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A hybrid optimization-based approach to solve environment constrained economic dispatch problem on microgrid system

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ABSTRACT

Generation of electricity comes with the emission of toxic gases into the atmosphere by the fossil fueled generators. Along with the promotion in the utilization of renewable energy sources (RES), it is also the duty of the power engineers to arrive at a compromised solution such that less emission of toxic gases occurs with economic generation of electricity. This paper proposes a balanced trade-off method for solving environment constrained economic dispatch (ECED) problems. A novel comparative analysis is performed among proposed ECED method with existing price-penalty-factor (PPF) and fractional programming (FP) methods for solving combined economic emission dispatch (CEED) problems on a 3-unit dynamic test system to sort out the method, which yields a better trade off solution between generation cost and pollutants emitted. An algorithm, following the hunting strategy of wolves, is improvised by incorporating strategies from population-based sine-cosine algorithm along with position updating methods of crows to form a robust hybrid algorithm, which was used as the optimization tool for the study. Involvement of RES diminished the generation cost to 5.5% for both economic dispatch and PPF based CEED, and 6.5% decrease in emission of pollutants was observed due to the same. The generation cost and amount of emitted pollutants, evaluated using proposed ECED approach, were much closer to the economic dispatch and emission dispatch values respectively compared to PPF based and FP based CEED solution. Furthermore, statistical analysis endorses the superiority of the proposed hybrid optimizer over other algorithms presented in the state-of-art literature.

1. Introduction

In the field of electricity industries, the efficacious and optimal operation and planning of electric power generating systems is of utmost importance. Problems based on cost efficient load dispatch (Economic Load Dispatch, ELD) are the most concerning issues in the field of control and operation of power system. Power system optimization problems employing ELD helps us determine the most appropriate, flawless and cost-effective operation by regulating the output of various generating units supplying the load demand. The sole ambition of ELD is reduction of the overall cost related to generation of power without violating any constraint.

On the basis of the power demand, generally referred as load, economic dispatch problems are broadly categorized into two parts: Static ELD, where the load demand is fixed for large intervals of time, which results in the fixed generator outputs for the duration in case of static load economic dispatch. The sole purpose is to obtain the minimum cost of generation and transmission, for every epoch of time, such that the total power generated can be exactly equal to the power required without violation of any constraint; Dynamic ELD, where the demand of the power system is consistently varying due to which the generators need to correspondingly adapt. In other words, with the increase in the load demand, the generator output needs to be increased and vice-versa. Thus, in dynamic load dispatch, the scheduling of generators committed to the grid is done as per the varying load at regular intervals of time with the intention of least cost of generation.

However, emission problems corresponding to the fossil fuels-based power plants cannot be neglected. With increasing environmental concern, it is our duty to not just optimize the operation of these power plants for our economic benefits but also, tackle the increasing emission problems as well. The major portion of the pollution is governed by the operation of thermal power plants which utilize fossil fuels for power generation. To deal with these serious environmental problems, Distributed Generation (DG) methodology is also adopted. DGs are combination of small power plants along with various other small scale

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List of abbreviations

AAA	Artificial Algae Algorithm
ANN	Artificial Neural Network
BBO	Biogeography Based Optimization
CCSA	Chaotic Crow Search Algorithm
CEED	Combined Economic Emission Dispatch
CHP	Combined Heat and Power
CSA	Crow Search Algorithm
DE	Differential Evolution
DELD	Dynamic Economic Load Dispatch
DG	Distributed Generation
DP	Dynamic Programming
DSG	Diesel Generator
DSM	Demand Side Management
ECED	Environmental Constrained Economic Dispatch
ELD	Economic Load Dispatch
ESS	Energy Storage System
EV/PEV	Electric Vehicle/Plug-in Electric Vehicle
FC	Fuel Cell
FP	Fractional Programming
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HMGWO	Modified Grey Wolf Optimizer Sine Cosine Algorithm Crow Search Algorithm
HSA	Harmony Search Algorithm
IFWA	Improved Fireworks Algorithm
ISA	Interior Search Algorithm
KHA	Krill Herd Algorithm
LMBP	Levenbergh Marquardt Back-Propagation
LV	Low Voltage
MG	Microgrid
MO-DE	Multi-Objective Differential Evolution
MODEED	Multi-Objective Dynamic Economic Emission Dispatch
MO-NN	Multi-Objective Neural Network
MT	Micro turbine
POZ	Prohibited Operating Zone
PPF	Price penalty factor
PSO	Particle Swarm Optimization
PV	Photo Voltaic System
RES	Renewable Energy Sources
RRL	Ramp rate Limits
SCA	Sine Cosine Algorithm
SSM	Simplex Search Method
VPE	Valve Point Effect
WOA	Whale Optimization Algorithm

List of symbols

ECD	Economic dispatch
EMD	Emission dispatch
j, n	Index representing generators
t	Index representing time period
a, b, c	Cost coefficients
x, y, z	Emission coefficients
G	Generators
ECED	Environmental constrained Economic Dispatch
max, min	Maximum, minimum values
μ	Weightage coefficient
CPI	Cost Performance Index
EPI	Emission Performance Index
D	Load Demand
UP	Utilization Percentage
un	Uncertainty
fc	Forecasted
PV	Power output from photo voltaic system
W	Power output from Wind system
n_1, n_2	Normally distributed random numbers
α, β, δ, Ω	Types of Grey Wolves
P	Distance among wolves
Y	Position of Wolves
R, Q, a	GWO coefficients
iter, max_iter	Iteration, maximum number of iterations
fl	Flight Length
AP	Awareness Probability
S	Solution Set

renewable energy sources which include wind turbine (WT), photovoltaic (PV) systems, Diesel engine, etc., which are installed at location near to user end. These help in reducing transmission losses due to reduction in the distance between the user and the plant and reduce environmental degradation as the load is now shared among various generating units, including renewable sources of energy. Despite of the aforementioned benefits of the DGs, issues like reliability and stability due to their large-scale incorporation cannot be neglected. To eliminate the issues related to DGs, the concept of microgrid was coined which provides the advantages of DGs and reduces their negative impact.

Every utility tries to fulfill the load demand with least cost of generation as well least value of emission. Being contradictory to each other, it is not possible to obtain, at the same time, the least value of both generation as well as emission. This heads to the concept of Combined Economic and Emission Dispatch (CEED). Unlike ELD, where the sole target is to minimize the cost of generation, the objective of CEED includes the concerns regarding pollution and emission along with the aim to minimize the overall cost. These calls, for certain rules and regulations, that need to be followed by both private and government firms, e.g., to reduce the various toxic effluents.

