evaluate their effectiveness, the results obtained from the proposed EHO algorithm at every stage are compared with standard algorithms, such as BAT [55], ALO [56], and those from other recently published works. The algorithm was tested on each test system 20 times to minimize the statistical errors, and the obtained results were compared with the previous literature. Further, the weighting factors, such as u_1 and u_2 in (17), are set to 0.5 in order to provide the equal preferences for the considered objectives [57]. Before proceeding to the simulated calculation, the careful selection of parameter settings is important to produce a competent result. The selection of the parameters, such as $iter_{max}$, considerably affects the performance of the EHO in terms of the present problem of interest. To successfully implement the EHO, the values of $iter_{max}$ were varied, namely as 100, 200, and 500 in order to obtain the best parameter setting. The results of this are presented in Table 3 for test system 1. Based on the results from Table 3, it can be observed that the EHO algorithm provides the best results when $iter_{max} = 200$ for test system 1.

Table 3. Parameter setting of EHO algorithm for test system 1.

$iter_{max}$	Best Cost (USD)	Worst Cost (USD)	Average Cost (USD)	Standard Deviations
100	15,299.62	15,428.46	15,339.83	34.78751
200	15,286.47	15,349.92	15,315.31	17.00265
500	15,293.25	15,351.38	15,308.31	15.80449

5.3. Computation Results and Comparisons

5.3.1. Test System 1

In this case, a six-unit static ELD problem considering losses is used to test the effectiveness of the proposed EHO algorithm. A general load demand $\sum P_d$ of 1263 MW is considered in the present test case. Twenty trials were utilized to evaluate each algorithm and the results were analyzed based on the best, worst, and standard deviation values obtained. Based on the static results obtained in Table 3 and to validate these, the $iter_{max}$ was set to 200 for the proposed EHO, ALO, and BAT algorithms, as shown in Table 4. The optimization results of the proposed and other reported approaches are shown in Table 5. The best fuel cost in this case is achieved through the EHO algorithm at 15,286.47 (USD/h), which is low compared to 15,443.0 (USD/h), 15,796.02746 (USD/h), and 15,814.97355 (USD/h) achieved by MKHA, ALO, and BAT algorithms, respectively. It is also clear from Table 5 that the proposed EHO algorithm provides a much better solution with less computational time compared to MKHA, ALO, and BAT algorithms. Furthermore, the convergence curves obtained by the proposed EHO and other reported approaches are shown in Figure 4. It can be observed that the EHO algorithm converges at a low number of iterations, which reinforces the superiority of the proposed approach. In addition, the results have been evaluated and validated using a medium-sized test bus system.

Table 4. Parameters considered for the reported algorithms.

Algorithm	$iter_{max}$	noP	Others	Reference
ALO	200	20	Not Reported	[56]
BAT	200	20	$\alpha = 0.99$, $\gamma = 0.9$	[58]
EHO	200	20	nClan = 5	Proposed Work

Table 5. Comparative results of the six-unit system with $\sum P_d = 1263$ MW.

i/Parameter	EHO	MKHA [25]	ALO [56]	BAT [58]
P_{g1}(MW)	439.858	447.3998	473.84	499.9837
P_{g2}(MW)	185.133	173.2424	181.75	148.8036
P_{g3}(MW)	247.6364	263.3833	265.87	270.8342
P_{g4}(MW)	133.7811	138.9778	129.85	127.1789
P_{g5}(MW)	160.6319	165.3929	165.35	179.3078
P_{g6}(MW)	96.18851	87.0495	85.081	75.5512
$\sum P_{gi}$(MW)	1263.229	1275.44	1301.74	1301.659
Losses (MW)	0.229	12.44	38.74	38.659
Best Cost (USD)	15,286.47	15,443.00	15,796.02746	15,814.97355
Worst Cost (USD)	15,349.92	15,443.00	15,796.02746	15,898.4937
Standard Deviations	17.00265	0.2318	7.46498×10^{-12}	23.83492754
Average Cost (USD)	15,315.31	15,443.00	15,796.02746	15,839.77276
CPU Time (secs)	2.29	7.41	2.46	2.72

