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Real-Data based Economic Emission Load Dispatch with Renewable Energy and Electric Vehicle Integration using Artificial Ecosystem-based Optimization

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This paper presents a data-driven approach to the Economic Emission Load Dispatch (EELD) problem that integrates Renewable Energy Sources (RES) and Plug-in Electric Vehicles (PEVs). The Artificial Ecosystem-Based Optimization (AEO) algorithm is used to address the stochastic nature of the power system of the future by including real wind and solar data from the 'Renewable.ninja' platform for Gujarat, India. This data-driven framework not only captures essential uncertainties in RES generation but also the arrival, departure, and waiting times for PEVs. The method uses the AEO algorithm to simulate ecosystem-like interactions that help the system achieve a good balance between exploration and exploitation, thereby minimizing both total generation costs and environmental emissions. The study has been conducted on 10-unit and 20-unit thermal generation systems, including practical Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operations. The main results reveal that the AEO algorithm is instrumental in improving system performance by offering a good balance of trade-off between economic and environmental goals. Also, a performance comparison of the AEO algorithm with the latest optimization methods shows that AEO is more effective and stable under complex dispatch scenarios. The paper argues that combining real-world data with ecosystem-based optimization not only provides a scalable, sustainable solution but also offers a way out of modern grid management. This study stands out for combining site-specific meteorological data with high-fidelity PEV behavioural modelling to provide a practical, field-ready strategy for utility operators to manage the volatility of green energy and electric mobility transitions.

Keywords: Dynamic economic emission load dispatch, Equilibrium optimizer, Plug-in electric vehicles (PEVs), Renewable energy sources, Wind-solar plug-in electric vehicle

Introduction

The increasing coupling of Renewable Energy Sources (RES) and Plug-in-Electric Vehicles (PEVs) to the standard power grid has made the operation of the modern power system more complicated but still fort has brought them new opportunities. On the one hand, RES like wind and solar power are the main sources of green electricity generation and have almost zero environmental impact, but their intermittency and unpredictability affect in a serious way the stability of the grid. On the other hand, PEVs by absorbing energy from the grid and, possibly, supplying it back through Vehicle-to-Grid (V2G) operations, thus, introducing additional dynamic loads and operational variability, are the main reasons for the fluctuation of the grid. All these changes call for the implementation of advanced optimization techniques in order to achieve the power system operation that is cost, effective, reliable, and environmentally sustainable.[1] Economic Emission Load Dispatch (EELD) has been considered as a major instrument to solve the problem of simultaneously minimizing generation cost and pollutant emissions.[2] The conventional EELD algorithms usually envisage generation conditions as deterministic and concentrate only on thermal units . But, the problem of Dynamic EELD (DEELD) has become more relevant with the presence of RES and PEVs, thus, the issue of DEELD is the account of time, varying demand, stochastic RES output, and the complex charging and discharging behaviour of PEVs.[3]. Moreover, the availability of real, world data for wind and solar generation as well as actual PEV usage patterns is very important to system modelling of uncertainties and, thus, the creation of dispatch strategies that can be implemented in practice.[4]

Metaheuristic algorithms have been very successful in breaking down complex, nonlinear, and large, scale optimization problems in power systems. In general, the Artificial Ecosystem, Based Optimization (AEO) algorithm provides a pretty good idea by simulating the interaction of natural ecosystems to manage the search space's exploration and exploitation.[5] In this

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paper, AEO is used for solving Real, Data Based EELD problems with 10 and 20 thermal units combined with RES and PEVs. The success of the method comes from the use of real wind, solar generation data and realistic PEV behaviour, so the generated load schedules are not only feasible and cheap but also clean.[6] The comparative analysis with the state-of-the-art methods shows that AEO is a powerful and efficient tool for dealing with dispatch problems in the presence of uncertainty in the real world.