Ma et al. (2017) propose load dispatch model for charging plug-in electric vehicles to obtain the reduced cost of generation and environmental emissions. Research was carried on three case studies: 6-unit without PEV; 6-unit with PEV, and; 10-unit with PEV. Levenbergh Marquardt Back-Propagation Algorithm (LMBP) based Artificial Neural Network (ANN) was used by Daniel et al. to solve Dynamic Economic Load Dispatch (DELD) problems (Daniel et al., 2018). Tests were carried on 9 generating unit considering ramp rate limit constraints (RRL). Hybridized algorithm constituted with the amalgamation of Artificial Algae Algorithm (AAA) and classical Simplex Search method (SSM) having dynamically tuned parameters was proposed by Kumar and Dhillon (2018), where AAA executes overall optimization while SSM searches locally. The proposed algorithm was applied on various test systems, considering 13 generating units, 40 generating units and 80 generating units and the effects of Valve Point Effects (VPE), 140 generating units and the prohibited operating zones (POZs) and VPE and 40 generating units with VPE and transmission losses. Lokeshgupta and Sivasubramani (2018) propose Demand Side Management (DSM) technique to solve optimization problems considering time varying emission dispatch (MODEED). The DSM approach is based on day ahead load shifting and tested on 6 units considering, ramp rate limits, coefficients related to fuel and emission and 24 h forecasted demand considering different cases using DSM. DELD problems considering VPE is solved using improved PSO (IPSO), proposed by Yuan et al. (2009). The inequality constraints are handled using feasibility-based selection technique, and power balance constraint using heuristic strategies without use of penalty factors. Tests were performed on 10- generator system with cases of inclusion and exclusion of transmission losses and tripled ten-unit system to obtain 30 units data. Xu et al. (2014) compared Genetic Algorithm (GA) and Dynamic Programming (DP) for ELD of 26 hydro units of the three Gorges Reservoir. Hybridized Bacterial Foraging (BF) algorithm with simplified swarm optimization combined with opposition-based initialization and new mutation operator is proposed by Azizipanah-Abarghooee (2013), and tested on test systems comprising different generators sets: 5 units, 10 units, 30 units and 100 units, considering POZs as well as VPE. Modified group search algorithm is presented by Daryani and Zare (2018) for solving problem based on the combination of economic and emission dispatch on IEEE 30 bus system with cases of inclusion and exclusion of system loss along with the other constraints. Solution to stochastic DELD system incorporating WT and PV based generation systems by Improved FireWorks Algorithm (IFWA) is presented by Jadoun et al. (2018). Table 1 shows a summarized of the state of the art in economic emission dispatch for dynamic systems. The Table is dissected with respect to the optimization algorithms used, dimension of the test system, and type of RES implemented and year of publication.

1.1. Research gap and objective of the paper

A detailed in-depth literature review performed above highlights the innovative research going on with respect to CEED problems on dynamic system considering various test systems and entities. However, it was also noticed that every research article emphasized on a particular multi-objective optimization algorithm to perform a fixed type of CEED on dynamic test systems. Most of the papers are based on the pareto-front using multi-objective technique of performing CEED. The literature review shows that there is a gap in a fair comparative analysis among two or more methods of CEED, and the reason of choosing the multi-objective type over the others is not studied enough.

The main objective of the paper is the production of electricity power in a way such that the generation cost is minimized and the atmosphere remains clean, i.e., least possible amount of toxic gases is emitted from the combustion of fossil fuels by the generators. Three methods of combined economic emission dispatch are compared and contrasted among themselves to sort out the way, which delivers the better compromised solution between minimized generation cost and pollutants emission. All the methods are theoretically defined and mathematically formulated in the succeeding sections of the paper.

Recent literature considers algorithms such as Grey Wolf Optimizer (GWO), Sine Cosine Algorithm (SCA) and Crow Search Algorithm (CSA) in tackling multi-modal and complex optimization problems. The advantages of GWO in a large search space is its outstanding facet, it avoids premature convergence, it has lesser number of control parameters and gives the same accurate result consistently even after many trials. SCA presents the advantage of extraordinary exploration potential, and its toggling between sine and cosine functions generates an adequate trade-off between diversification and intensification process. While CSA has the prominent feature of exploitation potential, which ensures handling enormous population size with ease and results in rapid convergence. This paper proposed a hybrid of these three algorithms as GWOSCACSA, which would ensure adaptation of the best attributes of all the three thereby delivering optimal solutions.

1.2. Contributions

The main contributions of this paper to the state of the art on CEED studied above are listed as follows:

i. Three different types of CEED methods are studied on a 3-unit RES integrated low voltage microgrid systems.

Table 1
Recent studies based on economic emission dispatch for dynamic systems.

Optimization tools used	System Description	RES	Year	Ref
MO-DE with self-adaptive parameter	10 units with EV	WT	2020	Qiao and Liu (2020)
Two stage compensation algorithm	IEEE-118 bus test system & provincial power grid	WT	2017	Xie et al. (2017)
Gradient based JAYA	Multi-area with 6, 10, 16, 40 & 120 units	NA	2016	Azizipanah-Abarghooee et al. (2016)
Tent-Map DE	6 units and microgrid with ESS	WT, PV	2020	Mandal and Mandal (2020)
BBO	6, 13 & 40 units with TL	NA	2012	Rajasomashekar and Aravindhababu (2012)
CSA with PPF	3, 5 units	WT, PV	2020	Dey et al. (2020a)
ISA with PPF	3 units	WT, PV	2018	Trivedi et al. (2018)
Modified HSA with PPF	3 units	WT, PV	2018	Elattar (2018)
WOA with PPF	3 units	WT PV	2019	Dey et al. (2019)
CCSA	6 units	NA	2018	Rizk-Allah et al. (2018)
Dinkebach's Algorithm	6 units with TL	NA	2016	Chen et al. (2016)
Hybrid GWO-PSO	10 unit- three areas 40-unit-four areas	NA	2020	Azizivahed et al. (2020)
PSO with clone selection	5-unit, 10-unit, 15-unit	NA	2020	Qian et al. (2020)
WOA	5-unit, 10-unit, 30-unit	PV, WT	2020	Padhi et al. (2020)
MO-NN based DE	5, 10, 15 units	NA	2018	Mason et al. (2018)
ϴ-modified KHA	Grid-connected MG with MT, FC, ESS	PV, WT	2020	Yin et al. (2020)
Modified ISA	Grid-connected MG with MT, FC, ESS and DSG	PV, WT	2018	Rabiee et al. (2018)
Improved PSO	Grid-connected MG with MT, FC, DSG and 3 EVs	PV, WT	2018	Lu et al. (2017)
Improved PSO	Grid-connected MG with MT, FC, DSG, EV and Load Variance as third objective	PV, WT	2018	Lu et al. (2018)
Ɛ-constrained method	Grid-connected MG with MT, CHP EV and frequency deviation as third objective	PV, WT	2018	Tabar et al. (2018)

ii. A comparative analysis among the three is performed to sort out the method that yields the best compromised solution between the generation cost and pollutants emitted.
iii. HMGWO is proposed for the first as the optimization tool for this problem, the efficiency and robustness of which is measured and compared with original GWO.

The rest of the paper is presented as follows; Section 2 defines the problem formulation; Section 3 highlights the implementation of the proposed hybrid algorithm in the current problem; Section 4 gives a detail account of simulation results, with the work being concluded in Section 5.

2. Objective function formulation

2.1. Cost function for DG units

Fuel comes with a price. Generation cost refers to the cost of the fuel utilized (or combusted) by the fossil fueled generator to produce per unit of power. The equation of the generation cost function in case of DG units is not a linear equation. It is a quadratic equation (Dey et al., 2020a; Trivedi et al., 2018; Elattar, 2018) represented by equation (1).

$$ECD = \sum_{t}^{24} \sum_{j=1}^{n} \left(a_j G_{j,t}{}^2 + b_j G_{j,t} + c_j\right) \tag{1}$$

where a_j, b_j and c_j are the cost coefficients, G_j is the power output of jth DG unit. Hence, the total cost is *ECD*, while n is the total number of involved DG units. In the case of dynamic economic load dispatch, the total cost for 24 h is calculated, where t is indication of hour.

2.2. Emission dispatch for DG units

The non-conventional fossil fueled generators emits toxic gases into the atmosphere while generating electricity. These toxic gases are usually oxides of carbon, sulphur and nitrogen which are released into the atmosphere as dark and dense smoke. Emission dispatch (EMD) is the scheduling of the generators in such a way so as to minimize the release of this harmful toxic gases. The objective function of emission dispatch can be calculated by equation (2) depending on the availability of the emission coefficients,

$$EMD = \sum_{t=1}^{24} \sum_{j=1}^{n} \left(x_j G_{j,t}{}^2 + y_j G_{j,t} + z_j\right) \tag{2}$$

where x_j, y_j and z_j are the emission coefficients, and EMD is the total emission (Dey et al., 2019, 2020a; Trivedi et al., 2018; Elattar, 2018).

