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Multi-objective dynamic economic emission dispatch integration with renewable energy sources and plug-in electrical vehicle using equilibrium optimizer

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Abstract
The thermal power plants, electrical industries, and transportation are the major source of emission of pollutant gases. Renewable energy sources (RES) such as wind plants and plug-in electric vehicles (PEVs) have been integrated in multi-objective dynamic economic emission dispatch (DEED) for a day to reduce wind–thermal energy cost and emission of pollutant gases. The several practical and nonlinear constraints have been considered to make system more realistic. The equilibrium optimizer (EO) has been proposed to solve the DEED model with RES and PEVs from different aspects. The four cases of ten and twenty thermal generating units have been considered to validate and analyze the efficacy of different types of integration in the proposed model. The results obtained by proposed technique have been compared with other recently developed techniques to show accuracy, efficiency, and speed of this technique in solving the proposed problem.

Keywords Economic emission load dispatch · Equilibrium optimizer · Valve point loading effect · Renewable energy sources · Plug-in electrical vehicle

1 Introduction

The electric power systems have become complex with increasing generation and energy consumption (Agrawal et al., 2022). Therefore, the power grid should be controlled to provide reliable and economic energy to consumers (Bhattacharjee et al., 2021). The static economic emission dispatch (EED) term has been introduced to minimize total fuel cost and emission of pollutants like sulfur oxides (SO_X), nitrogen oxides (NO_X), and carbon oxides (CO_X) by satisfying load demand with various operating constraints (Bhattacharjee, 2018). However, the static EED problem is unable to solve after considering the ramp rate limit (RRL) and variation in load greatly (Soni et al., 2020). The Dynamic EED (DEED)

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considers a load cycle of 24 h and RRL constraints between different time intervals (Bhattacharjee & Patel, 2020).

Government agencies have developed and favored electric vehicles (EV) due to many advantages like energy-saving, zero-emission, and low-noise characteristics (Nourianfar & Abdi, 2021). Therefore, many electric cars have been produced by car companies. These large numbers of EVs will make the unsafe operation of the power grid (Peng et al., 2012). The rechargeable batteries, an important part of electric vehicles, have gotten much attention from researchers in recent years because the batteries are a good source of energy for electric vehicles (Hou et al., 2020). The charging and discharging schedule should be properly managed according to the load curve and electricity prices at each hour of day and night. There are two EV modes: vehicle to grid (V2G) technology and vehicle to grid (G2V) technology. In the V2G technology, the batteries have been connected with other energy sources through a bi-directional DC–DC converter. The batteries can be charged during off-peak hours at a lower price. In G2V technology, the batteries are discharged to provide power in peak hours (Andervazh & Javadi, 2017). Therefore, the EVs in power dispatching, smart charging, and battery discharge have become an emerging research focus. The smart charging behavior of EVs in the urban areas has been proposed by Narimani et al. (2017). The EVs can be used as small portable power plants in the V2G technology. The Particle Swarm Optimization (PSO) has been applied in the EED model for unit commitment with EVs to minimize fuel cost and emission of pollutants gases in the power system (Zhao et al., 2012). The hierarchical decomposition method has been proposed by Yao et al. for scheduling EVs (Gholami et al., 2014). The EVs have been considered as a load in the DEED model. The Teaching- and Learning-Based Optimization (TLBO) has been proposed to solve the DEED model without considering the constraints of EVs (Piperagkas et al., 2011). Biography-Based Optimization (BBO) has been proposed to optimize the DEED problem by considering the charging of EVs (Liu et al., 2020). The emission constrained economic dispatch model with EVs has been proposed by Jadhav and Roy (2013). The charging and discharging behavior of EVs in the DEED problem has been developed by Qu et al. (2016).The Bat Algorithm (BA) has been proposed by Liang et al. to solve the DEED model with EVs Jadhav et al. (2011).

1.1 Literature review

Renewable Energy Sources (RES) have gotten much attention from researchers to avoid environmental pollution and mitigate the energy crisis (Liao, 2011). In RES, wind energy is the most promising and fast-developing energy source. Researchers have published several research articles on wind power with the DEED model (Basak et al., 2022). The Chao Quantum Genetic Algorithm (CQGA) has been proposed to solve the DEED model with wind power. The DEED model with an uncertain output power of wind has been developed by Rajan and Malakar (2016) The DEED model with a hydro–wind–thermal system has been developed. The uncertainty of wind power generation leads to underestimation if the active output power is less than dispatch power and overestimation if active power is more than dispatch power (Jiang et al., 2015). The economic dispatch (ED) model with underestimation and overestimation of wind power was first proposed by Qu et al. (2016) The Weibull Probability Density Function (PDF) has been proposed to obtain the stochastic wind speed. The emission dispatch model considering wind power as a constraint has been proposed by Yang et al. (2021). The EED model with underestimation/overestimation of

wind power has been presented by Jin et al. The models mentioned above mostly focus on minimizing the penalty cost of wind power (Das et al., 2020).

The V2G technology of EV is mostly used to smooth underestimation and overestimation cost of wind power (Guesmi et al., 2020). The DEED model with EVs has been developed to smooth the underestimation and overestimation cost of wind power (Zhao et al., 2020). The ED model with uncertain EVs and wind farms has been presented by Li et al. (2021). The PSO method has been used to optimize the ED model with EVs and wind power. The Multi-Objective Evolutionary Algorithm (MOEA) has been presented by Zhang et al. to optimize the DEED model with large-scale EVs and uncertain wind power (Dhiman & Kaur, 2019). The improved PSO method has been presented by Zhang et al. to solve multi-objective dynamic hydro–thermal–wind with the EVs model (Ali et al., 2020). The EVs can be charged during off-peak hours. However, if several EVs are connected, the peak load will rise. Therefore, it becomes costly economically and environmentally. The smart charging of EVs has been used to lessen the cost and emissions (Abdelaziz et al., 2016). Therefore, many researchers have solved the interaction between wind power and EVs. The Constriction Factor-Based Particle Swarm Optimization (CFBPSO) has been presented to solve the DEED problem with EVs and wind–solar power (Behera et al., 2021). However, the methods mentioned above failed to solve the DEED problem with RES and EVs, charging and discharging control of EVs while minimizing cost and emission. Therefore, a strong optimization method is required to solve the DEED problem with large-scale EVs and RES. The previous published research papers have been summarized, and research gap has been pointed out in Table 1.

1.2 Importance, objectives, and contributions of this research work

The demand of electricity is increasing day-by-day. Therefore, Dynamic Economic Emission Dispatch (DEED) term has been introduced by researchers to reduce total fuel cost and emission level of pollutant gases from the thermal generating units while fulfilling electricity to the consumers. However, the objective function of DEED problem becomes highly complex and nonlinear after integrating renewable energy sources and plug-in electric vehicles in the microgrid with considering various operating constraints. Therefore, the strong and effective optimization method is required to optimize the objective function in less convergence time and give better solution as compared to other newly developed optimization methods. Therefore, this research is important for reducing fuel cost and emission level of thermal generating units after integrating renewable sources and electric vehicles for making better sustainability development.

The research objectives have been listed below:

- To propose mathematical model and multi-objective function of DEED problem with integrating wind plants and electric vehicles
- To propose Weibull and beta distribution for getting random wind velocity and solar irradiance, respectively. To predict output power of wind and solar units.
- To consider various operating constraints of wind farms, solar plants, and Evs in the objective functions to make smooth and reliable system.
- To purpose strong and effective optimization technique to solve highly complex and nonlinear DEED problem with high penetration of RES and EVs in less convergence time and give better solution as compared to other optimization techniques.

Table 1 Scope and drawbacks of published research works in this study

Literature	Main objective	Methods	Drawbacks
Dodu et al. (1972)	Formulation of ED problem	Gradient method	These classical methods require more efforts to solve ED problem.
Farag et al. (1995)	Solution of ED problem	linear programming techniques	
Song and Chou (1997)	ED problem with the quadratic form of fuel cost function	lambda iteration method	
Jayabarathi (2000)	ED problem with quadratic cost function	classical evolutionary programming	
Park et al. (2005)	ED problem by considering both VPLE and multiple fuels	Particle Swarm Optimization	Need a long computational time
Selvakumar and Thanushkodi (2007)	ED problem with VPLE, multiple fuels, POZ, and generation ramp rate limits	Modified Particle Swarm Optimization	Slow in computational time, trap in local optima
Bhattacharya and Chattopadhyay (2010)	convex and also a non-convex ED problem by considering VPLE and multiple fuel options	biogeography-based optimization	Poor exploitation capability, poor in global optima
Khamsawang and Jiriwibhakorn (2010)	ED problem with three types of fuel cost functions such as ED with VPLE, ED with VPLE and multiple fuels and finally ED with POZ	Hybrid PSO-DE	Cannot maintain the population diversity in the swarm
Lu et al. (2010)	Stochastic EELD	used the ED and EM both as a single objective	More computational time
Neyestani et al. (2010)	EED problem considering the generator constraints such as ramp rate limits and POZ	PSO	Particles trap into local optima
Hemamalini and Simon (2011)	emission is taken as a constraint	Biogeography-Based Optimization (BBO)	Difficult to define the relation between ED and EM
Cai et al. (2010)	EELD with ramp rate limit, POZ, and transmission loss	Multi-objective differential evolution (DE)	Weak capacity of local search
Goudarzi et al. (2020)	Hybrid techniques	hybrid approach based on GA and PSO	Complex size
Jin et al. (2017)	EELD with wind energy by considering WT EED model	Gravitational acceleration enhanced particle swarm optimization Algorithm(GAE-PSO)	Weak capacity of local search

Table 1 (continued)

Literature	Main objective	Methods	Drawbacks
Zare et al. (2021)	Probabilistic multi-objective wind–thermal economic emission dispatch	Modified teaching-learning algorithm	Slow convergence rate
Hagh et al. (2019)	EED problem by considering the wind energy	exchange market algorithm	complex size & A long period of time to execution
Srivastava and Das (2020)	Probabilistic ED with wind and solar energy	Dragonfly Algorithm	Complicated structure & Need a long time for the implement
Ma et al. (2017)	Dynamic power problem by considering electric vehicles.	Dynamic non-dominated sorting multi-objective biogeography-based optimization (Dy-NSBBO)	Convergence into local points and the absence of a strong global search engine in these algorithms.
Liu et al. (2018)	Dynamic ELD with EV and wind farms	Teaching–Learning-based optimization (TLBO)	
Hou et al. (2020)	Dynamic EELD with EV	Multi-objective differential evolution algorithm	
Behera et al. (2022)	Dynamic EELD with EVs and wind farms	Constriction Factor-Based Particle Swarm Optimisation (CFBPSO)	

- To validate the proposed optimization methods in several small, medium, and large test systems and confirm the effectiveness of the proposed algorithm.