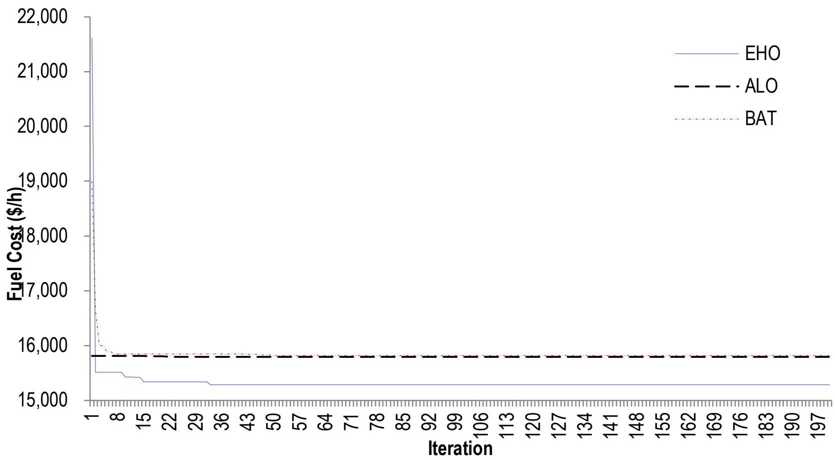

Figure 4. Convergence curve for various algorithms for a six-unit system with $\sum P_d = 1263$ MW.

5.3.2. Test System 2

This case study consists of 40 generators, meeting a demand of $\sum P_d = 10,500$ MW. The optimal scheduling of the generators in this case by the EHO, ALO, and BAT algorithms is shown in Figure 5. Similarly, the results obtained in this case by the EHO algorithm are compared with recent similar approaches, such as KSO [32], HDE [8], Beta-HC-GWO [59], and CBPSO-RVM [21], and are shown in Table 6. From the comparisons shown in Table 6, it can be seen that, among the reported algorithms such as BAT, ALO, and EHO, EHO performs well in respect to fuel costs. Furthermore, amongst all other algorithms listed, EHO performs better while producing minimum fuel costs as well as time consumptions. The convergence curves for the algorithms EHO, BAT, and ALO are shown in Figure 6. The micro-level examination of the figure reveals that the proposed EHO algorithm converges in the early stage (before 80 iterations), while the other two only settled with difficulty. The results demonstrate the superiority and practicability of the proposed EHO over the large test systems. Furthermore, to confirm the feasibility of the proposed EHO algorithm, the problem involving a dynamically varying load is discussed in the next section.

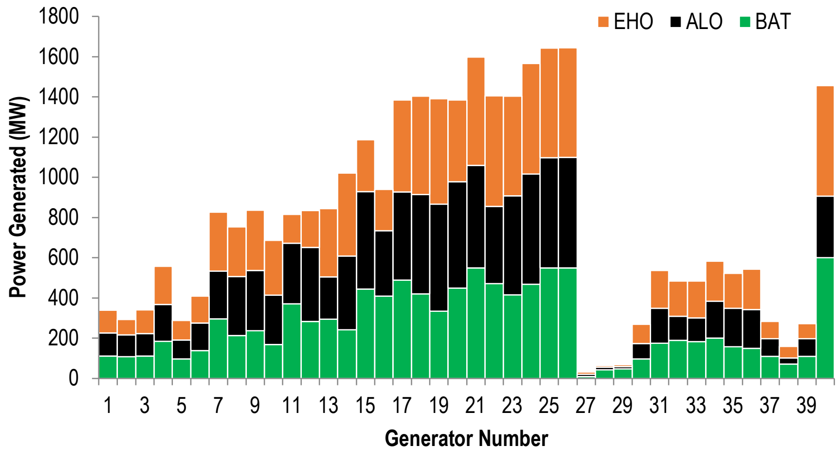

Figure 5. Active power generation of a 40-unit system with $\sum P_d = 10,500$ MW.

Table 6. Comparative results of a 40-unit system with $\sum P_d = 10,500$ MW.

Method	Best Cost (USD)	Time Consumption
BAT	124,835.00	21.0129
ALO	124,229.97	27.5294
KSO [32]	125,491.00	Not Reported
Self Turing HDE [8]	123,496.02	16.86025
Beta-HC-GWO (0.5) [59]	123,162.04	Not Reported
CBPSO-RVM [21]	122,281.14	Not Reported
EHO	121,478.96	21.2882