2.3. Combined economic emission dispatch using PPF method

ECD deals with the minimization of the fuel costs, while EMD deals with the minimization of the emission of harmful pollutants from the conventional fossil fueled generators to the atmosphere. Hence, a compromised solution must arrive at that can achieve both reduced fuel costs releasing fewer pollutants in the atmosphere. This is achieved by formulating a CEED by combining equations (1) and (2) and also the Price Penalty Factor (PPF), a parameter used to get a mixed objective function involving both ECD and EMD as mentioned in equation (3) (Dey et al., 2020a; Trivedi et al., 2018; Elattar, 2018).

$$CEED_{ppf} = \sum_{t}^{24} \sum_{j=1}^{n} \left[\left(a_j G_{j,t}{}^2 + b_j G_{j,t} + c_j\right) + ppf_j * \left(x_j G_{j,t}{}^2 + y_j G_{j,t} + z_j\right)\right] \tag{3}$$

Various types of price penalty factors (PPF) are given in equations (4)–(9) according to references (Dey et al., 2020a) and (Dey et al., 2019). Here $P^{max/min}$ denotes the maximum and minimum values of the j[th] generator.

$$ppf_{j,\max,\max} = \frac{ECD\left(P_j^{\max}\right)}{EMD\left(P_j^{\max}\right)} \tag{4}$$

$$ppf_{j,\min-\min} = \frac{ECD\left(P_j^{\min}\right)}{EMD\left(P_j^{\min}\right)} \tag{5}$$

$$ppf_{j,\max-\min} = \frac{ECD\left(P_j^{\max}\right)}{EMD\left(P_j^{\min}\right)} \tag{6}$$

$$ppf_{j,\min-\max} = \frac{ECD\left(P_j^{\min}\right)}{EMD\left(P_j^{\max}\right)} \tag{7}$$

$$ppf_{j,avg} = \frac{pf_{\max,\max} + pf_{j,\min-\min} + pf_{j,\max-\min} + pf_{j,\min-\max}}{4} \tag{8}$$

$$ppf_{j,\text{com}} = \frac{pf_{j,avg}}{no.\ of\ DGs} \tag{9}$$

2.4. Combined economic emission dispatch using FP method

This method considers two different competing and conflicting objective functions, comprising of the same decision and control variables and are solved as a ratio of each other. For instance, ECD is considered as the economic dispatch equation mathematically expressed by equation (1), and EMD is the emission function given by equation (2). Then, a compromised solution can be obtained by FP method by minimizing the ratio *EMD: ECD*. This is mathematically expressed by equation (10) (Rizk-Allah et al., 2018; Chen et al., 2016).

$$CEED_{FP} = \frac{\sum_{t=1}^{24} \sum_{j=1}^{n} \left(x_j G_j{}^2 + y_j G_j + z_j\right)}{\sum_{t=1}^{24} \sum_{j=1}^{n} \left(a_j G_j{}^2 + b_j G_j + c_j\right)} \tag{10}$$

2.5. Environment constrained economic dispatch (ECED)

The above two methods of CEED focused on reducing the emission of harmful pollutants to the atmosphere. In the process the generation cost of the system rises much more than the best value obtained during economic dispatch. Rajasomashekar and Aravindhababu (2012) presented a simple equation to bring together two differently aimed objective functions and attain a better-quality compromised solution, given by equation (11). It depends, whether unimodal or multimodal, upon the nature of the economic dispatch and emission dispatch equations expressed in (1) and (2) respectively.

$$ECED = \mu^* \left[\frac{ECD - ECD_{\min}}{ECD_{\max} - ECD_{\min}}\right] + (1-\mu)^* \left[\frac{EMD - EMD_{\min}}{EMD_{\max} - EMD_{\min}}\right] \tag{11}$$

where μ lies in the range of 0 and 1, ECD_{min} is the best value of generation cost obtained by minimizing (1), EMD_{min} is the best value of pollutants emitted obtained by minimizing equation (2), ECD_{max} is the generation cost obtained by substituting the optimal parameters of EMD_{min} in equation (1), EMD_{max} is the amount of pollutants emitted obtained by substituting the optimal parameters of ECD_{min} in equation (2). Results obtained in (Rajasomashekar and Aravindhababu, 2012) also points toward three important steps and assumptions as follows:

i. It is to be noted that the swift and successful steps to obtain the best compromised solution can be attained by setting the value of μ as 0.5, i.e., giving equal emphasis to both the objective functions.
ii. A better quality compromised solution will have the least value of absolute difference between cost performance index (CPI) and emission performance index (EPI). Equations (12) and (13) expresses the formulae of CPI and EPI respectively.

$$CPI = \left[\frac{ECD - ECD_{\min}}{ECD_{\max} - ECD_{\min}}\right]*100\% \tag{12}$$

$$EPI = \left[\frac{EMD - EMD_{\min}}{EMD_{\max} - EMD_{\min}}\right]*100\% \tag{13}$$

iii. The better-quality compromised solution will have the value of generation cost nearer to ECD_{min} and amount of pollutants emitted nearer to EMD_{min}.

2.6. Equality and inequality constraints

Equations (14) and (15) are the equality constraints for without including RES and including RES problems respectively. Equation (16) is the inequality constraint restricting the DERs within their limits.

$$\sum_{j=1}^{n} G_{j,t} = D_t \tag{14}$$

$$\sum_{j=1}^{n} G_{j,t} + P_{RES,t} = D_t \tag{15}$$

$$G_{j,\min} \le G_j \le G_{j,\max} \tag{16}$$

where D_t is the demand of tth hour, $P_{RES,t}$ is RES output in terms of power.

2.7. Utilization percentage

The utilization percentage, UP, is given by equation (17) (Kumar and Saravanan, 2019; Dey et al., 2020b).

$$UP = \frac{\sum_t G_j^t}{24 * G_j^{\max}} \tag{17}$$

UP is normally used when it is an unclear and confusing attempt to represent the hourly outputs of test systems which have larger number of DERs.

2.8. Uncertainty modelling

Due to the stochastic nature of RES, the day ahead forecasted values of the RES are modelled to evaluate the uncertainty in them using equations (18) and (19) (Dey et al., 2020b; Jamshidi and Askarzadeh, 2019; Li et al., 2008):

$$\begin{aligned} PV_{un}^t &= dPV_{un} * n_1 + PV_{fc}^t \\ dPV_{un} &= 0.7 * \sqrt{PV_{fc}^t} \end{aligned} \tag{18}$$

$$\begin{aligned} W_{un}^t &= dP_w * n_2 + W_{fc}^t \\ dP_w &= 0.8 * \sqrt{W_{fc}^t} \end{aligned} \tag{19}$$

where dPV_{un} is the standard deviation of the PV output, PV_{un}^t is the is PV output considering the uncertainty, and PV_{fc}^t is the day ahead forecasted PV output. Similarly, W_{un}^t is uncertainty of wind, dP_w is standard deviation of wind power and W_{fc}^t is the day ahead forecasted wind output. n_1 and n_2 are randomly evaluated normal distribution function with mean 1 and standard deviation 0.