The newly developed physics-based Equilibrium Optimizer (EO) has been used in this study as the solution to the DEED problem with large-scale EVs and wind farms Faramarzi et al. (2020). The mass balance equation has inspired the EO method for a control volume. The proposed method has two-stage to search for a solution: exploratory and exploitative. Initially, the search agents have been randomly placed to look for the solution. The search agents update their positions about the best solution, called equilibrium candidates. The generation rate term helps avoid local optima and move toward the optimum solution. Such a feature helps to find a solution in very less computational time. It has been noticed that the EO method gives a better solution compared to other methods. This fact has motivated authors to use the EO method to solve the DEED problem with EVs and wind farms. The main contributions of this research work have been listed below:

- Faramarzi et al. have suggested an efficient soft computing technique named EO. Faramarzi et al. optimized 58 unimodal, multimodal, engineering, and composition benchmark functions to demonstrate the approach's robustness (Faramarzi et al., 2020). It has been discovered that EO produces far superior results than most recently developed algorithms. As a result, the EO has been used for the first time in this study to tackle a complicated and nonlinear DEED problem with the penetration of large-scale EVs and wind farms.
- The probability density functions like Weibull distributions have been used to predict uncertain values of wind velocity.
- The EVs have been considered storage, energy sources, and loads for smart and reliable operation.
- The maximum RES penetration has been obtained through EVs to minimize fuel costs and emissions in a smart grid.
- The proposed optimization algorithm has been tested in small, medium, and many thermal generators with highly penetrated RES and EVs in microgrids.
- The results illustrate a better and more efficient performance than other recently developed algorithms in optimizing the DEED model with RES and EVs.

The problem formulation of the DEED problem with RES and EVs and modeling of wind, solar, and EVs are discussed in Sect. 2. Section 3 provides information on the original EO method. Section 4 shows the simulation results of a test case. Finally, the conclusion of the manuscript is pointed out in Section 5.

2 Problem formulation

The main objective of the DEED problem is to minimize the total fuel cost and emission of pollutants by satisfying all system constraints (Nazari-Heris et al., 2020). The objective function becomes highly complex and nonlinear after connecting wind, solar, and EVs. The mathematical expression of the DEED problem with RES and EVs is shown below.

2.1 Objective function

The multiple steam valves have been connected to the boiler. Valves are opened sequentially to get the highest possible efficiency for the given output (Nandi & Kamboj, 2021). Therefore, the sinusoidal term has been added to the objective function (Bhattacharjee et al., 2014). The objective function of the DEED problem is given below:

$$C_T = \sum_{i=1}^{N} a_{iT} + b_{iT}T_{iT} + c_{iT}T_{iT}^2 + e_{iT}sin[f_{iT}(T_{iT}^{\min} - T_{iT})] \tag{1}$$

$$E_T = \sum_{i=1}^{N} \alpha_{iT} + \beta_{iT}T_{iT} + \gamma_{iT}T_{iT}^2 + \zeta_{iT}\ exp(\lambda_{iT}T_{iT}) \tag{2}$$

where a_{iT}, b_{iT}, and c_{iT} are thermal cost co-efficient of iTth unit; e_{iT} and f_{iT} are co-efficient of thermal iT^{th} unit representing VPLE; N is total connected thermal units; T_{iT} is the power generated by each thermal generator; T^{min}_{iT}, T^{max}_{iT} are the minimum and maximum power boundary of each generator; α_{iT}, β_{iT}, and γ_{iT} are emission co-efficient of iTth unit; ξ_{iT} andλ_{iT} are co-efficient of emission iTth unit representing VPLE. The multi-objective EED problem can be solved by converting it into a single objective using the linear weighting method. Eqs. (1) and (2) are the objective function for calculating fuel cost and emission level of thermal generators, respectively. These both equation has been converted into single objective function by using weighting factor w. The PPF is integrated with emission cost with fuel cost to give equal importance (Bhattacharjee et al., 2014). The mathematical expression of the total cost is given below:

$$\text{Total cost} = \min[((w \times C_T) + (1 - w) \times PPF\ \times E_T) + \sum_{j=1}^{N_w} W_{p,j} \times C_{w,j}] \tag{3}$$

where $W_{p,j}$ is the output power of jth wind unit; $C_{w,j}$ is cost co-efficient of jth wind unit in \$/h; N_w is a Total number of wind farms; w is weighting factor which varies uniformly between 0 and 1. Eq. (3) has been used to calculate the total cost after integrating wind farms with the thermal generators. The second term in Eq. (3) is representing the operating cost of wind farms. The operating cost of wind farm has been calculated by direct cost multiplied by the output power of wind farms.

2.2 Constraints

The various operating constraints should be considered in the system to make the system more realistic (Roy et al., 2017). The following constraints have been considered in this research work.

2.2.1 Thermal generator operating constraints

The output power from thermal and wind farms should be between boundary limits for reliable and continuous operation (Patel & Bhattacharjee, 2020):

$$T_i^{\min} \le T_i \le T_i^{\max};\ i = 1, 2, 3, ..., N \tag{4}$$

$$0 \leq w_j \leq w_{p,j}; j = 1, 2, 3, ..., N_w \tag{5}$$

Where $w_{p,j}$ is the rated output power by jth wind farms.$T^{min}{}_{iT}$, $T^{max}{}_{iT}$ are the minimum and maximum power boundary of each generator. Equation (4) represents the boundary limit of output power for the thermal generators. If output power of thermal generators goes beyond their limit, the generator will go into out of synchronization. Equation (5) represents the boundary limit of the output power of the wind farms. If output power of wind farms go beyond their limit, the wind turbine will go into out of synchronization and will damage to connected other generators. Therefore, these constraints are very important for smooth operation of turbine and generators.

2.2.2 Power balance constraints

The total power generated by thermal and wind units should be equal to total load demand plus total transmission loss in the transmission lines (Bhattacharjee et al., 2021).

$$\sum_{i=1}^{N} T_{iT} + \sum_{j=1}^{N_w} W_{p,j} - (T_D + T_L) = 0 \tag{6}$$

Where T_D is total load demand; T_L is total transmission loss. The total transmission losses can be calculated by using Kron's loss formula as given below (Li et al., 2021). Equation (6) represents the power balance for the total network. If there is unbalance in power system, the connected generators will be damaged. Therefore, it may occur total shutdown of the system:

$$T_L = \sum_{m=1}^{N} \sum_{n=1}^{N} T_m B_{mn} T_n + \sum_{m=1}^{N} B_{m0} T_m + B_{00} \tag{7}$$

Where B_{mn}, B_{m0}, and B_{00} are elements of the B matrix can be evaluated using methods as discussed in Li et al. (2021). Further, T_m and T_n are the power outputs of generators m and n in MW, respectively. The above equation has been formulated as shown below (Shouman et al., 2021). Equation (7) has been used to calculate total transmission loss when power is transferred from generation side to distribution side. The transmission losses have been calculated for 3-phase transmission line from supply side to substation side.

2.3 Modeling of wind plant

The output power of wind farms has been dependent on wind velocity. Therefore, the Weibull distribution has been used to randomly generate the wind velocity (Ghasemi et al., 2019). The mathematical expression of wind velocity is given below:

$$f_v(v) = \frac{k}{c}(\frac{v}{c})^{k-1} \exp[1 - (\frac{v}{c})^k]; for\ 0 < v < \infty \tag{8}$$

where k and c are the shape factor and scale factor of the wind turbine; v is instantaneous wind velocity (Dasgupta et al., 2021). The expression of wind output power is given as follows:

$$W_p = \begin{cases} 0; & : \ v < v_{\text{in}}, v > v_{\text{out}} \\ W_{pt}(\frac{v-v_i}{v_r-v_i}) & : \ v_r < v < v_{\text{out}} \\ W_{pr}; & : \ v_r < v < v_{\text{out}} \end{cases} \tag{9}$$

where v_{i} and v_{r} are instantaneous speed and rated velocity of wind unit; v is output speed from the PDF; v_{in} and $v_{\text{out}}$are cut in and cut out the velocity of wind unit; W_{p} and W_{pt} are output power and rated power of wind turbine.