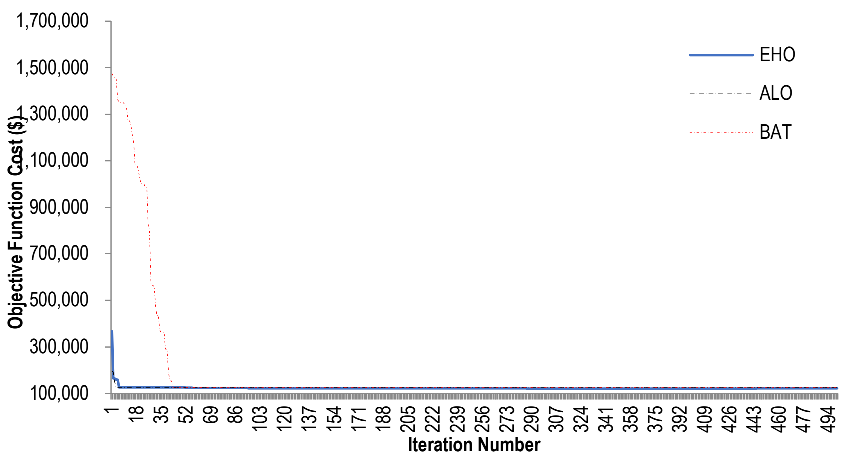

Figure 6. Convergence curve for various algorithms for a 40-unit system with $\sum P_d = 10,500$ MW.

5.3.3. Test Case 3

In this case, a 10-unit DEELD problem is used to evaluate the 24 h period fuel cost utilizing the proposed EHO algorithm. The data-related costs and up/down limits of the 10-unit system are taken from [24]. The general load profile referred to by most recent works such as [48] and [49] is depicted in Figure 7 below. Here also, in order to obtain the best setting of iter$_{max}$, iter$_{max}$ has been varied as 100, 200 and 500. The results of this are presented in Table 7 for test system 2. Based on the results from Table 6, it can be observed that the EHO algorithm provides the best results when the $\text{iter}_{\text{max}} = 500$ (as in test system 2).

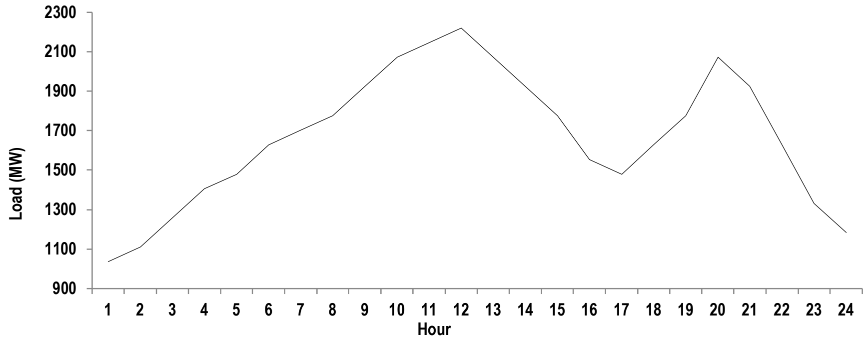

Figure 7. Load profile for a 10-unit system.

Table 7. Parameter setting of EHO algorithm for test system 3.

iter_{max}	Best Cost (USD)	Worst Cost (USD)	Average Cost (USD)	Standard Deviations
100	1,019,633.2	1,042,786.93	10,357,443.29	789.6
200	1,018,657.22	1,036,723.74	1,024,656.78	742.86
500	1,013,950.00	1,019,502.00	10,301,860.00	889.1759

The optimal dispatch of the 10-unit system in a period of 24 h by the proposed EHO algorithm is shown in Figure 8. The results, such as fuel costs and emissions on an hourly basis, are depicted in Table 8. It can be observed that the total fuel costs, f_{FCF}, and total emissions, f_{EDF}, for a period of 24 h, obtained by the proposed EHO algorithm, are 1,013,950 (USD) and 648,085 (kg) respectively. Furthermore, the comparative analysis of the obtained results with those of the previous benchmark approaches, such as ICA [60], CDE [61], DE [62], AIS [63], ECE [64], IPSO [65], DGPSO [66], BAT, ALO, SOA-SQP [67], PSO-SQP [68], MHEP-SQP [69], AIS-SQP [70], and CS-DE [71] algorithms, are shown in Table 9. From the table, it can be declared that the proposed EHO algorithm outperforms the previous approaches. In addition, the convergence characteristics of the proposed EHO and other reported approaches, such as ALO and BAT, are shown in Figure 9. From the figure, it can be seen that the proposed approach converges in a smaller number of iterations, as compared to other reported approaches. The comprehensive result analysis also demonstrates that the proposed approach has a remarkable impact on both static and dynamic EELD problems.