3. Hybrid grey wolf optimizers

The proposed optimization tool for this study is a robust and powerful hybrid of modified version of GWO (Mirjalili et al., 2014), SCA (Mirjalili, 2016) and CSA (Askarzadeh, 2016). Proposed hybrid, called HMGWO, has already outperformed other hybrids and modifications of GWO when realised on benchmark functions (Dey and BhattacharyyaRamesh, 2021) and have been useful in solving energy management and electricity market pricing problems on microgrid systems (Dey et al., 2020b; Dey and BhattacharyyaRamesh, 2021; Dey et al., 2020c). The mathematical formulation of GWO and HMGWO are detailed below:

3.1. Grey Wolf Optimizer (GWO)

GWO is a recently developed optimization algorithm based on the hunting behaviour of the wolves. Wolves hunts in packs of 10 or 12. The leader wolf is known as alpha (α), and is the most nearer to the prey. Alpha is followed by its successor beta (β), responsible for maintaining harmony in the group. Then, in hierarchy, comes the delta (δ) wolves, which acts as scapegoat. Rest of the wolves are termed as omega (Ω). GWO algorithm mainly involves the top three class of wolves for searching the best possible solution to an optimization problem. Equation (20) formulates the Manhattan distance between the wolves during the hunting strategy.

$$\left.\begin{aligned} \vec{P}_\alpha &= \left|\vec{Q}_1.\vec{Y}_\alpha - \vec{Y}\right| \\ \vec{P}_\beta &= \left|\vec{Q}_2.\vec{Y}_\beta - \vec{Y}\right| \\ \vec{P}_\delta &= \left|\vec{Q}_3.\vec{Y}_\delta - \vec{Y}\right| \end{aligned}\right\} \tag{20}$$

Equation (21) shows the positing updating formulation of the GWO algorithm,

$$\left.\begin{aligned} \vec{Y}_1 &= \vec{Y}_\alpha - \vec{R}_1.\left(\vec{P}_\alpha\right) \\ \vec{Y}_2 &= \vec{Y}_\beta - \vec{R}_2.\left(\vec{P}_\beta\right) \\ \vec{Y}_3 &= \vec{Y}_\delta - \vec{R}_3.\left(\vec{P}_\delta\right) \end{aligned}\right\} \tag{21}$$

$$\vec{Y}_{(iter+1)} = \frac{\vec{Y}_1 + \vec{Y}_2 + \vec{Y}_3}{3} \tag{22}$$

The value of vectors R and Q can be calculated by equation (Qian et al., 2020),

$$\begin{aligned} \vec{R} &= 2.\vec{a}.\vec{r}_1 - \vec{a} \\ \vec{Q} &= 2.\vec{r}_2 \end{aligned} \tag{23}$$

Mathematically, the value of R converges or diverges the wolves towards or away from its prey. The vector 'a' changes with respect to iteration as mentioned in equation (24) and, thereby, controls the value of 'R' throughout the search.

$$\vec{a} = 2*\left(1 - \frac{iter}{Max\_iter}\right) \tag{24}$$

3.2. HMGWO

The three major modifications in GWO to formulate HMGWO are listed as follows:

a Involvement of omega set of wolves (Khandelwal et al., 2018).
b. Tossing the Manhattan distance calculation between wolves with sine and cosine functions (Dey and Bhattacharyya, 2019; Dey and

Das, 2019; Devarapalli et al., 2020; Devarapalli and Bhattacharyya, 2020).

c. Using the CSA strategy of position updating procedure (Dey and Bhattacharyya, 2019; Dey and Das, 2019; Devarapalli et al., 2020; Devarapalli and Bhattacharyya, 2020).

The mathematical formulation of MGOWSCACSA are as follows:

$$\left.\begin{array}{ll}\vec{P}_{\alpha} = rand^{*}\sin(rand)^{*}\left|\vec{Q}_{\alpha}.\vec{Y}_{\alpha} - \vec{Y}\right| & if\ rand > 0.5 \\ \vec{P}_{\alpha} = rand^{*}\cos(rand)^{*}\left|\vec{Q}_{\alpha}.\vec{Y}_{\alpha} - \vec{Y}\right| & otherwise\end{array}\right\} \tag{25}$$

$$\left.\begin{array}{ll}\vec{P}_{\beta} = rand^{*}\sin(rand)^{*}\left|\vec{Q}_{\beta}.\vec{Y}_{\beta} - \vec{Y}\right| & if\ rand > 0.5 \\ \vec{P}_{\beta} = rand^{*}\cos(rand)^{*}\left|\vec{Q}_{\beta}.\vec{Y}_{\beta} - \vec{Y}\right| & otherwise\end{array}\right\} \tag{26}$$

$$S = \begin{bmatrix} S^{1}_{1,DER1}, & S^{2}_{1,DER1}, \cdots & S^{T}_{1,DER1}, & S^{1}_{1,DER2}, & S^{2}_{1,DER2}, \cdots & S^{T}_{1,DER2} \cdots S^{1}_{1,DER\ D}, & S^{2}_{1,DER\ D}, \cdots & S^{T}_{1,DER\ D} \\ S^{1}_{2,DER1}, & S^{2}_{2,DER1}, \cdots & S^{T}_{2,DER1}, & S^{1}_{2,DER2}, & S^{2}_{2,DER2}, \cdots & S^{T}_{2,DER2} \cdots S^{1}_{2,DER\ D}, & S^{2}_{2,DER\ D}, \cdots & S^{T}_{2,DER\ D} \\ S^{1}_{3,DER1}, & S^{2}_{3,DER1}, \cdots & S^{T}_{3,DER1}, & S^{1}_{3,DER2}, & S^{2}_{3,DER2}, \cdots & S^{T}_{3,DER2} \cdots S^{1}_{3,DER\ D}, & S^{2}_{3,DER\ D}, \cdots & S^{T}_{3,DER\ D} \\ \cdots\cdots\cdots & & & & & & & \\ \cdots\cdots\cdots & & & & & & & \\ S^{1}_{N,DER1}, & S^{2}_{N,DER1}, \cdots & S^{T}_{N,DER1}, & S^{1}_{N,DER2}, & S^{2}_{N,DER2}, \cdots & S^{T}_{N,DER2} \cdots S^{1}_{N,DER\ D}, & S^{2}_{N,DER\ D}, \cdots & S^{T}_{N,DER\ D} \end{bmatrix} \tag{33}$$

$$\left.\begin{array}{ll}\vec{P}_{\delta} = rand^{*}\sin(rand)^{*}\left|\vec{Q}_{\delta}.\vec{Y}_{\delta} - \vec{Y}\right| & if\ rand > 0.5 \\ \vec{P}_{\delta} = rand^{*}\cos(rand)^{*}\left|\vec{Q}_{\delta}.\vec{Y}_{\delta} - \vec{Y}\right| & otherwise\end{array}\right\} \tag{27}$$

$$\left.\begin{array}{ll}\vec{P}_{\Omega} = rand^{*}\sin(rand)^{*}\left|\vec{Q}_{\Omega}.\vec{Y}_{\Omega} - \vec{Y}\right| & if\ rand > 0.5 \\ \vec{P}_{\Omega} = rand^{*}\cos(rand)^{*}\left|\vec{Q}_{\Omega}.\vec{Y}_{\Omega} - \vec{Y}\right| & otherwise\end{array}\right\} \tag{28}$$

Thereafter Y_1, Y_2, Y_3 and Y_4 are calculated as shown in equation (29).

$$\left.\begin{array}{l}\vec{Y}_{1} = \vec{Y}_{\alpha} - \vec{R}_{1}.\left(\vec{P}_{\alpha}\right) \\ \vec{Y}_{2} = \vec{Y}_{\beta} - \vec{R}_{2}.\left(\vec{P}_{\beta}\right) \\ \vec{Y}_{3} = \vec{Y}_{\delta} - \vec{R}_{3}.\left(\vec{P}_{\delta}\right) \\ \vec{Y}_{4} = \vec{Y}_{\Omega} - \vec{R}_{4}.\left(\vec{P}_{\Omega}\right)\end{array}\right\} \tag{29}$$