2.4 Modeling of solar power

The solar units have been modeled into mathematical form in this subsection. The output power of solar is dependent on solar irradiance and temperature. The beta PDF has been used to randomly generate solar irradiance in this study (Zamli et al., 2021). The mathematical formula is given below:

$$\text{PDF(ir)} = \begin{cases} \frac{\omega+\psi}{\omega\psi} \times ir^{\omega-1}(1-ir^{\psi-1}) & : \ 0 \leqslant ir \leqslant 1, \omega \geq 0, \psi \geq 0 \\ 0 & : \ \text{otherwise} \end{cases} \tag{10}$$

where ω and ψ are beta PDF parameters; Γ is the gamma function. The reactive power from the solar system is assumed to be zero. The output solar power is calculated using the below formula (Singh et al., 2022):

$$S_p(t) = \left[S_{p,\text{st}} \times \frac{S_{\text{rad}}(t)}{S_{\text{rad,st}}} \times \left\{ 1 - \gamma \times (T_{\text{cell}} - T_{\text{cell,st}}) \right\} \right] \times N_s \times N_p \tag{11}$$

where T_{cell} is the temperature of the solar cell; $T_{\text{cell,st}}$ is the temperature of solar cell in standard test condition; $S_{\text{rad}}(t)$ is solar radiation of cell at t; $S_{\text{rad,st}}(t)$ is solar radiation for the standard condition; $S_{\text{p,st}}(t)$ is solar power for the standard condition; γ is co-efficient of temperature in °C; N_{p} and N_{s} are the numbers of the parallel and series solar cell. The temperature of cell T_{cell} can be computed using the following formula:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{S_{\text{rad}}(t)}{S_{\text{rad,stc}}} \times (\text{NTC} - 20) \tag{12}$$

where T_{cell} is the ambient temperature in °C and NTC is the normal temperature of the solar cell.

2.5 Modeling of EV

In V2G technology, there is controllable and bi-directional power flow between EV and grid. The charging, discharging, and operation of batteries depend upon the load demand. The owner of EVs can sell power in on-peak hours and absorb power in off-peak hours from the energy market (Abdelaziz et al., 2016). Therefore, the mode of batteries can be controlled by the management system. It requires communication and information technology to monitor load demand, online price, and preference between EVs. The EVs have been considered as load and as energy sources depending upon the operation mode:

$$\sum_{i=1}^{N} P_i(t) + P_{\text{solar}}(t) + \sum_{j=1}^{N_{\text{PEV}}(t)} \eta P_j^{\text{PEV}}(t)(\psi_{\text{pre}} - \psi_{\text{dep}}) + P_{\text{wind}}(t) = D(t) \tag{13}$$

If the PEVs have been considered as loads, the mathematical expression is as follows:

$$\sum_{i=1}^{N} P_i(t) + P_{\text{solar}}(t) + P_{\text{wind}}(t) = D(t) + \sum_{j=1}^{N_{\text{PEV}}(t)} \eta P_j^{\text{PEV}}(t)(\psi_{\text{pre}} - \psi_{\text{dep}}) \tag{14}$$

$$\sum_{j=1}^{T} N_{\text{PEV}}(t) = N_{\text{PEV}}^{\max} \tag{15}$$

3 Equilibrium optimizer (EO)

The EO method has been based on the physics law of controlling the balance between mass and volume. The particles (solutions) with concentration (position) are considered as the search agents. The search agents update their positions about the optimum solution. The generation rate term has been used in the methods to strengthen the exploration and exploitation stage (Faramarzi et al., 2020). The expression of the mass balance has been formulated as follows:

$$V\frac{dC}{dt} = (C_{\text{eqs}} - C) + G \tag{16}$$

where V dC/dt is the rate of change in mass; Q is flow rate; V is control volume; Ceqs is concentration in equilibrium state; C is inside concentration; G is generation rate of mass. The equation (17) becomes zero when a steady position is reached. After the integration, the concentration has been formulated as follows:

$$C = C_{\text{eqs}} + (C_0 - C_{\text{eqs})}e^{\phi(t_0 - t)} - \frac{G}{Q}[e^{\phi(t_0 - t)} - 1] \tag{17}$$

where C_0 is the initial concentration; ϕ=Q/V is the turnover rate; t_0 is the initial time. There is three-term in Eq. (18). The first term is randomly selected from the equilibrium pool. The second term represents the search mechanism called explorers. The third term is generation rate called exploiters. The positions of each search agent are initialized by the expression as given below:

$$C_i^0 = C_{\text{low}} + u \times \left(C_{\text{high}} - C_{\text{low}}\right) \tag{18}$$

where u is the random number between 0 to 1; C_{low} is lower concentration; C_{high} is higher concentration; N is the total number of search agents. The fitness values of each search agent are stored to reach the equilibrium state. The equilibrium state is formulated as follows:

$$C_{\text{ep}} = C_{\text{eqs1}} + C_{\text{eqs2}} + C_{\text{eqs3}} + C_{\text{eqs4}} + C_{\text{eqsav}} \tag{19}$$

where C_{eqs1}, C_{eqs2}, C_{eqs3}, C_{eqs4}, and C_{eqsav} are the equilibrium search agents; C_{eqsav} is the average of equilibrium search agents for the exploitation. The search agents will update their position in each iteration by making a balance between exploitation and exploration.

$$F = e^{\phi(t_0 - t)} \tag{20}$$

where ϕ is between 0 to 1. The function of the iteration number is expressed as follows:

$$t = \left(1 - \frac{\text{iter}}{\text{itermax}}\right)^{w_1 \times \frac{\text{iter}}{\text{itermax}}} \tag{21}$$

where iter is the number of iterations; itermax is the highest number of iterations; w_1 is a constant factor to strengthen the ability of exploitation. The initial time is calculated using the formula as follows:

$$t_0 = \frac{1}{\phi} ln(-w_2 \text{sign}(r - 0.5)[1 - e^{-\phi t}]) + t \tag{22}$$

where w_2 is constant for the ability in the exploration stage.

4 Results and discussion

The EO technique has been applied to ten and twenty thermal generating units DEED model integrated with RES and EVs. The results attained by the EO method are compared with other recently developed methods. The simulations have been done on the MATLAB 2021a software in 1.7GHz intel core and 4 GB RAM personal computer.

The pollutants gases like CO_2, SO_2, CH_4, and NO_X emitted from thermal generating units. However, the amount of CO_2 gas is much more than other gases. Thus, the only amount of CO_2 gas is considered in this research work. The approximate method for calculating number of EVs is given in Abdelaziz et al. (2016). The 50,000 EVs have been considered. The rated output power of wind and solar is 30 MW and 40 MW, respectively. The average distance traversed and needed energy by EVs are 12,000 miles and 8.22 kWh per day, respectively. The input data of wind and solar are given in Basu (2011). The solar isolation and wind speed for 24 h are shown in Fig. 1.The wind speed for 24 h is shown in Fig. 2.The different four cases for ten and twenty thermal generating unit test system have been considered: 1. Without EVs and RES 2. With EVs as load leveling 3. With EVs as energy source 4. With EVs and RES. The ten-thermal generating units have been integrated with 50,000 EVs and RES like wind and solar energy. The input data of thermal generating units are given in Basu (2008). The transmission losses have been neglected in this test system. The average amount of pollutant gases emitted by conventional vehicles is 0.276 kilo tons per year.

4.1 Ten-unit system

4.1.1 Case 1: ten-unit system without EVs and RES

The EO technique has been applied to ten-unit system without considering EVs and RES for an 24 h time interval to get optimal power dispatch of DEED function. The output results obtained by EO are given in Table 2.The values of weights w_1 and w_2 have been

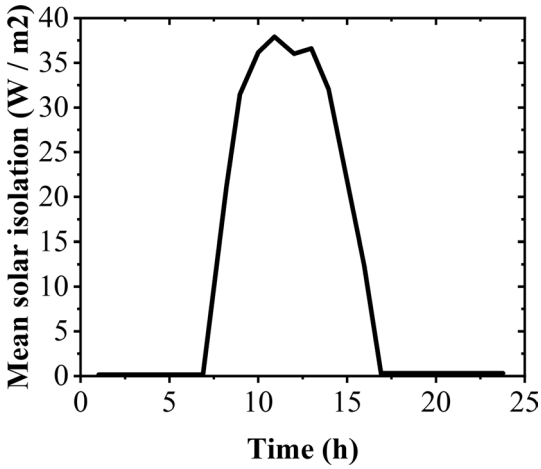

Fig. 1 Solar isolation for 24 h

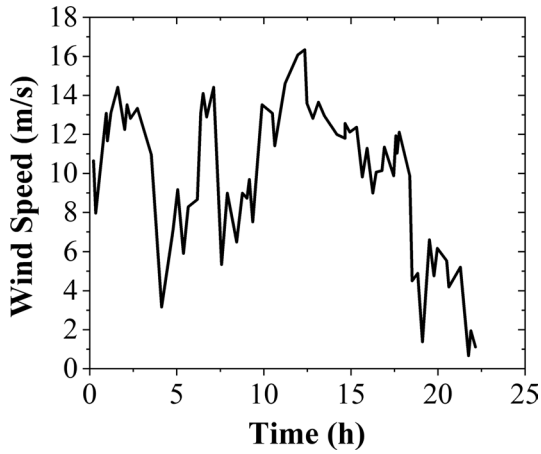

Fig. 2 Wind speed for 24 h

changed from 0 to 1 for getting minimum and maximum values of fuel cost and emission. At $w_1 = 1$, $w_2 = 0$, the minimum fuel cost obtained by EO is \$ 643875.1211. At $w_1 = 0$, $w_2 = 1$, the minimum emission obtained by EO is \$ 19458.6954. The obtained minimum fuel cost, minimum emission, and best compromise solution are shown in Table 3.