Literature Survey

The introduction of RES such as wind and solar power into conventional power grids has called for major innovations in the fields of EELD problems. The initial studies were mainly concerned with thermal generation units, figuring out the best power output to achieve the lowest generation costs while meeting system constraints. As the need for sustainability and environmental regulations has become stronger, the EELD problem has taken a turn to include emission constraints to make sure that generation decisions result in less environmental impact.[7] The dynamic versions of ELD that also consider time, varying demand and renewable generation have been introduced to reflect real operational scenarios and show how uncertainty and intermittency in RES are challenging issues.[8]

PEVs bring about a new challenge to load dispatch management. PEVs are not only energy consumers but also potential energy suppliers through interactions with the grid via the V2G technology; hence, their presence has an impact on both power demand and the flexibility of generation. A number of studies have investigated ways to grant power and energy exchanges through charging and discharging operations that would minimize the change in power demand and increase the stability of the grid.[9] Zhang *et al*., for instance, employed peak shaving and valley filling techniques to smoothen the power demand while also taking users' preferences and different charging/discharging scenarios into consideration.[10] Behera *et al*. demonstrated that cooperative G2V and V2G operations could not only significantly reduce emissions but also operating costs drastically in the case of DEED, PEV systems.[11] Numerous researchers have tackled the EELD and DEED problem from different perspectives using various optimization techniques. Different types of metaheuristic algorithms (e.g. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Artificial Bee Colony (ABC)) have been applied for a long time in processing non-linear, non-convex, and large-scale search problems.[12–14] Basu *et al*. (2016) were the first to introduce RES into the EELD models by using GA and PSO methods, but they only partially captured the intermittent nature of the RES.[15] Fauziyah *et al*. (2023) conducted the DEELD with the inclusion of RES using Mixed Integer Linear Programming (MILP), which provided accuracy to the mathematical model but had limited practical application due to uncertainty issues involved.[16]

For a while now, the issue of how to integrate PEVs into energy management has been considered. Zou *et al*. suggested that applying mathematical techniques and analyzing the interaction of different components can improve the plans when the PEVs are in and out.[17] Qiao *et al*. employed computer-aided methods together with sophisticated optimization techniques to analyze costs.[18] Chen *et al*. had a similar approach, only that they used a different math model to the uncertainty that accompanies energy management when PEVs are present; however, it is still very difficult to handle large systems this way.[19] In 2019, some other people employed Optimal Power Flow, and life-cycle cost analysis to determine the extent of wind, and solar, and PEVs integration.[20] Their goal was to identify the advantages of the combination of wind, solar, and PEVs. We are still facing the same difficulties; dealing with large-scale wind and solar together with PEVs installations is still not feasible. The PEVs charging station operators have also been considered as a source of data for the DEED-PEV studies.[21] Researchers such as Goel and his colleagues were able to suggest that the battery swapping can turn out to be a profitable venture for charging stations. They applied a certain methodology to arrive at this conclusion. Other researchers, like Kang *et al*., offered ways of organizing the charging station activities remotely.[22] Then, there are the researchers including Gao *et al*. team who applied game theory for the management of charging stations. In addition, optimization was also utilized by them. The shortcoming of their proposal is that it presumes that people will always behave rationally and will be fully informed, which is not necessarily the case.[23] Moghaddam *et al*. have also contributed to the research in the field of Electric Vehicle Charging

Stations. They created dynamic pricing models that worked in coordination with other stations to cut down travel time and charging costs, but the users' resistance to such behavioural changes and the requirement for high penetration rates create hurdles in the practice.[24]

There has been a lot of discussion around the advantages of utilizing real data for the purpose of improving dispatch performance. Some researchers like Yan *et al*. 2022 and Soni *et al*. 2023, for instance, have made their models more accurate with the help of data from wind and solar power as well as PEVs.[25–27] They employed techniques such as decentralized optimization and multi-criteria decision-making among others. Still, they faced difficulties in obtaining results and ensuring smooth communications among the various components. Dispatch performance remains an issue. In the same way, others like Sun *et al*. attempted to map and analyze how the distribution of RES and PEV demand in the regions using location data.[28] They resorted to mapping techniques for achieving this. The studies presented here reveal the necessity of having solid metaheuristic frameworks like the AEO to reduce combined uncertainties of the integration of RES and PEV in the real power systems effectively.