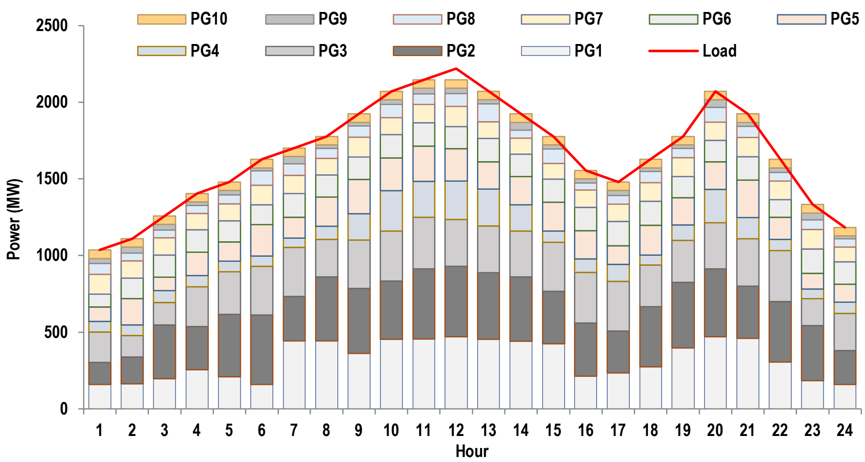

Figure 8. Hourly generation and the corresponding load of DEED problem via the EHO algorithm.

Table 8. Cost-based results for test system 3.

t	$f_{FCF,t}$	$f_{EDF,t}$	t	$f_{FCF,t}$	$f_{EDF,t}$
1	28,466	22,085	13	51,341	30,031
2	30,231	23,954	14	47,737	30,462
3	33,190	22,353	15	44,481	26,528
4	36,406	25,311	16	39,467	24,031
5	38,248	29,537	17	38,078	26,984
6	41,081	24,784	18	41,240	23,879
7	42,784	27,220	19	44,597	25,721
8	44,425	28,461	20	51,694	30,470
9	47,801	28,854	21	47,638	27,604
10	51,476	31,531	22	41,236	25,644
11	53,038	31,366	23	34,649	23,745
12	53,079	33,799	24	31,567	23,731
			Total	1,013,950	648,085

Table 9. Comparative results of a 10-unit system with dynamic loading.

Method	Best Cost (USD)	Average Cost (USD)	Worst Cost (USD)	Standard Deviation
		Individual approaches		
ICA [60]	1,018,467.49	1,019,291.358	1,021,795.773	687.56
CDE [61]	1,019,123.00	1,020,870.00	1,023,115.00	-
DE [62]	1,019,786.00	-	-	-
AIS [63]	1,021,980.00	1,023,156.00	1,024,173.00	-
ECE [64]	1,022,271.58	1,023,334.93	-	-
IPSO [65]	1,023,807.00	1,026,863.00	-	-
DGPSO [66]	1,028,835.00	1,030,183.00	-	-
BAT	1,033,416.00	-	-	-
ALO	1,035,431.00	-	-	-
		Hybrid approaches		
SOA-SQP [67]	1,021,460.00	-	-	-
PSO-SQP [68]	1,027,334.00	1,028,546.00	-	-
MHEP-SQP [69]	1,028,924.00	1,021,179.00	-	-
AIS-SQP [70]	1,029,900.00	-	-	-
CS-DE [71]	1,023,432.00	1,026,475.00	1,027,634.00	-
Proposed EHO	1,013,950.00	1,019,502.00	10,301,860.00	889.1759

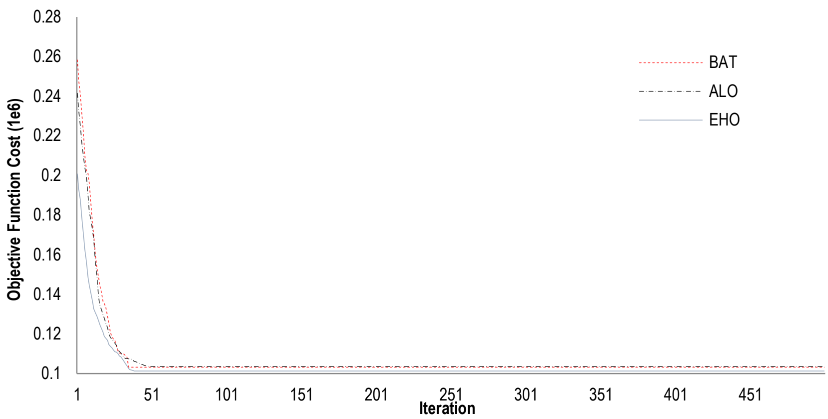

Figure 9. Convergence curve for various algorithms for the 10-unit system DEED problem.