4.1.2 Case 2: ten-unit system with considering EVs as load leveling

In the load-leveling scheme, the EVs are in charging mode during off-peak hours like 10 PM to 10 AM. Therefore, these EVs will impose extra load of 50,000 $$ \times $$ 8.22 kWh = 411 MWh. The extra load has been divided during off-peak hours which will increase load demand around 34.3 MW. Therefore, the load management system is required to schedule load of EVs. In this research work, it is assumed that all EVs will associate with load-leveling program. The load profile for 24 h time interval before and after load

Table 2 Fuel cost and emission for ten-unit system without PEV and RES

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	PD (MW)	Cost ($)	Emission (Ton)
1	197.4896	154.4776	95.0526	122.9118	73.8864	23.8427	4.0757	4.8363	2.5403	20.8870	700	19091.8367	398.9857
2	200.4826	175.0136	128.1512	114.6458	71.7558	12.5722	10.9524	14.2845	7.1307	15.0110	750	20022.9259	432.8903
3	219.4696	206.9545	150.6306	123.2715	77.1673	31.0591	9.4161	11.0581	9.3734	11.5998	850	21788.1073	511.0576
4	260.7774	232.8921	137.9956	160.4667	71.7417	38.2690	12.4807	4.9671	19.9342	10.4755	950	23575.1817	614.1676
5	267.1152	243.5066	164.8569	159.3058	92.1877	30.8633	10.6670	13.2075	7.1743	11.1155	1000	24386.6799	671.3335
6	272.2896	293.2443	186.4664	133.5264	145.3911	26.4363	12.1907	5.9051	4.6631	19.8869	1100	26297.5848	776.2411
7	288.5888	314.5651	176.3304	140.9008	157.0295	24.5552	4.9000	10.6720	11.0474	21.4109	1150	27226.3701	835.1683
8	304.6946	285.0156	222.4714	178.3793	125.2295	15.5427	11.4456	8.8709	6.4488	41.9015	1200	28138.8944	914.8311
9	331.7454	338.9206	201.7215	198.0799	106.5728	40.0522	6.3070	20.8629	6.0859	49.6516	1300	30050.8664	1033.5733
10	417.0798	386.9452	198.0686	150.8125	102.3388	52.8220	30.0111	41.2385	10.3666	10.3170	1400	31847.7255	1232.1489
11	408.4554	386.4183	198.4221	184.4777	165.6188	20.6937	15.7219	19.4907	15.7254	34.9759	1450	32725.9580	1292.3864
12	370.5413	362.6050	212.0531	241.0726	198.1954	44.7114	14.1886	4.1926	17.0387	35.4013	1500	33745.1130	1311.0830
13	395.6078	338.5562	194.9359	213.0132	136.3455	36.9058	26.9488	8.3716	6.3649	42.9503	1400	31858.6545	1188.3064
14	353.0325	278.6391	224.0865	220.8657	104.0181	37.7819	12.5288	6.6583	7.8098	54.5792	1300	30021.2606	1052.2292
15	332.4262	293.1790	209.0844	150.1833	118.1839	38.9197	16.8018	14.9051	3.6455	22.6711	1200	28097.6697	908.2527
16	233.5179	271.9358	182.5840	172.3028	130.2187	12.1743	7.0389	13.3080	9.7534	17.1662	1050	25361.4948	724.2440
17	290.9412	240.0037	125.7813	141.3650	132.0083	40.2051	10.6365	2.8792	5.2932	10.8865	1000	24444.7455	658.7193
18	280.4270	269.2650	178.0708	185.4969	114.6283	8.1058	13.5168	12.0146	9.8042	28.6706	1100	26291.0885	786.7532
19	329.5690	226.4712	200.6102	207.3336	144.8163	27.1320	4.6209	5.0876	14.6214	39.7377	1200	28192.0994	894.7349
20	368.0979	411.0129	207.2497	188.1077	101.0354	50.2996	16.2738	28.2491	16.8173	12.8566	1400	31695.2386	1242.9912
21	373.9356	299.9360	205.0922	190.9309	129.3237	23.0470	16.8257	5.2508	11.1147	44.5433	1300	29967.7636	1054.3297
22	319.5353	277.6589	164.9991	142.1553	110.6350	38.3761	16.9538	9.0759	9.5445	11.0662	1100	26234.5534	786.0562
23	245.8228	223.1007	135.0227	141.4975	84.7651	23.2119	11.9825	10.0545	13.6509	10.8913	900	22663.9296	562.7790
24	188.0867	202.6209	146.8585	133.2190	72.4059	21.5311	7.5179	6.9464	10.0017	10.8119	800	20826.3359	482.2729
											Total	644552.0779	20365.5357

Table 3 Minimum fuel cost, minimum emission, and best compromise solution for ten-unit without PEV and RES

Only economic dispatch method		Only emission dispatch method		Best compromise solution	
TC in $	TE in Ton	TC in $	TE in Ton	TC in $	TE in Ton
643875.1211	22459.1244	646078.9865	19458.6954	644552.0779	20365.5357

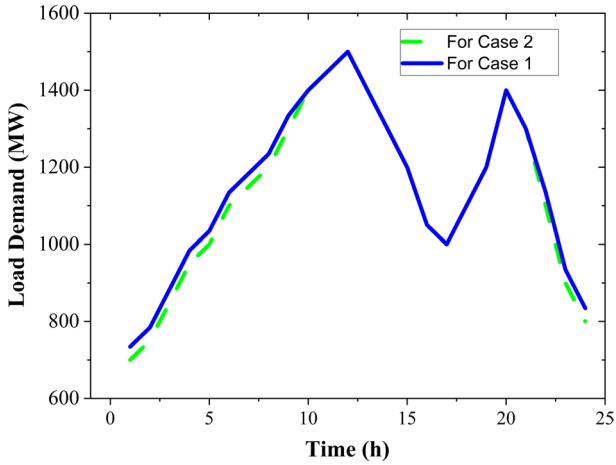

Fig. 3 Load demand for 24 h in case 1 and case 2

leveling is given in Fig. 3. The output results obtained by EO for the case 2 has been given in Table 4. By comparing Table 2 and Table 4, The total emission has been increased by 627.88 tons (20365.54 - 20993.42 tons) in load leveling. These additional emission emitted by thermal units is to supply load demand of 50,000 EVs during 24 h. Therefore, the total extra emission per year is 627.88 $$ \times $$ 365= 2,29,176.2 tons. However, these extra emission is still positive as compared to conventional vehicles by 2,67,000 $$ - $$ 2,29,176.2 = 37,823.8 tons. Therefore, the load leveling by EVs will increase the total emission of pollutant gases. At $w_1 = 1$, $w_2 = 0$, the minimum fuel cost obtained by EO is $ 649142.2361. At $w_1=0$, $w_2=1$, the minimum emission obtained by EO is $ 19875.6549. The obtained minimum fuel cost, minimum emission, and best compromise solution are shown in Table 5.

4.1.3 Case 3: ten-unit system with considering EVs as energy source

The EVs are charged or discharged in a smart way. The generation scheduling, total fuel cost, and emission obtained by EO for this case are shown in Table 6. The EVs can be charged during off-peak hours during 1–7 AM, 4–6 PM, and 10 PM–midnight. The EVs can be discharged during on-peak hours during 8 AM–3 PM and 7–9 PM. Therefore, the EVs can be worked as loads from 10 PM–7 AM. The EVs can be worked as energy sources from 8 AM–3 PM. The highest quantity of power like 73.10 MW has

Table 4 Fuel cost and emission for ten-unit system with load leveling

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	PD (MW)	Cost ($)	Emission (Ton)
1	255.8588	195.6605	78.8606	142.7196	25.5849	9.0839	7.9498	4.5585	3.1308	10.8926	734	19364.1213	520.0988
2	193.6155	202.5283	129.7721	105.5846	43.8303	14.3717	9.1225	9.9616	3.7546	21.7587	784	19672.2821	447.2159
3	272.4251	194.3819	139.4668	111.7919	106.8715	17.6634	12.7125	9.3439	8.5127	11.1304	884	22367.4559	556.0152
4	265.6742	241.0848	157.3537	137.8544	124.8054	16.3084	12.5254	12.5104	5.9542	10.2292	984	24141.6608	648.6846
5	292.3525	256.7476	138.5214	176.5760	94.9427	19.7559	12.3429	13.4310	10.2226	19.4074	1034	25048.4851	718.6101
6	316.0213	254.2900	185.0118	174.0428	136.5363	14.1921	12.0256	21.8254	9.4237	10.9310	1134	26838.5743	827.9190
7	362.7843	255.0277	150.1524	186.2129	144.3698	24.1856	25.1796	11.3348	14.1554	10.8974	1184	27843.7944	888.9660
8	367.0493	316.9048	170.3306	133.4683	150.4962	27.9818	17.6341	28.7499	5.0767	16.6083	1234	28802.5597	955.5098
9	310.2729	348.8251	196.6111	251.4370	103.3961	41.3137	4.3787	10.6647	17.1867	50.2141	1334	30675.0415	1105.5160
10	417.0798	386.9452	198.0686	150.8125	102.3388	52.8220	30.0111	41.2385	10.3666	10.3170	1400	31847.7255	1232.1489
11	408.4554	386.4183	198.4221	184.4777	165.6188	20.6937	15.7219	19.4907	15.7254	34.9759	1450	32725.9580	1292.3864
12	370.5413	362.6050	212.0531	241.0726	198.1954	44.7114	14.1886	4.1926	17.0387	35.4013	1500	33745.1130	1311.0830
13	395.6078	338.5562	194.9359	213.0132	136.3455	36.9058	26.9488	8.3716	6.3649	42.9503	1400	31858.6545	1188.3064
14	353.0325	278.6391	224.0865	220.8657	104.0181	37.7819	12.5288	6.6583	7.8098	54.5792	1300	30021.2606	1052.2292
15	332.4262	293.1790	209.0844	150.1833	118.1839	38.9197	16.8018	14.9051	3.6455	22.6711	1200	28097.6697	908.2527
16	233.5179	271.9358	182.5840	172.3028	130.2187	12.1743	7.0389	13.3080	9.7534	17.1662	1050	25361.4948	724.2440
17	290.9412	240.0037	125.7813	141.3650	132.0083	40.2051	10.6365	2.8792	5.2932	10.8865	1000	24444.7455	658.7193
18	280.4270	269.2650	178.0708	185.4969	114.6283	8.1058	13.5168	12.0146	9.8042	28.6706	1100	26291.0885	786.7532
19	329.5690	226.4712	200.6102	207.3336	144.8163	27.1320	4.6209	5.0876	14.6214	39.7377	1200	28192.0994	894.7349
20	368.0979	411.0129	207.2497	188.1077	101.0354	50.2996	16.2738	28.2491	16.8173	12.8566	1400	31695.2386	1242.9912
21	373.9356	299.9360	205.0922	190.9309	129.3237	23.0470	16.8257	5.2508	11.1147	44.5433	1300	29967.7636	1054.3297
22	287.5190	296.4307	188.2828	173.3026	119.9615	14.0281	12.2256	22.8922	9.6404	10.0170	1134	26814.1863	838.8993
23	276.2813	244.7110	162.9608	114.2213	70.7749	8.7352	17.6526	9.0298	10.4976	19.4356	934	23230.3565	637.1713
24	229.9039	189.7251	151.0154	115.7452	81.0548	29.7067	6.8095	7.0315	9.2969	14.0110	834	21474.4878	502.6365
											total	650521.8175	20993.4215