The position updating step of HMGWO is:

$$\left.\begin{array}{l}\vec{Y}_{(iter+1)} = \vec{Y} + fl^{*}rand^{*}\left\{\left(\vec{Y}_{1} - \vec{Y}\right) + \left(\vec{Y}_{2} - \vec{Y}\right) + \left(\vec{Y}_{3} - \vec{Y}\right)\right\}\Big/3 \quad if\ AP > rand \\ \vec{Y}_{(iter+1)} = \vec{Y} + fl^{*}rand^{*}\left(\vec{Y}_{1} - \vec{Y}\right)\ otherwise\end{array}\right\} \tag{30}$$

where *fl* is the flight length of the crows.

$$\vec{Y}_{3} = \frac{\vec{Y}_{3} + \vec{Y}_{4}}{2} \tag{31}$$

Awareness probability (AP) acts as a decisive variable to judge the involvement of wolves in hunting the prey and obtain the best possible solution. AP changes with iterations as mentioned in equation (32).

$$AP = 1 - \left(\frac{1.01^{*}iter^{3}}{Max\_iter^{3}}\right) \tag{32}$$

3.3. Analogy relating HMGWO with the dynamic CEED problem

If T is the time period for optimal scheduling, D is the number of DERs involved in powering the microgrid system on which the energy management is to be performed, and N is the number of search agents of the population, then the matrix depicting the population is given by equation (33), wherein every search agent of the population follows the system constraints mentioned in equations (2)–(14).

The position of the wolves is depicted by particles in the population matrix which acts the control variables. The distance of wolves from the prey is taken as the fitness value for the objective function. Considering the proposed work as a constrained minimization approach, the position of search agent with least fitness function value is the best solution among all search agents in the search space and is termed as χ_{α}.

4. Case studies

4.1. Overview of the subject test system

A dynamic test system of 3 fossil fueled generating units are considered on which CEED is performed using PPF, FP and proposed ECED methods. It is to be noted that the cost and emission equation of 3-units contains only quadratic terms and are unimodal in nature. The cost coefficients, emission coefficients and the maximum and minimum limits of operation of the DERs are shown in Table 2.

Table 3 shows the load demand of the test system and highlights the forecasted values of RES contribution for the system. Uncertainty evaluations have been done based on these forecasted values based on the equations mentioned in Section 2. The cost of the RES were not considered for the test system. The optimization was coded and executed in a laptop configured with Intel Core i5 8th Gen processor 8 GB RAM on a MATLAB R2013a software. The population size of the optimization

Table 2
Generator parameters of the 3 unit system (Dey et al., 2019, 2020a; Trivedi et al., 2018; Elattar, 2018).

Generators	Operating limits		Fuel cost coefficients			Emission coefficients		
	min	max	a	b	c	x	y	z
	MW	MW	USD/MW^{2}h	USD/MWh	USD/h	kg/MW^{2}h	kg/MWh	kg/h
G1	37	150	0.0024	21	1530	0.0105	−1.355	60
G2	40	160	0.0029	20.16	992	0.008	−0.6	45
G3	50	190	0.021	20.4	600	0.012	−0.555	90

Table 3
Day ahead forecasted hourly output of PV and wind and hourly load demand. (Dey et al., 2019, 2020a; Trivedi et al., 2018; Elattar, 2018).

Hour	Load (MW)	PV (MW)	WT (MW)
1	140	0	1.7
2	150	0	8.5
3	155	0	9.27
4	160	0	16.66
5	165	0	7.22
6	170	0.03	4.91
7	175	6.27	14.66
8	180	16.18	25.56
9	210	24.05	20.58
10	230	39.37	17.85
11	240	7.41	12.8
12	250	3.65	18.65
13	240	31.94	14.35
14	220	26.81	10.35
15	200	10.08	8.26
16	180	5.3	13.71
17	170	9.57	3.44
18	185	2.31	1.87
19	200	0	0.75
20	240	0	0.17
21	225	0	0.15
22	190	0	0.31
23	160	0	1.07
24	145	0	0.58

Table 4
Generation cost (in USD) of ELD and CEED for microgrid 3 unit system.

Algorithms	ELD		PPF based CEED	
	With RES	Without RES	With RES	Without RES
RGM (Trivedi et al., 2018)	183520	177291	232053	240780
ACO (Trivedi et al., 2018)	173343	176212	217655	229887
CSA* (Trivedi et al., 2018)	167044	176370	192309	202867
ISA (Trivedi et al., 2018)	167012	176320	192250	202799
DE (Dey et al., 2020a)	166815.8024	176226.8178	192438.3157	203244.7612
SOS (Dey et al., 2020a)	166793.2985	176166.5832	192543.2341	202868.7606
JAYA (Dey et al., 2020a)	166794.9367	176166.0276	192254.6732	202871.3677
CSA ** (Dey et al., 2020a)	166792.8781	176165.789	192169.3625	202782.7539
HMGWO	**166792**	**176165**	**192179**	**202780**

CSA* cuckoo search algorithm; CSA** crow search algorithm; – results not reported.

algorithms was fixed at 80 and maximum number of iterations was considered as 500. A parameter *fl* was set as 2.

4.2. Descriptive analysis on the results obtained

The detailed analysis of the CEED based study on the test system are listed below:

Table 5
Microgrid emission dispatch (in kg) using optimization techniques.

Algorithms	With RES	Without RES
PSO (Dey et al., 2019)	2189.6784	2385.7962
DE (Dey et al., 2019)	2187.4739	2383.2908
SOS (Dey et al., 2019)	2185.2421	2381.9505
GWO (Dey et al., 2019)	2184.7448	2380.519
WOA (Dey et al., 2019)	2183.9629	2379.4554
HMGWO	**2142**	**2282**

Table 6
FP and ECED value (with RES).

Algorithms	FP	ECED (μ = 0.5)
GWO	0.12792	0.26445
HMGWO	**0.12769**	**0.26146**

a. Initially ECD was conducted on the test system with and without considering the RES using proposed HMGWO as the optimization tool. Table 4 shows that the generation cost of the system was *176165 USD* without RES and *166792 USD* considering the RES. This marked a savings of 5.5% if RES was considered for the generation of power to suffice the load demand. It can also seen from Table 4 that proposed HMGWO outperformed a long list of population-based swarm intelligence metaheuristic optimization algorithms to yield the minimum value of ELD.
b. When EMD was evaluated for the test system with and without RES, there was a 6.5% decrease in the emission of harmful pollutants in the atmosphere when the power output from RES was utilized. Table 5 shows that 2282 kg of toxic pollutants was released in the atmosphere when RES was not considered whereas this amount reduced to 2142 kg after considering the involvement of RES in delivering power to the system. The superiority of the proposed optimization tool can be noticed in this case too.
c. It was evident from (Dey et al., 2020a) and (Dey et al., 2019) that min-max price penalty factor was the best and least for this test system. As per the records mentioned in the aforementioned articles, the *PPF* values for G1, G2 and G3 are 25.1597 *USD*/kg, 11.9948 *USD*/kg and 4.6750 *USD*/kg respectively. Thereafter, *PPF* based CEED was conducted on the test system and the generation cost was recorded for the same. It can be seen from Table 4 that generation cost without RES was *202780 USD*. This cost reduced to *192179 USD* when RES was considered thus saving 5.6% in the generation cost. The amounts of pollutants emitted using PPF based CEED method were 2453 kg and 2243 kg without and with RES respectively. Similar to ELD, proposed HMGWO delivered the best possible results and proved superior to many other optimization tools as listed in Table 4.
d. FP based CEED was evaluated using equation (10) for the test system with and without considering RES. The generation cost when evaluated based on the optimal variables obtained after minimizing equation (10) was 177011 *USD* without considering RES and 167398