Research Novelties

Integrating RES and PEVs into the power system is rather difficult to control because there is always some uncertainty in the energy produced or consumed by them. It is very variable and thus it is not easy to make forecasts. The traditional methods for planning and optimization of power systems have turned out to be inefficient for such new and complex issues.[29] The adoption of both modern and cutting-edge technologies in power system management is a must; for instance, the utilization of proper information and data to know the generation profile of the RES and the operation of the PEVs so that we can group up power systems in a manner that is safe and reliable without interrupting the supply.[30] The RES and PEV have become unavoidable components, so the power systems interfacing centres need to become more efficient. In such cases metaheuristic algorithms become a way of solving the power dispatch issue that is complex and multi-objective. The present work employs the AEO algorithm to tackle the EELD problem.[31] This issue belongs to the realm of the EELD problem. It also considers the integration of RES and PEVs. The AEO algorithm is applied to uncover a solution, to the EELD problem.

- The study uses wind and solar power information from the renewable.ninja platform for Gujarat, India. This helps to understand the uncertainties in RES and make the study more useful in practice. The study looks at PEVs. Considers when they arrive, when they leave how long they wait and how they interact with the power grid. This allows us to get a picture of how much energy they use and how they can store energy. The study models PEVs to see how they work with the power grid, including when they give energy back to the grid and when they take energy from the grid. This is important for understanding how RES like wind and solar power can work with PEVs.
- The AEO algorithm is used to solve the EELD problem in a way. This problem is complicated. Has many goals. The AEO algorithm helps to balance looking for solutions and using the solutions we already have. We tried the AEO algorithm with 10 and 20 units. It worked well with both which means it can handle small systems with many different parts. The AEO algorithm is good because it is flexible and works with EELD systems of all sizes.
- The new method really helps to cut down on the costs of generating power and the bad stuff that gets released into the air, which's good for the environment and it also makes sure that the power grid keeps working properly and does not stop. The proposed method does this by making sure that the power grid operation is reliable and that the generation costs and pollutant emissions from the power generation are as low, as possible which helps with sustainability of the proposed method and the power grid.
- Operational constraints such as ramp rates, spinning reserve, and prohibited operating zones are considered, enhancing feasibility for real-world power system implementation. The method is benchmarked against existing optimization techniques, showing superior efficiency, convergence, and robustness under real-world RES and PEV uncertainties.

Problem Formulation and Objective Function

The WSPEV DEED model is a multi-objective optimization framework designed to minimize both the total operating costs and environmental emissions.[32] To solve this, a weighting factor w is employed to transform the multi-objective problem into a single-objective function:

$$\mathrm{Min}\ J = w \times (F_T + F_W + F_S) + (1 - w) \times E_{total} \qquad \ldots (1)$$

In this formulation, J represents the aggregated objective function value, while w is the weighting factor ranging from 0 to 1, allowing the system operator to prioritize between cost and emission reduction. F_T, F_W, and F_S denote the total costs associated with thermal, wind, and solar units, respectively. E_{total} represents the total environmental pollutants emitted by the conventional thermal generators over the dispatch horizon T.