Table 5 Minimum fuel cost, minimum emission, and best compromise solution for ten unit with load leveling

Only economic dispatch method		Only emission dispatch method		Best compromise solution	
TC in $	TE in Ton	TC in $	TE in Ton	TC in $	TE in Ton
649142.2361	21512.3215	651012.6598	19875.6549	650521.8175	20993.4215

been discharged to grid in on-peak hours. At $w_1 = 1$, $w_2 = 0$, the minimum fuel cost obtained by EO is $ 645785.3874. At $w_1 = 0$, $w_2 = 1$, the minimum emission obtained by EO is $ 19041.6578. The obtained minimum fuel cost, minimum emission, and best compromise solution are shown in Table 7.

4.1.4 Case 4: ten-unit system with PEVs and RES

The RES like wind farms and solar plants and large-scale EVs has been integrated with the ten-thermal generating unit in this case. The EVs can be charged in off-peak hours like 1–7 AM, 4–6 PM, and 10 PM–midnight. In the on-peak hours like 8 AM–PM and 7–9 PM, the EVs have been discharged into the grid. The 11,466 number of EVs are discharged to grid in peak hours. The generation scheduling, total fuel cost, and emission obtained by EO method are shown in Table 8. Therefore, the EVs reduce 20993.4215 $$ - $$ 19771.94 = 1,221.4815 tons emissions per day.

At $w_1 = 1$, $w_2 = 0$, the minimum fuel cost obtained by EO is $ 624875.6. At $w_1 = 0$, $w_2 = 1$, the minimum emission obtained by EO is $ 18784.98. The obtained minimum fuel cost, minimum emission, and best compromise solution are shown in Table 9. The comparison of fuel cost and emission of ten-unit system in all cases are shown in Fig. 4. The results obtained by EO algorithm have been compared with other recently developed algorithm as shown in Table 10.

4.2 Twenty-unit system

The twenty-unit system has been simulated by EO method to check effect of network topology on the emission value. The transmission loss has been considered in this test system. The input thermal data, B matrix data, and load data have been given in Behera et al. (2021). The 120,000 PEVs have been connected in this test system. The rated capacity of the wind and solar plants is 61.5 MW and 100 MW, respectively.

4.2.1 Fuel cost and emission for twenty-unit system without PEVs and RES

The output of each generating unit, fuel cost, and emission for 24 h obtained by EO is shown in Table 11.

Table 6 Fuel cost and emission for ten-unit system with considering PEVs as energy source

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	PD (MW)	Cost ($)	Emission (Ton)
1	203.8366	185.4253	105.7221	87.7070	75.9274	27.0755	4.9253	10.9583	7.8338	13.5507	722.96	19555.5405	411.0545
2	193.4566	180.9783	128.5285	126.8994	77.4707	12.6976	16.2482	13.7532	7.0312	12.0172	769.08	20393.2869	441.8627
3	225.1380	201.8009	142.0213	136.9525	100.1015	19.5665	10.8298	5.4423	8.3477	15.4545	865.66	22057.5860	523.6926
4	278.7037	224.5883	139.4891	139.4965	115.0420	23.0247	12.6965	10.2789	15.7528	13.0955	972.17	24033.7090	620.5119
5	263.6942	253.6805	147.7613	158.2148	110.9876	44.3165	11.4929	9.8651	13.9179	11.1962	1025.13	25009.1692	661.2342
6	324.2294	254.8612	185.3122	127.3349	110.4881	60.9783	13.6742	7.6213	13.2591	19.7422	1117.50	26742.7907	772.7294
7	329.2422	260.6569	165.3605	175.3778	115.7963	52.0138	8.8851	7.8500	7.1105	41.7410	1164.03	27625.2443	819.3824
8	283.3929	280.5976	180.4146	201.0141	104.7046	64.5762	11.4530	6.7924	14.7253	24.0324	1171.70	27740.5351	825.7997
9	342.6363	292.3695	187.3191	180.4956	163.6292	29.8944	14.9325	7.6325	15.1073	34.9177	1268.93	29548.9095	955.0708
10	382.7024	342.0658	177.0908	191.6475	138.0806	82.5594	23.9394	14.5546	12.6372	10.9553	1376.23	31472.4306	1108.6345
11	353.8922	389.3495	207.3650	219.3896	164.6963	27.9502	14.5228	17.5913	5.0755	29.6107	1429.44	32256.3849	1256.8694
12	371.0781	331.1077	213.9946	220.1784	192.1021	23.3608	27.5945	12.8975	10.9046	23.6757	1426.89	32365.0961	1209.5867
13	376.9006	361.5356	176.3129	219.1399	166.8698	22.8968	19.0498	16.2044	5.6958	20.3584	1384.96	31387.7928	1200.1387
14	327.1166	339.5582	173.7374	192.5297	136.8238	33.3353	11.8035	6.5357	12.5165	49.2814	1283.24	29821.6683	990.2459
15	292.9311	299.6290	165.4924	184.6117	145.6236	25.9643	8.9498	33.4488	17.2657	11.0526	1184.97	27983.4493	844.7614
16	279.8030	240.4612	165.7021	166.6110	137.1864	29.9472	8.5982	16.9845	10.6439	15.5206	1071.46	25847.3537	712.1474
17	249.7390	236.6706	166.2300	165.0679	128.1084	51.3829	11.7036	14.6930	3.7236	10.0190	1037.34	25255.5903	660.2528
18	292.0403	269.6088	176.7758	158.7891	116.4869	48.5140	10.1486	9.2819	15.3822	19.2505	1116.28	26684.6147	762.4556
19	298.2522	295.2604	188.6771	175.3869	112.5329	19.4468	18.4177	37.7270	16.0008	18.9452	1180.65	27965.8934	845.6728
20	382.8074	346.4556	181.5866	191.0423	135.2432	39.3585	19.5812	13.7543	23.7836	15.6613	1349.27	30852.7456	1116.6525
21	308.4285	335.7067	199.5142	172.5371	161.1557	30.3278	9.8535	17.2374	10.0952	30.1638	1275.02	29611.8276	974.9610
22	288.2652	265.0813	168.8322	178.5309	123.7729	32.9669	25.5210	6.7458	14.6079	11.2841	1115.61	26663.2711	769.6148
23	260.0961	208.5339	153.9656	146.0731	90.4697	28.6527	5.4626	5.2026	9.8838	26.8869	935.23	23323.0712	592.0197
24	207.7439	195.7378	152.3705	147.6029	77.4067	38.6763	12.7684	2.6362	9.1455	12.1777	856.27	21909.0496	513.2168
											TOTAL	646107.0103	19588.5685

Table 7 Minimum fuel cost, minimum emission, and best compromise solution for the ten-unit system with considering PEVs as energy storage

Only economic dispatch method		Only emission dispatch method		Best compromise solution	
TC in $	TE in Ton	TC in $	TE in Ton	TC in $	TE in Ton
645785.3874	20198.2651	646954.1256	19041.6578	646107.0103	19588.5685

4.2.2 Fuel cost and emission for twenty-unit system considering load leveling

PEVs are charged in off-peak hours to smooth load profile in this case. Therefore, there will be extra load of PEVs around 111.43 MW. The results obtained by EO are shown in Table 12.The emission of pollutant gases have been increased to 60080.84 tons. Therefore, the emission level has been increased significantly in this case.

4.2.3 Fuel cost and emission for twenty-unit system with PEVs and RES

The PEVs and RES have been connected with twenty thermal generating units in this case. The results are shown in Table 13. The results show that the total fuel cost and emission level have been decreased significantly.

4.3 Tuning of parameter and Wilcoxon signed-rank test

To find the best solution with less iterations, the different EO algorithm parameters like G, Q, and u should be tweaked. For each test system, the minimal fuel cost and emission level have been determined using various parameter settings (Melzi et al., 2014). Through the selection of a single value for one parameter, the other parameters have been altered (Özgülşen et al., 1992). For instance, G has been adjusted from 3 to 7 in the appropriate stages. Q and u have also been altered, with ranges of 1–4.2 and 0–1, respectively. In order to determine the minimal fuel cost and emission for each test system, a 50 trail run was performed and obtained results are given in Table 14. Therefore, the tuning of parameter is required to get better solution in less convergence time.

A statistical tool to examine outcomes from any algorithm is the Wilcoxon signed-rank test. The Wilcoxon signed-rank test is a nonparametric hypothesis test that, at a 5% level of significance, can show that there are significant differences in continuous variables between two groups (Hamdi et al., 2019). It was utilized to compare other algorithms side by side in each benchmark function. A nonparametric statistical test called the Friedman test may be used to track changes in a number of linked data. It was used to determine how each algorithm performed in each benchmark function.It has been said that an algorithm is resilient if it can demonstrate its statistical validity (Narang et al., 2017). To sufficiently refute the null hypothesis, the algorithm must thus provide adequate evidence. A sample size of 50 (n=50) was used for the suggested algorithm's test run. Below are the procedures for doing the Wilcoxon signed-rank test (Yang et al., 2022).