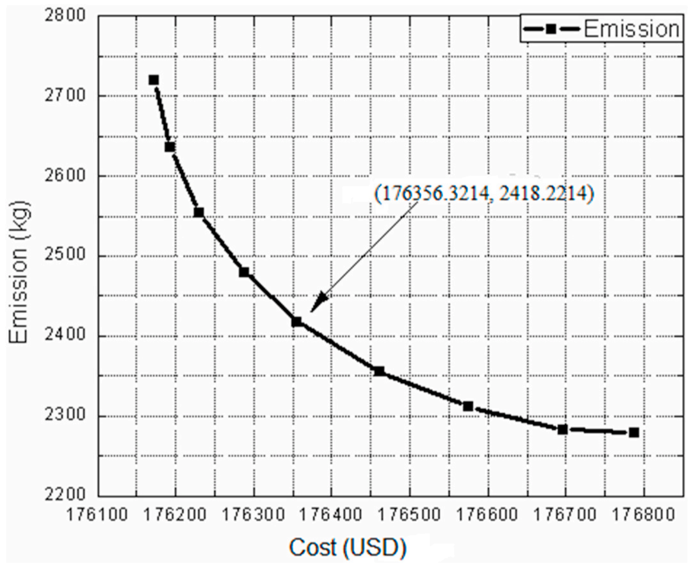

Fig. 1. Cost vs. Emission using HMGWO (without RES).

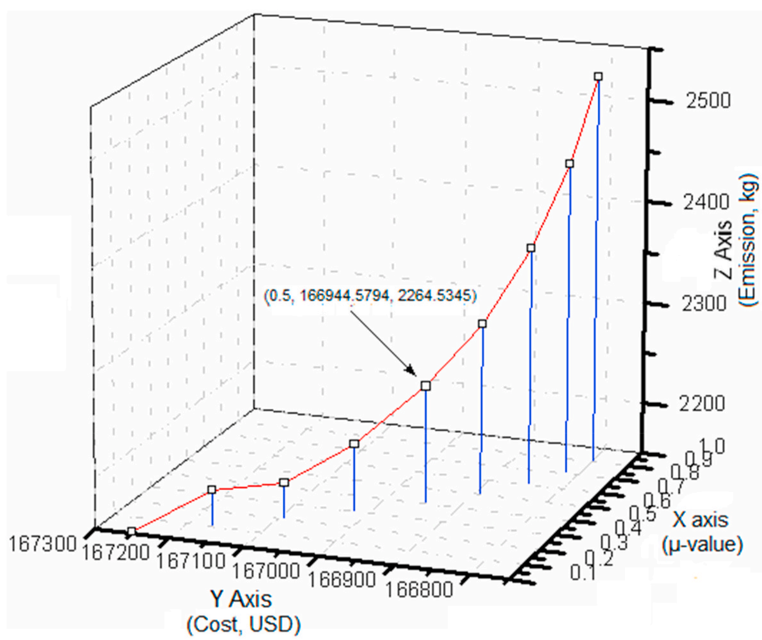

Fig. 2. Cost vs. Emission for different μ values using HMGWO (with RES).

USD when RES outputs were involved. The amount of toxic emissions in this case was 2136 kg and 2263 kg with and without RES respectively. FP was evaluated using GWO and HMGWO and the best value of fitness function is displayed in Table 6.

e. From the aforementioned points (a) and (b) and from the steps mentioned in Section 2, the following data to conduct ECED were obtained.

Parameters	Without RES	With RES
ECD_{min} (USD)	176165	166792
ECD_{max} (USD)	176900	167382
EMD_{min} (kg)	2282	2142
EMD_{max} (kg)	2805	2602

Thereafter, ECED was performed with and without considering RES for different values of μ ranging from 0.1 to 0.9. The generation cost and amount of toxic emissions were noted down for every value of μ and 2D graph was plotted for the values when ECED was evaluated without considering RES. The graph is shown in Fig. 1. It can be seen that the best compromised solution obtained at μ = 0.5 without RES is (176356 *USD*, 2418 kg).

Likewise, a 3D graph was plotted when ECED was evaluated using proposed HMGWO with RES for different values of μ. The value of μ was in the X axis, generation cost was plotted in the Y-axis and emission value in the Z axis. It can be seen from Fig. 2 that the best compromised value in this case was (0.5, 166944 *USD*, 2136 kg). GWO was also implemented as the optimization tool to evaluate ECED and the results are recorded in Table 6.

Fig. 3 shows a graph of the value of ECED fitness function and the absolute difference between CPI and EPI for various values of μ. It can be seen that the least difference was obtained at μ = 0.5.

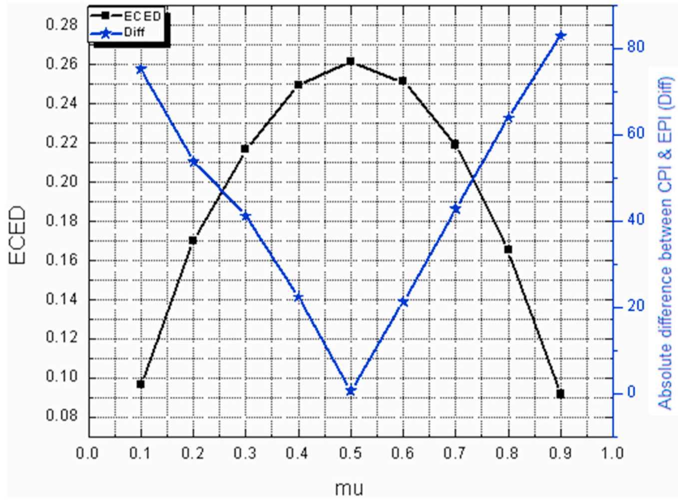

Fig. 3. Change in value of ECED fitness function and $|CPI \sim EPI|$ with μ

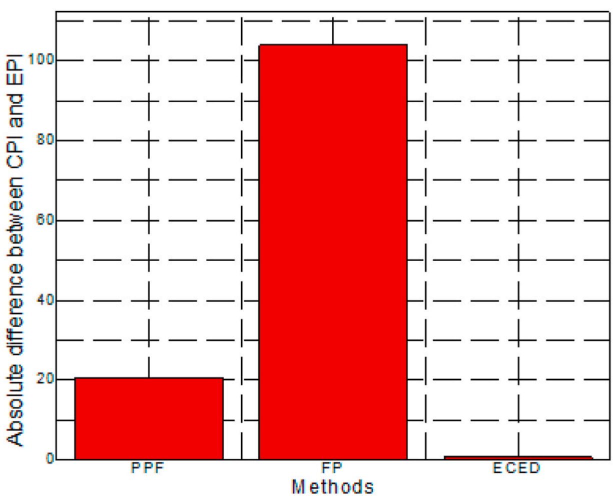

Fig. 4. $|CPI \sim EPI|$ for various methods of CEED evaluation.

Table 7
Cost and Emission for various fitness functions using HMGWO.

		ECD	EMD	PPF	FP	ECED
With RES	Cost (*USD*)	[a]**166792**	[b]167382	192179	167398	**166944**
	Emission (kg)	[d]2602	[c]**2142**	2243	2136	**2264**
Without RES	Cost (*USD*)	[a]**176165**	[b]176900	202790	177011	**176356**
	Emission (kg)	[d]2805	[c]**2282**	2453	2263	**2418**

[a] ECD_{min}.
[b] ECD_{max}.
[c] EMD_{min}.
[d] EMD_{max}.

Further an attempt was made to assemble the absolute difference between CPI and EPI for all the three aforementioned methods of evaluating CEED, and the same is shown in Fig. 4. It can be seen that among the PPF based CEED, FP based CEED and ECED methods, the least difference was obtained for proposed ECED method. The above study proves the discussion in Section 2 that the best compromised solution is obtained when the absolute difference between CPI and EPI is the least and when the value of μ is 0.5.