Thermal Unit Characteristics

The thermal generation cost F_T incorporates the non-linearities of the valve-point loading effect, which occurs when steam admission valves are opened in a multi-valve turbine, creating ripples in the cost curve.[33]

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 + \left| d_i \sin\left(e_i\left(P_{i,min} - P_i\right)\right)\right| \qquad \ldots (2)$$

Here, N is the total number of thermal units and P_i is the power output of the ith unit at time t. The coefficients a_i, b_i, and c_i represent the quadratic fuel cost parameters, while d_i and e_i are constants modelling the valve-point loading effect. The parameter $P_{i,min}$ denotes the minimum operating limit of the generator. The emission characteristics of these units are modelled as a combination of quadratic and exponential functions to account for various pollutants like NO_2 and SO_2.[34]

$$E_{total} = \sum_{t=1}^{T} \sum_{i=1}^{N} \alpha_i + \beta_i P_i + \gamma_i P_i^2 + \zeta_i \exp(\Upsilon_i P_i) \qquad \ldots (3)$$

In this expression, α_i, β_i, and γ_i are the standard emission coefficients, whereas ζ_i and Υ_i represent the exponential coefficients that capture the rapid increase in emissions at higher generation levels.

Renewable Energy Source Modelling

The cost functions for wind and solar units include direct generation costs and penalty costs related to the uncertainty of renewable output. These penalties address Overestimation (OE) where the grid must provide reserve power and Underestimation (UE)—where available renewable energy is curtailed.[35]

$$F_W = \sum_{t=1}^{T} \sum_{j=1}^{N_W} C_{w,j} P_{w,j,t}^{sch} + K_{oe,w,j}\left(P_{w,j,t}^{av} - P_{w,j,t}^{sch}\right) + K_{ue,w,j}\left(P_{w,j,t}^{sch} - P_{w,j,t}^{av}\right) \qquad \ldots (4)$$

For wind power, N_W is the number of wind farms. $C_{w,j}$ is the direct cost coefficient, and $P_{w,j,t}^{sch}$ is the scheduled power. $P_{w,j,t}^{av}$ represents the actual available power. The penalty factors $K_{oe,w,j}$ and $K_{ue,w,j}$ correspond to overestimation and underestimation costs, respectively.[36]

$$F_S = \sum_{t=1}^{T} \sum_{k=1}^{N_S} C_{s,k} P_{s,k,t}^{sch} + K_{oe,s,k}\left(P_{s,k,t}^{av} - P_{s,k,t}^{sch}\right) + K_{ue,s,k}\left(P_{s,k,t}^{sch} - P_{s,k,t}^{av}\right) \qquad \ldots (5)$$

In the solar model, N_S represents the number of photovoltaic units. $C_{s,k}$ is the direct cost for solar power, while $P_{s,k,t}^{sch}$ and $P_{s,k,t}^{av}$ are the scheduled and available solar outputs. The factors $K_{oe,s,k}$ and $K_{ue,s,k}$ represent the penalty coefficients for solar power uncertainty.

Plug-in Electric Vehicle Modelling

PEVs are modeled as bidirectional energy storage entities. The power status of the vth vehicle is defined by its maximum power rating P_v^{max} and a status function $S_{v,t}$.[37]

$$P_{v,t} = S_{v,t} \times P_v^{max} \qquad \ldots (6)$$

where, $P_{v,t}$ is the instantaneous power of the vth PEV at time t. The status function $S_{v,t}$ equals 1 for charging, −1 for discharging, and 0 for idle state. The dynamic state of the PEV battery, or the energy stored $E_{v,t}$, is tracked as follows:[38]

$$E_{v,t} = E_{v,t-1} + \left[\eta_c P_{v,t}^{c} - \frac{P_{v,t}^{d}}{\eta_d}\right]\Delta t - (d_{v,t}\mu_v) \qquad \ldots (7)$$

where, $E_{v,t}$ is the energy in the vth PEV battery. $P_{v,t}^{c}$ and $P_{v,t}^{d}$ are charging and discharging powers. η_c and η_d are the respective efficiencies. The term $d_{v,t}$ denotes the travel distance, and μ_v is the energy consumption rate per unit distance.