Table 8 Fuel cost and emission for ten-unit system with PEV and RES

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	Wind (MW)	Solar (MW)	PD (MW)	Cost ($)	Emission (Ton)
1	202.5230	191.2359	62.9731	107.1973	90.3184	13.4900	8.2166	7.1376	12.2141	11.0158	16.6400	0.00	722.96	19282.07	414.65
2	213.8724	163.7619	100.0084	133.1622	66.6869	26.8505	13.3741	12.1250	3.3035	11.1560	24.7800	0.00	769.08	19939.14	444.08
3	202.7071	214.8038	158.8697	106.5541	105.8580	12.6947	16.0166	6.4673	5.6343	12.4094	23.6400	0.00	865.66	21675.62	515.99
4	265.1852	220.6652	144.3279	155.8707	103.1698	14.3295	8.9154	15.7232	3.7891	21.4620	18.7300	0.00	972.17	23659.49	624.90
5	291.6089	228.1204	185.5509	135.5944	117.2973	14.0350	4.9284	9.1493	19.7649	16.9877	2.0900	0.00	1025.13	24887.49	712.41
6	284.7512	274.4291	151.3176	194.4149	131.1751	22.1636	11.8407	8.3705	14.1580	17.2303	7.6500	0.09	1117.59	26501.79	808.87
7	289.9484	325.4505	174.7099	142.6976	138.6327	31.9645	17.2135	7.8158	9.6435	13.1777	12.7800	17.46	1181.49	27297.92	851.20
8	328.5899	301.9186	140.4914	148.2155	136.3327	35.4532	14.5035	12.0678	5.1173	10.7002	20.8200	31.45	1185.66	26948.45	834.71
9	315.5140	314.6365	192.0985	199.3388	108.2814	18.2336	8.2763	10.6624	12.0894	51.9791	6.3600	36.01	1273.48	28792.47	957.79
10	342.0426	320.2178	206.3968	247.7605	98.5881	50.6577	10.5453	12.2566	4.9758	35.9487	10.7900	38.06	1378.24	30582.40	1123.04
11	401.9253	379.4825	150.4920	184.4779	124.8940	66.3334	16.5265	27.0012	10.1978	12.1794	17.8500	35.93	1427.29	31397.74	1200.75
12	391.4823	386.9680	173.6379	177.2544	110.9696	40.4093	20.5176	15.9224	8.0653	43.1931	22.5400	36.78	1427.74	31314.87	1187.56
13	366.2577	341.1239	212.1222	168.6910	114.9335	54.9707	11.1776	23.6482	7.9910	17.2441	30.0000	31.59	1379.75	30402.77	1094.33
14	306.4364	279.5646	198.4588	220.2638	121.9494	39.7081	6.4123	17.4504	9.8236	25.5526	26.0300	9.70	1261.35	28678.77	953.38
15	319.5018	280.8294	178.6280	182.4867	91.0767	32.1159	15.3772	16.3309	17.6630	15.5603	25.6400	12.92	1188.13	27238.73	858.71
16	269.9811	266.7944	147.9233	163.2710	96.7151	44.7206	9.2732	13.8156	7.6619	15.3438	22.9900	0.00	1058.49	25118.82	725.39
17	276.1023	267.6714	137.8331	175.9787	70.4240	35.9523	11.7308	17.9632	11.7200	12.8322	19.1300	0.00	1037.34	24791.87	709.37
18	292.6327	289.7524	148.5315	174.5850	114.5759	21.7647	11.6639	16.3066	7.7360	22.0691	16.6600	0.00	1116.28	26316.33	795.11
19	294.5907	265.8872	182.7851	199.0667	136.1340	26.3901	20.8449	12.3853	6.1934	18.6697	17.7000	0.00	1180.65	27517.92	866.00
20	379.5508	297.2646	191.3046	222.6054	143.0302	16.8028	15.3602	4.4653	10.9671	51.7629	16.1600	0.00	1349.27	30664.93	1124.30
21	379.0353	307.9950	158.5113	158.2092	143.5540	79.9268	6.9999	8.4548	15.2108	17.1128	0.0100	0.00	1275.02	29599.54	1025.80
22	331.1492	237.3222	151.5891	180.5495	130.2298	19.9351	9.2421	22.1049	9.4853	20.4207	3.5800	0.00	1115.61	26562.22	804.66
23	234.8782	223.3466	139.2663	185.0705	70.4069	30.5084	8.4349	20.4592	8.3469	11.5791	2.9300	0.00	935.23	23265.48	607.77
24	207.7439	195.7378	152.3705	147.6029	77.4067	38.6763	12.7684	2.6362	9.1455	12.1777	0.0000	0.00	856.27	21920.61	531.17
													Total	634357.44	19771.94

- The null-hypothesis H_0 has been removed from the 50 trail run findings. Each trail run result has been given a marked rank, from the lowest to highest.
- Pick the proper test statistic. Calculate T^+ and T^-. where T^+ is the summation of positive signed rank, and T^- is the summation of negative signed rank. Calculate T, which is the minimum of T^+ and T^-.
- Determine the Wilcoxon test statistics T by summing the positive and negative signed ranks individually. Calculate mean T, σ, and z.

$$\text{mean}T = \frac{n(n+1)}{4} \tag{23}$$

$$\sigma = \sqrt{\frac{n(n+1)(2n+1)}{24}} \tag{24}$$

$$z = \frac{T - \text{mean } T}{\sigma} \tag{25}$$

- The probability value (p-value) should be considered strong evidence against the null hypothesis. The p-value of T under the null hypothesis may be calculated using the probability distribution of T.

The Wilcoxon signed-rank test p-values at the 5% level of significance for all test systems has been calculated for all the test system. However, considering the length of this manuscript, we have shown final p values for all the test system in Table 15. The p values are significantly lower than the target value of 0.05 in each of the test systems. Therefore, from the standpoint of statistical analysis, the suggested method may be regarded as reliable and significant.

5 Conclusion

The RES and PEVs integration with thermal generating units have been described in terms of total generation cost and total emission. The DEED model has been employed for getting optimal power dispatch among generating units in a day. The EO optimization technique has been applied in ten and twenty thermal generating units of four special cases. The results show that the total fuel cost and emission level have been decreased significantly after integration of RES and PEVs. The main outcomes of this research work have been listed as follows:

- The conventional thermal generators are expensive in terms of economically and environmentally for electrical transportation. Therefore, the thermal generators should be operated economically and environmental friendly while satisfying continues increasing load demand. Thus, In this research, the renewable sources and EVs integration with the thermal generators model have been proposed to smooth operation of system.
- The Weibull distribution and beta distribution have been successfully implemented to get random wind velocity and solar irradiance in this study. The output power of RES has been calculated to integrate it in microgrid to further reduce fuel cost and

Table 9 Minimum fuel cost, minimum emission, and best compromise solution for the ten-unit system with PEVs and RES

Only economic dispatch method		Only emission dispatch method		Best compromise solution	
TC in $	TE in Ton	TC in $	TE in Ton	TC in $	TE in Ton
624875.6	22985.69	642598.7	18784.98	633011.8632	19410.929

Table 10 Comparison of total fuel cost and emission obtained by EO and other recently developed techniques

Methods	Total cost	Total emission
EO	633011.9	19410.93
PSO	634357.4	19771.93
CFBPSO	635041	19552.31
BBO	636112.1	19782.36
CQGA	636541.9	19985.11
TLBO	636958.1	20158.69
MOEA	637223.6	20748.69

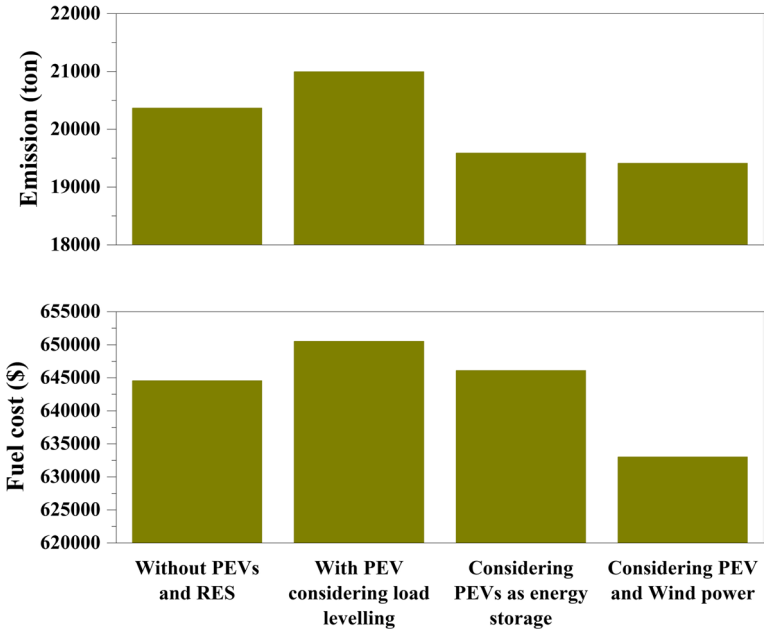

Fig. 4 Comparison of all cases in ten-unit system

emission level. However, The integration of PEVs with thermal generators is not so much useful in reducing the emission of pollutants.