6. Conclusions

In this study, a novel EHO method was used to resolve the power system's static and dynamic EELD problems. For both small- and large-scale test systems, the performance of the EHO algorithm was investigated in a variety of instances, involving both the static ELD and dynamic EELD problems. The numerical simulation demonstrates that the suggested EHO method is capable of finding the best scheduling for the test systems in regard to static and dynamic EELD problems. The comparative analysis of the fuel cost function value obtained by the EHO algorithm, with respect to the BAT and ALO algorithms, demonstrates its superiority and could save billions of USD annually by making the generating units eco-friendlier.

Furthermore, the convergence results also demonstrate that the proposed approach provides a significant reduction in fuel costs and convergence time for both small- and large-scale test systems, while solving complicated optimization problems in power systems. Finally, it can be concluded that the proposed approach is a superior alternative for power system operators to obtain an improved dispatch schedule for static and dynamic EELD problems in small- and large-scale systems, irrespective of their complexities.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

$F_g(P_g)$	The quadratic cost function of gth generator in ($/h)
a_g,b_g and c_g	The cost coefficients of the gth generator in $\left(\$/\mathrm{MW}^2\mathrm{h}\right)$
P_g	The active power output from the gth generator in MW
N_g	The total number of CFTGU
P_d	The power demand at the d^{th} load in MW
$[B], B_0, B_{00}$	The loss coefficient matrices
P_g^{max}	Maximum limit of active power generation of gth generator
P_g^{min}	Minimum limit of active power generation of gth generator
$x_{new,ci,j}$	Recently refreshed for elephant$j$ in clan ci
$x_{ci,j}$	Recently refreshed for elephant$j$ in clan ci
$x_{best,ci}$	Matriarch ci which is the fittest elephant individual in clan ci
r	Random value between [0, 1]
β	Random value between [0, 1]
D	Total dimension
n_{ci}	Quantity of elephants in ci clan
$x_{ci,j,d}$	The dth elephant individual of $x_{ci,j}$
x_{max}	The upper bound of the position of elephant individual
x_{min}	The lower bound of the position of elephant individual
$x_{worst,ci}$	Worst elephant individual in clan ci
$x_{centre,ci}$	Centre of clan ci
$rand \in [0,1]$	A real between the range [0 1]

Acronyms

GHGs	Greenhouse Gases
ELD	Economic Load Dispatch
DEELD	Dynamic Economic Emission Load Dispatch
EHO	Elephant Herd Optimization
CFTGU	Coal-Fired Thermal Generating Unit
VPE	Valve Point Effects
PTS	Partial Transmit Sequence
SFG	Switched Reluctance Generator
UFMC	Universal Filtered Multicarrier
GA	Genetic Algorithm
EP	Evolutionary Programming
SQP	Sequential Quadratic Programming
PSO	Particle Swarm Optimization
TL	Transmission Losses
IGAMU	Improved Genetic Algorithm with Multiplier Updating
HDE	Self-Tuning Hybrid Differential Algorithm
AP-PSO	Anti-Predatory PSO
ESO	Evolutionary Strategy Optimization
Q-PSO	Quantum Mechanics Inspired PSO
BBO	Biogeography Optimization
HPSO	Hybrid PSO
GSA	Gravitational Search Algorithm
EMOCA	Enhanced Multi-Objective Cultural Algorithm
IDPSO	Improved Orthogonal Design PSO
MKHA	Modified Kill Herd Algorithm
MCSA	Modified Crow Search Algorithm
SA-ANS	Self-Adapted Across Neighborhood Search
FBTDA	Flooding Based Topology Discovery Algorithm
HGWO	Hybrid Grey Wolf Optimization
ESSA	Emended Salp Swarm Algorithm
EMAM	Exchange Market Algorithm Method
POA	Peafowl Optimization Algorithm
Dy-NSBBO	Dynamic Non-Sorted Biogeography-Based Optimization
MO-VCS	Multi-Objective Virus Colony Search
MFO-PDU	Moth–Flame Optimization with Position Disturbance Updating Strategy
ITSA	Improved Tunicate Swarm Algorithm
ISFO	Improved Sailfish Algorithm
IBFA	Improved Bacterial Foraging Algorithm

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