Table 7 shows the best values of generation cost and amount of pollutants emitted throughout the study using proposed hybrid HMGWO algorithm.

Fig. 5 shows the utilization of the three fossil fueled generators when RES was considered for evaluating all the fitness functions mentioned in Section 2 using proposed HMGWO algorithm. Generator unit G1 was utilized the least when ELD was performed as G1 have the maximum values of cost coefficients. Generator unit G3 was utilized least when EMD was evaluated as it has the highest value of emission coefficients. A reasonable balance between the utilization of all the three generators can be seen in ECED method when compared to all the other fitness functions evaluated.

Fig. 6 shows the convergence curve when proposed HMGWO yielded the best quality results for various objective functions evaluated considering the involvement of RES. The convergence curves shows the value of the objective function attained by the algorithm during each iteration until the maximum number of iteration is reached.

Since the objective of the paper was to evaluate ECED, GWO along with proposed HMGWO was used as the optimization tool to evaluate ECED on the test system with and without RES for 30 individual trials and the results and execution time was recorded for every trial. Table 8 shows the statistical analysis data when ECED was evaluated for 30 different individual trials with $\mu = 0.5$ using both GWO and HMGWO algorithms. The least value of standard deviation claims the robustness of proposed HMGWO algorithm. The decrease in the value of algorithm execution time to attain 500 iterations can also be seen from Table 8 compared to original GWO algorithm.

Based on the values mentioned in Table 8, the box plot figure was formed and is shown in Fig. 7. The boxplot is a summary of 30 sets of results obtained by each algorithm while evaluating ECED for the considered test system. The median is the line dividing the box, the upper and lower quartiles of the data define the ends of the box. The minimum and maximum data points are drawn as points at the ends of the lines (whiskers) extending from the box. These box-plots show the distribution of quantitative data in a way that facilitates comparisons between ECED between GWO and HMGWO. From these plots, it is seen that the chances of getting minimum ECED is very high as the median from HMGWO is nearer to the lower quartile.

5. Conclusions

This paper proposed a unique and novel approach of performing a comparative analysis among three different methods of evaluating CEED on a 3-unit dynamic test system configured with RES. Uncertainty calculation of the forecasted values of RES was employed to attend the

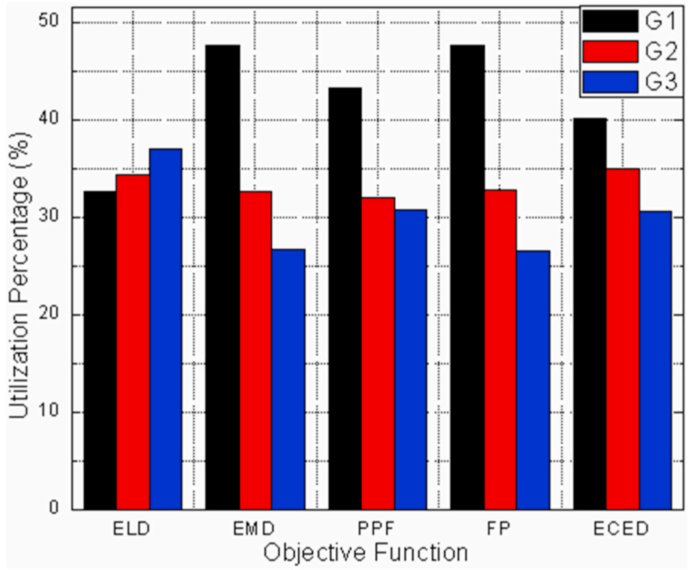

Fig. 5. Utilization Percentage of G1, G2 and G3 for various objectives (with RES).

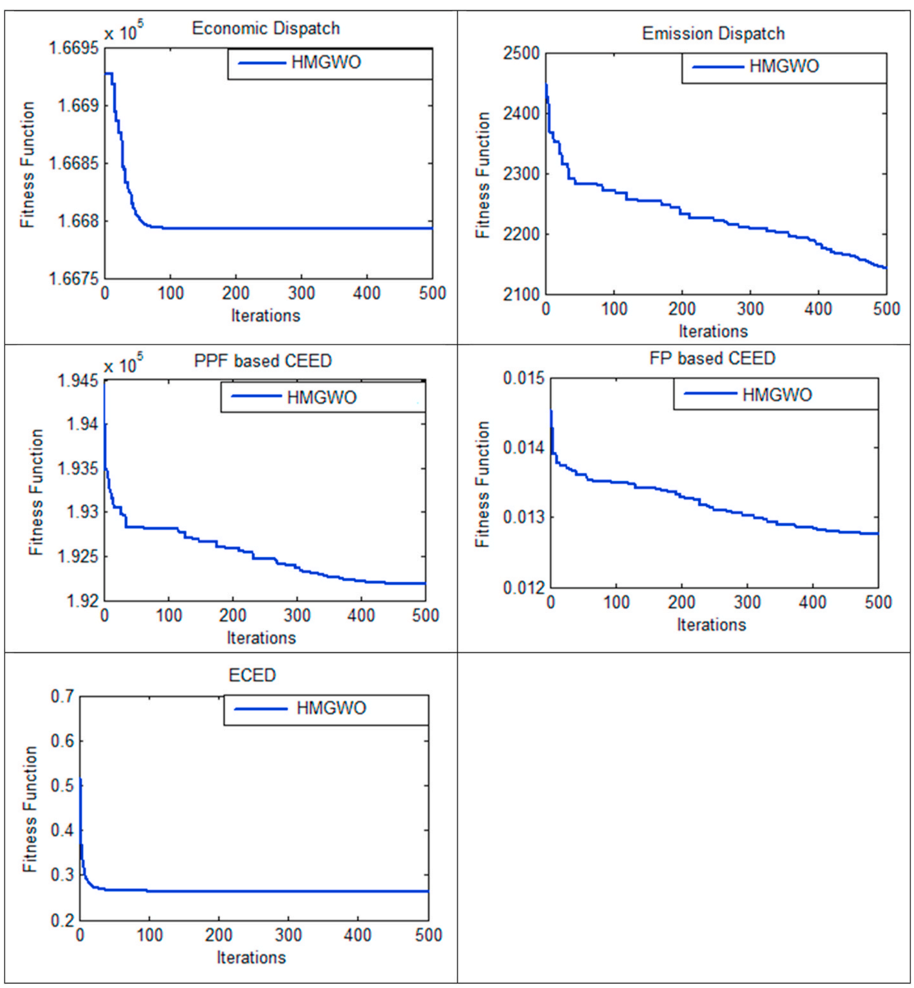

Fig. 6. Convergence curve characteristics obtained for various objective functions using HMGWO.

Table 8
ECED evaluated for 30 trials with μ = 0.5

	Algorithms	Min	Max	Mean	STD	Time (s)
With RES	GWO	0.26393	0.26442	0.26410	0.00024	210.95
	HMGWO	0.26146	0.26152	0.261464	1.52e-05	180.36
Without RES	GWO	0.26202	0.26280	0.262254	0.000364	223.52
	HMGWO	0.25984	0.26001	0.25986	6.44e-05	202.68

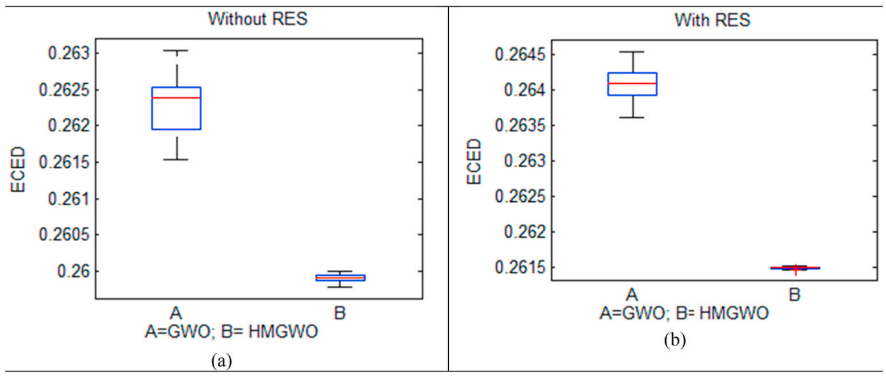

Fig. 7. Box plot evaluation for ECED calculations a) Without RES b) With RES.