- The strong and effective EO optimization method has been successfully applied in the highly complex and multi-objective DEELD model to get solution. The high

Table 11 Fuel cost and emission for twenty-unit system without PEVs and RES

Time	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
1	143.543	92.785	33.115	53.406	124.208	67.891	144.517	122.776	128.373	125.041	162.381
2	145.490	97.613	43.737	110.608	133.099	67.799	132.438	75.884	137.426	125.475	156.864
3	123.169	89.536	37.620	83.256	112.140	64.298	155.557	122.599	138.537	56.521	162.210
4	146.456	105.155	58.871	112.657	106.837	68.851	135.993	76.397	135.522	80.640	175.600
5	149.441	62.213	37.489	73.667	133.901	55.486	141.045	106.433	145.660	82.270	180.277
6	172.447	91.377	55.537	44.469	142.438	65.053	145.081	81.913	141.640	125.350	144.249
7	135.946	102.311	88.845	94.545	136.999	41.643	144.733	128.737	161.306	138.437	155.756
8	167.407	126.919	107.267	90.473	142.845	129.620	155.165	136.726	144.765	130.238	165.847
9	172.156	113.060	107.314	122.325	164.021	141.318	169.320	89.157	156.876	108.615	158.783
10	154.887	114.120	94.079	143.784	155.356	161.373	158.471	40.549	162.593	132.348	176.324
11	158.382	84.743	90.032	107.300	181.187	125.420	140.157	128.014	161.533	150.433	167.093
12	167.974	83.678	98.559	137.546	151.476	93.870	151.470	142.763	147.359	113.299	168.332
13	163.392	100.186	110.611	74.242	163.433	102.194	166.199	107.541	177.271	136.640	169.978
14	166.774	97.529	94.280	110.718	151.976	140.433	147.429	116.423	152.263	122.648	173.130
15	154.810	116.057	83.502	132.478	172.839	124.754	150.930	94.777	168.498	167.487	143.247
16	135.193	112.872	83.064	124.118	139.601	147.821	165.324	151.337	150.021	119.494	183.155
17	156.830	115.617	92.912	115.516	150.802	162.893	179.093	101.039	158.836	120.276	195.558
18	172.671	112.979	106.564	151.774	176.445	132.513	168.214	96.007	190.066	128.245	178.173
19	187.713	119.263	98.260	134.333	171.693	136.060	169.082	100.628	186.321	154.287	174.320
20	160.334	111.135	91.700	167.654	167.606	142.516	167.435	120.312	160.142	153.385	164.048
21	173.063	118.137	109.465	130.377	147.330	155.010	154.896	120.588	169.677	150.039	192.902
22	166.110	108.232	91.521	124.972	144.678	117.998	163.037	142.274	147.876	139.448	172.534
23	161.470	87.697	71.452	118.451	135.988	135.054	166.529	86.924	147.097	149.173	174.089
24	156.098	98.169	89.354	120.029	141.189	68.236	124.963	99.810	151.245	132.420	141.260
T12	T13	T14	T15	T16	T17	T18	T19	T20	Load demand	Fuel cost	Emission
148.894	133.506	158.852	19.387	16.768	12.398	40.201	43.859	32.702	1804.602	47503.350	187.373

Table 11 (continued)

T12	T13	T14	T15	T16	T17	T18	T19	T20	Load demand	Fuel cost	Emission
146.392	115.809	80.537	16.805	14.882	13.357	25.368	41.539	43.079	1724.200	45923.024	171.331
159.226	146.066	102.379	16.858	13.765	14.221	31.518	19.269	55.373	1704.117	45546.365	176.117
125.170	104.712	79.736	14.451	9.562	14.847	54.860	45.537	42.231	1694.085	45350.663	173.337
155.378	134.681	111.535	9.173	14.644	15.647	25.577	37.248	32.364	1704.130	45462.997	174.638
151.982	137.942	125.981	16.882	16.106	13.811	24.554	45.676	42.003	1784.492	47075.888	186.428
171.800	152.350	142.794	14.878	16.799	10.801	37.810	30.936	47.850	1955.276	50536.205	208.697
169.477	149.971	140.450	14.840	14.351	19.485	57.836	47.425	30.092	2141.199	54198.169	249.376
167.695	173.820	148.241	19.611	20.915	10.499	35.085	13.046	54.358	2146.215	54333.156	258.844
165.577	158.861	153.999	16.922	17.500	12.336	43.582	51.728	46.917	2161.305	54618.930	262.391
171.839	140.753	165.166	13.152	20.119	22.257	48.349	52.820	47.649	2176.400	54934.131	260.125
167.884	155.617	161.567	26.961	12.072	20.306	55.566	31.262	48.597	2136.159	54129.834	255.156
149.263	174.658	133.013	11.649	17.557	17.255	51.323	43.147	46.509	2116.062	53729.657	249.154
154.490	133.023	139.720	20.689	11.483	23.778	55.647	61.000	52.684	2126.116	53920.516	249.214
166.701	150.899	134.860	16.142	22.079	23.937	42.190	43.189	36.843	2146.220	54337.964	256.499
181.791	135.509	146.166	25.174	18.380	20.078	27.261	49.385	50.580	2166.322	54712.748	261.722
162.065	169.078	156.739	18.727	22.387	19.592	48.419	41.443	38.875	2226.696	55871.130	281.839
171.837	170.795	140.946	22.324	17.940	22.258	55.657	39.153	52.642	2307.203	57489.340	309.750
194.316	168.427	162.040	20.420	30.120	25.052	58.152	53.548	38.665	2382.700	58883.822	344.335
214.912	172.079	151.488	22.837	27.660	21.223	38.828	47.786	34.315	2337.395	58043.146	325.193
170.370	164.332	124.441	22.309	24.160	19.766	59.842	56.025	34.412	2297.139	57252.002	303.259
178.453	163.097	143.438	20.206	26.159	21.055	50.505	52.155	42.885	2216.632	55639.236	273.624
159.125	158.394	149.383	17.294	19.391	12.819	42.100	26.211	47.169	2065.810	52695.036	232.106
143.265	143.623	111.045	13.426	18.506	18.717	44.286	50.320	49.130	1915.092	49758.518	200.784
									Total	1261945.829	5851.293

Table 12 Fuel cost and emission for twenty-unit system with considering load leveling

Time	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
1	135.76	107.56	93.21	89.99	161.67	112.98	135.85	108.51	104.70	153.03	165.88
2	143.68	104.19	93.73	81.51	140.37	66.53	158.43	63.82	144.98	144.12	153.09
3	155.19	95.38	68.55	129.78	91.07	103.83	121.54	60.97	121.48	96.48	145.28
4	147.62	92.80	68.23	89.05	150.18	29.15	145.08	71.33	142.14	131.21	161.46
5	155.19	95.38	68.55	129.78	91.07	103.83	121.54	60.97	121.48	96.48	145.28
6	152.47	83.25	79.26	62.19	142.47	107.02	136.11	81.34	150.28	119.28	149.18
7	144.94	95.93	92.12	115.78	146.69	133.98	166.28	126.49	158.15	95.33	163.97
8	160.35	109.41	40.71	101.48	159.21	121.21	163.87	138.31	148.45	155.53	173.62
9	185.29	107.17	49.75	96.01	153.48	122.91	176.67	154.27	164.16	153.10	167.37
10	164.90	111.77	109.00	127.36	157.80	85.48	160.86	128.83	144.48	124.20	168.46
11	150.75	111.20	76.71	142.94	155.18	121.19	165.37	81.43	180.66	148.27	170.39
12	177.50	112.67	40.47	127.87	148.50	135.84	150.59	130.82	156.33	151.72	160.03
13	163.39	100.19	110.61	74.24	163.43	102.19	166.20	107.54	177.27	136.64	169.98
14	166.77	97.53	94.28	110.72	151.98	140.43	147.43	116.42	152.26	122.65	173.13
15	165.38	100.51	93.55	115.36	147.55	86.92	166.13	155.07	153.77	155.93	178.67
16	135.86	119.84	92.95	123.35	137.95	134.08	130.11	131.19	155.13	158.47	165.48
17	156.83	115.62	92.91	115.52	150.80	162.89	179.09	101.04	158.84	120.28	195.56
18	172.67	112.98	106.56	151.77	176.44	132.51	168.21	96.01	190.07	128.24	178.17
19	187.71	119.26	98.26	134.33	171.69	136.06	169.08	100.63	186.32	154.29	174.32
20	160.33	111.14	91.70	167.65	167.61	142.52	167.43	120.31	160.14	153.39	164.05
21	173.06	118.14	109.47	130.38	147.33	155.01	154.90	120.59	169.68	150.04	192.90
22	166.11	108.23	91.52	124.97	144.68	118.00	163.04	142.27	147.88	139.45	172.53
23	158.38	84.74	90.03	107.30	181.19	125.42	140.16	128.01	161.53	150.43	167.09
24	140.99	96.78	69.32	142.86	138.17	82.82	156.82	96.19	138.11	144.67	142.69
T12	T13	T14	T15	T16	T17	T18	T19	T20	Load demand	Fuel cost	Emission
159.71	130.77	73.05	15.61	23.12	14.27	40.54	49.76	40.57	1916.53	49792.19	2057.52

Table 12 (continued)

T12	T13	T14	T15	T16	T17	T18	T19	T20	Load demand	Fuel cost	Emission
149.22	142.81	102.40	16.14	17.68	18.29	27.50	37.66	30.02	1836.17	48153.11	1911.83
162.65	136.77	157.90	13.06	12.60	12.41	37.25	37.37	56.51	1816.08	47781.87	1859.84
153.36	150.95	111.07	9.98	15.60	19.07	37.89	39.32	40.54	1806.04	47593.02	1894.78
162.65	136.77	157.90	13.06	12.60	12.41	37.25	37.37	56.51	1816.08	47519.38	1859.84
147.76	141.98	159.84	13.24	21.28	10.27	33.28	56.32	49.62	1896.44	49360.04	1990.26
162.01	150.75	143.79	15.30	15.37	22.43	46.57	38.26	33.08	2067.25	52768.93	2275.22
165.58	156.38	145.44	22.02	20.88	14.95	50.50	45.92	47.36	2141.19	54159.71	2566.44
140.71	156.88	160.56	15.99	17.18	19.93	24.65	46.12	34.01	2146.21	54334.56	2589.45
163.86	139.61	187.85	16.44	13.85	19.00	51.88	39.99	45.68	2161.29	54631.06	2579.05
159.55	156.22	146.64	22.67	15.51	15.89	53.72	54.28	49.27	2177.82	54919.86	2666.92
178.29	144.50	156.42	13.41	17.21	11.03	38.22	45.31	39.44	2136.16	54063.07	2476.82
149.26	174.66	133.01	11.65	17.56	17.26	51.32	43.15	46.51	2116.06	53729.66	2491.54
154.49	133.02	139.72	20.69	11.48	23.78	55.65	61.00	52.68	2126.12	53920.52	2492.14
148.45	147.94	149.68	19.13	20.50	16.15	45.67	49.18	30.67	2146.23	54321.95	2513.27
174.22	144.72	157.85	27.48	17.51	21.75	39.03	52.50	46.87	2166.33	54712.75	2592.34
162.07	169.08	156.74	18.73	22.39	19.59	48.42	41.44	38.87	2226.70	55871.13	2818.39
171.84	170.79	140.95	22.32	17.94	22.26	55.66	39.15	52.64	2307.20	57489.34	3097.50
194.32	168.43	162.04	20.42	30.12	25.05	58.15	53.55	38.66	2382.70	58883.82	3443.35
214.91	172.08	151.49	22.84	27.66	21.22	38.83	47.79	34.31	2337.40	58043.15	3251.93
170.37	164.33	124.44	22.31	24.16	19.77	59.84	56.02	34.41	2297.14	57252.00	3032.59
178.45	163.10	143.44	20.21	26.16	21.06	50.51	52.15	42.89	2216.63	55639.24	2736.24
171.84	140.75	165.17	13.15	20.12	22.26	48.35	52.82	47.65	2176.40	54934.13	2601.25
171.44	168.49	161.87	13.17	19.94	19.56	30.85	42.30	50.03	2027.04	51954.33	2282.30
									Total	49783.37	60080.84

Table 13 Fuel cost and emission for twenty-unit system with PEVs and RES

Time	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
1	147.48	99.62	66.65	78.46	126.22	78.38	149.00	110.32	144.24	78.35	173.65
2	144.93	92.33	66.92	104.37	123.78	107.71	155.35	54.47	94.08	118.32	156.58
3	162.46	98.84	47.85	110.51	118.06	41.52	148.68	74.86	133.07	121.02	145.94
4	165.13	113.09	55.93	120.27	99.19	61.29	159.17	97.64	121.71	104.23	154.05
5	166.35	108.17	88.32	142.27	142.55	92.64	137.55	84.50	153.41	45.39	126.22
6	134.36	92.95	73.65	106.92	143.96	64.95	129.90	119.66	135.48	111.37	155.18
7	139.86	92.36	72.56	141.30	148.79	104.42	141.83	99.74	156.74	98.79	164.90
8	155.14	97.03	90.13	118.26	144.84	150.54	146.32	38.27	152.06	131.46	163.97
9	161.90	110.25	52.55	124.29	135.38	92.56	154.10	110.56	169.24	144.28	168.17
10	164.50	102.77	81.76	130.14	131.01	100.54	132.35	115.42	149.22	122.25	132.18
11	158.72	102.99	61.52	127.19	143.35	134.67	140.90	121.95	168.04	135.81	176.84
12	136.24	102.07	100.35	127.10	150.91	123.16	111.14	100.71	143.71	66.67	162.99
13	154.49	108.51	48.11	115.90	147.36	127.54	169.30	127.93	118.53	111.06	179.62
14	148.11	96.50	70.08	83.78	140.08	139.88	136.43	81.37	138.63	146.59	170.54
15	162.86	120.61	62.24	92.21	129.01	121.24	177.82	141.64	117.31	129.07	173.65
16	176.16	94.76	81.57	128.20	146.82	134.50	159.49	125.60	148.09	126.75	158.41
17	163.06	96.16	117.29	108.07	160.63	95.71	150.85	138.56	123.11	162.18	181.24
18	181.41	107.82	109.51	112.21	153.38	136.09	149.50	141.66	168.70	43.19	177.85
19	178.36	110.21	105.61	148.00	118.78	86.38	176.75	156.76	140.11	141.33	161.49
20	161.68	118.34	77.66	139.17	109.89	161.32	154.83	128.62	168.99	138.48	163.67
21	183.66	117.80	98.57	134.25	135.74	119.40	141.58	145.85	167.58	145.57	159.76
22	171.47	101.86	114.95	109.01	165.13	124.59	99.47	146.50	134.66	138.72	169.99
23	151.45	103.30	71.22	123.62	172.26	82.62	163.02	86.08	155.25	151.49	164.52
24	155.70	88.03	56.64	116.11	137.96	78.41	137.38	119.36	156.89	144.00	175.93
T12	T13	T14	T15	T16	T17	T18	T19	T20	Wind output	Fuel cost	Emission
163.69	148.43	120.02	12.79	17.33	12.09	54.90	44.57	32.68	36.55	48505.41	1959.61

Table 13 (continued)

T12	T13	T14	T15	T16	T17	T18	T19	T20	Wind output	Fuel cost	Emission
153.03	151.43	110.30	15.13	16.81	17.75	17.38	40.42	50.18	52.34	47266.51	1834.39
149.39	132.44	145.63	11.28	19.28	15.02	35.88	36.45	33.60	48.94	47021.27	1834.96
139.86	107.49	134.92	18.82	7.93	16.37	40.88	25.79	41.61	38.90	47160.91	1844.29
165.02	117.67	106.51	8.98	20.04	13.28	35.68	30.80	40.62	4.94	47973.53	1930.04
161.71	100.52	152.79	15.64	18.36	19.13	53.33	41.88	34.50	16.33	48764.07	1943.62
160.66	127.42	133.67	12.36	17.12	19.26	47.90	42.28	41.46	28.74	50669.53	2092.50
167.88	136.98	147.01	15.37	18.75	16.31	51.69	39.41	42.07	44.58	51867.67	2265.80
137.13	151.11	152.35	13.16	15.03	14.35	30.88	45.29	39.09	14.65	51834.10	2214.25
188.84	128.91	138.21	17.46	12.84	15.26	50.50	50.66	46.78	22.91	51612.79	2207.37
157.81	124.41	109.44	15.19	15.81	17.79	20.41	34.26	34.11	37.78	51434.85	2164.79
166.56	142.65	159.22	11.13	17.98	19.79	38.56	54.38	36.36	46.78	50879.52	2143.29
153.44	84.20	128.79	12.68	9.86	12.13	49.98	45.89	36.48	61.50	50271.88	2076.80
150.72	138.04	165.90	13.44	19.52	14.22	31.96	37.87	44.94	54.24	50807.04	2085.46
147.92	141.41	157.56	20.71	12.21	12.82	35.19	42.69	39.51	53.10	52163.01	2277.74
164.41	138.47	91.47	18.28	16.12	21.54	18.42	53.56	45.34	47.67	52351.18	2317.10
163.90	132.16	138.75	22.17	19.56	22.45	47.94	37.50	44.72	40.94	53930.27	2536.65
171.47	181.37	132.41	23.97	14.06	18.27	63.95	52.40	44.18	35.34	55029.95	2636.14
178.65	150.34	173.48	21.50	16.03	20.47	55.68	57.69	31.87	37.76	55948.69	2850.08
172.88	154.36	160.66	18.25	21.57	24.36	37.20	43.01	48.19	35.01	55451.87	2705.50
163.70	142.81	149.05	24.24	19.17	23.78	54.79	31.05	52.51	1.60	55609.93	2744.00
177.47	158.10	160.43	16.02	18.55	9.38	36.67	46.58	52.48	8.61	54433.95	2513.42
179.41	156.23	143.05	15.81	11.41	13.08	39.04	36.44	37.84	6.50	52499.12	2332.18
152.00	150.07	123.89	14.99	15.22	22.70	46.81	33.87	40.72	0.00	50715.65	2148.82
									Total	1234202.70	53658.80

Table 14 Best compromise solution for various values of EO parameter

G	*Q*	*u*	Result (Best fuel cost in $)	Result (Best emission in lb)
7	4.2	1	1256932.60	59635.41
6.5	3.8	0.9	1289684.45	58555.89
6	3.4	0.8	1293652.65	59748.69
5.5	3	0.7	1234202.70	53658.80
5	2.6	0.6	1229848.36	583621.47
4.5	2.2	0.5	1225968.69	596341.21
4	1.8	0.4	1276253.52	57653.51
3.5	1.4	0.3	1264421.78	55123.36
3	1	0.2	1246978.45	57142.22

penetrated RES and PEVs minimize the total cost and emission exceptionally in both single and multi-objective DEED problems.

- The integration of PEVs with ten-thermal generators increases the emission of pollutants in the load-leveling strategy. The various operating constraints of RES and EVs have also been considered in all test system to make system more realistic and practical.
- The efficient EO optimization technique has been tested in the four-cased of ten-thermal generating units to reduce total cost and total emission. The results obtained by the EO optimization technique have been compared with results obtained by other recently developed optimization techniques.
- The results confirm that the proposed method is better in terms of performance and effectiveness compared to other recently developed methods.
- The proposed model and optimization method can be used for solving other complicated engineering problems and make system more sustainable. Further, the researchers can include more other constraints of RES and EVs in this test system to verify the effectiveness of the proposed model and algorithm.

Table 15 Wilcoxon signed-rank test across all testing platforms

Test systems		Fuel cost	Emission	No. of trail run	Standard deviation	p value
1	1	644552.07	20365.53	50	61.05	1.45E-05
	2	650521.81	20993.42	50	46.25	1.12E-05
	3	646107.01	19588.56	50	94.50	1.10E-05
	4	633011.86	19410.92	50	103.59	1.15E-05
2	1	1261945.82	5851.29	50	52.59	1.32E-05
	2	49783.37	60080.84	50	45.89	1.21E-05
	3	1234202.70	53658.80	50	59.74	1.41E-05

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