stochastic behavior of the same. The major distinct findings of the paper are listed below:

a. There was a decrease in the generation cost while economic dispatch and PPF based CEED was evaluated by approximately 5.5% each due to the involvement of the RES. Also, the emission of toxic pollutants in the atmosphere diminished by 6.5% for the same reason.
b. The difference between the values of EPI and CPI was least for the proposed ECED method amongst the three, which indicates that the proposed approach yields a better compromised solution than the other two. The fact that the generation cost and amount of emitted pollutants, evaluated using proposed ECED approach, were much closer to the economic dispatch and emission dispatch values respectively compared to PPF based and FP based CEED solution also verifies the same.
c. HMGWO outperformed a number of optimization algorithms in providing better quality solutions throughout the study. This is a satisfactory reason of choosing the hybrid optimization algorithm for further solving large dimensioned complex optimization problems.

The values of ECD and EMD are needed to be calculated before evaluating ECED. This might be a disadvantage of the proposed approach compared to FP based CEED and PPF based CEED, but the satisfactory results in delivering a compromised solution with the least possible value of generation cost and toxic emissions make up for the aforementioned disadvantage. The proposed hybrid optimization technique might be somewhat cumbersome while coding given the number of equations, but the algorithm is robust enough in yielding consistently better and superior quality solutions for any number of trials.

As a scope of future work, the horizon of the study based on ECED approach can be expanded by solving large dynamic and multimodal test systems including MG energy management problems given the availability of cost and emission coefficients.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Hourly outputs of generators (in MW) when best value of ECD was obtained using HMGWO

Hours	G1	G2	G3
1	37.0000	44.9389	56.3611
2	37.9433	45.8979	57.6588
3	39.3849	47.0612	59.2839
4	38.6000	46.3854	58.3546
5	43.4237	50.4334	63.9229
6	45.8783	52.4586	66.7231
7	42.1955	49.3881	62.4865
8	37.0000	44.5125	55.7475
9	45.9855	52.5414	66.8432
10	48.4851	54.6023	69.6926
11	64.3082	67.7035	87.7783
12	66.9686	69.9059	90.8255
13	57.2526	61.8676	79.7198
14	50.1389	55.9825	71.5886

(continued on next page)

Table A1 (*continued*)

Hours	G1	G2	G3
15	51.4657	57.0821	73.1122
16	44.5121	51.3204	65.1575
17	43.1638	50.2039	63.6223
18	51.1867	56.8485	72.7848
19	57.3902	61.9835	79.8763
20	71.0561	73.2856	95.4882
21	66.0113	69.1096	89.7291
22	54.1766	59.3134	76.2000
23	43.8131	50.7505	64.3664
24	38.9384	46.7010	58.7807

Table A2
Hourly outputs of generators (in MW) when best value of EMD was obtained using HMGWO

Hours	G1	G2	G3
1	48.2955	40.0000	50.0045
2	48.3209	42.6476	50.5315
3	53.4013	42.1053	50.2233
4	52.7740	40.2442	50.3218
5	67.3749	40.3534	50.0517
6	68.0801	46.7422	50.2377
7	63.1215	40.8447	50.1039
8	45.7068	41.2861	50.2671
9	69.3990	45.9613	50.0097
10	70.9331	51.6635	50.1834
11	95.0519	73.7666	50.9714
12	94.2403	79.9026	53.5571
13	90.4377	56.7981	51.6042
14	80.2214	46.7596	50.7290
15	79.6775	51.7999	50.1825
16	65.3710	45.3587	50.2603
17	65.2901	41.2797	50.4202
18	74.1806	55.9488	50.6907
19	84.0169	64.9413	50.2918
20	98.7570	85.5441	55.5289
21	97.8798	74.1834	52.7868
22	78.0132	61.2699	50.4070
23	67.8189	40.5823	50.5288
24	52.3253	42.0431	50.0516

Table A3
Hourly outputs of generators (in MW) when best value of PPF based CEED was obtained using HMGWO

Hours	G1	G2	G3
1	48.2991	40.0004	50.0005
2	51.4998	40.0001	50.0001
3	55.7287	40.0011	50.0002
4	53.3390	40.0001	50.0009
5	64.9868	42.7319	50.0613
6	65.8771	49.0278	50.1551
7	62.5719	41.4906	50.0076
8	47.2591	40.0005	50.0004
9	66.6405	48.0352	50.6942
10	67.8585	51.3637	53.5579
11	74.2552	66.4967	79.0381
12	74.9518	70.0631	82.6851
13	71.8914	60.1474	66.8012
14	68.4856	53.1018	56.1226
15	69.1135	55.6661	56.8804
16	65.9934	44.9680	50.0286
17	64.5816	42.4068	50.0015
18	68.6636	55.5676	56.5889
19	71.2575	61.0768	66.9157
20	77.3478	73.2830	89.1992
21	74.4825	69.9037	80.4638
22	70.0646	57.8047	61.8207
23	65.2457	43.6549	50.0294
24	54.4187	40.0012	50.0001

Table A4
Hourly outputs of generators (in MW) when best value of FP based CEED was obtained using HMGWO

Hours	G1	G2	G3
1	47.5521	40.6998	50.0481
2	50.9773	40.4611	50.0616
3	55.5774	40.1023	50.0503
4	51.4409	41.8709	50.0282
5	67.2639	40.4378	50.0783
6	68.3415	46.6678	50.0506
7	63.7018	40.3464	50.0218
8	47.0286	40.1835	50.0479
9	69.6940	45.6220	50.0540
10	74.1663	48.5451	50.0686
11	95.7270	70.5146	53.5484
12	94.6521	82.3143	50.7335
13	84.2946	64.3950	50.1504
14	73.7501	53.4926	50.4673
15	72.9463	58.5748	50.1389
16	69.0407	41.8626	50.0867
17	65.8635	41.0119	50.1146
18	82.0755	48.6933	50.0512
19	84.7533	64.4092	50.0874
20	100.4495	83.8613	55.5192
21	98.1673	74.5988	52.0839
22	77.8654	61.5551	50.2695
23	68.1709	40.6490	50.1101
24	54.1873	40.2232	50.0095

Table A5
Hourly outputs of generators (in MW) when best value of ECED was obtained using HMGWO

Hours	G1	G2	G3
1	45.6568	42.6407	50.0025
2	47.4941	44.0055	50.0004
3	49.8204	45.9063	50.0033
4	48.5576	44.7806	50.0018
5	54.2826	51.9885	51.5089
6	57.1287	53.5692	54.3621
7	53.7327	50.1723	50.1651
8	45.4166	41.8399	50.0035
9	57.9916	53.5397	53.8387
10	60.0026	55.9600	56.8174
11	76.2781	70.7248	72.7871
12	78.4809	73.6212	75.5979
13	69.0228	64.1749	65.6423
14	62.0349	57.4882	58.1868
15	63.1637	58.4556	60.0407
16	56.0277	52.0910	52.8714
17	54.8036	51.0521	51.1343
18	62.6443	58.6812	59.4945
19	69.0372	64.3516	65.8611
20	82.9531	77.0748	79.8021
21	77.6485	72.5340	74.6674
22	66.2958	60.9224	62.4719
23	55.4805	51.4703	51.9791
24	48.7232	45.6928	50.0040

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