Constraints

The WSPEV DEED model is subject to a range of constraints that govern the performance and operation of its components. Key examples of such constraints in the WSPEV DEED problem include the following:

Thermal Generator Operating Limit

The maximum power output that a thermal generator can produce is referred to as its operational limit. This limit is determined by the generator's mechanical and thermal capabilities. Such constraints are implemented to ensure the safe and reliable operation of the plant while preventing potential damage to its equipment.[39]

$$T_i^{min} \leq T_i \leq T_i^{max};\ i = 1,2,3,\ldots,N \quad \ldots (8)$$

$$0 \leq w_{outj} \leq w_{outr,j};\ j = 1,2,3,\ldots,N_w \quad \ldots (9)$$

$$0 \leq S_{outk} \leq S_{outr,k};\ k = 1,2,3,\ldots,N_S \quad \ldots (10)$$

where, $W_{outr,j}$ denotes the maximum power output of the jth wind farm, while $S_{outr,k}$ represents the maximum power that the kth solar unit can generate.

Constraint of Power Balance

The power balance constraint ensures that the total power generated in a system equals the total power demand, maintaining equilibrium within the power grid.[40]

$$\sum_{i=1}^{N} T_i + \sum_{k=1}^{N_w} W_{p,k} - (T_D + T_L) = 0 \quad \ldots (11)$$

The total transmission loss in the power system is calculated using the following equation:[41]

$$T_L = \sum_{m=1}^{N} \sum_{n=1}^{N} T_m\, B_{mn} T_n + \sum_{m=1}^{N} B_{m0}\, T_m + B_{00} \quad \ldots (12)$$

The elements of the B matrix are denoted as B_{mn}, B_{m0}, and B_{00}.

PEV Storage Capacity Constraints

To preserve the cycle life of the PEV batteries and prevent hardware degradation due to deep discharge or overcharging, the energy stored in each vehicle's battery at any given time interval t must be maintained within strictly defined physical and safety limits. This is mathematically represented by the following inequality:[42]

$$E_v^{min} \leq E_{v,t} \leq E_v^{max} \quad \ldots (13)$$

In this formulation, $E_{v,t}$ represents the instantaneous energy level (or state-of-charge energy equivalent) of the vth vehicle at time t. The parameter E_v^{max} denotes the upper storage capacity, typically limited to prevent thermal runaway and cell swelling during charging. Conversely, E_v^{min} is the lower allowable limit, which acts as a buffer to ensure the battery is not depleted to a point that would cause permanent capacity loss or leave the driver with insufficient range for unexpected travel.[43]

AEO Algorithm Applied to Solve the WSPEV DEED Problem

Ecosystems were divided into two groups: biotic and abiotic. Light, water, air, and other physical elements are examples of abiotic factors, while all living things are examples of biotic factors. Energy flow and nutrient cycling, in particular, are essential to the equilibrium of an ecosystem, in which every living thing is vital. Using this energy, plants create a variety of goods, including wood, roots, leaves, and fruits. The low-energy animal receives energy from the high-energy animal.[44]

A production worker in AEO allows an arbitrary creation of a new person, x_{rand}, to replace the previous one. Regarding the production operator:[45]

$$x_1(t+1) = (1-\alpha)x_n(t) + \alpha x_{rand}(t) \quad \ldots (14)$$

where, αis used to balance global and local search.

$$\alpha = (1 - \frac{t}{T_{max}})r_1 \quad \ldots (15)$$

where, T_{max} is the maximum iteration and $r_1$is the random number between 0 and 1.

Herbivore: A consumer deemed to be a herbivore at random if the producer is the sole food on its diet list. Herbivores who solely eat the producer x_1 are the consumers x_2 and x_5.

$$x_i(t+1) = x_i + C(x_i(t) - x_1(t)), i \in [2,\ldots,n] \quad \ldots (16)$$

Carnivore: It restricted to consuming another consumer with a greater energy value when they are randomly chosen to be carnivores. Since all of the consumers from x_2 to x_5 have greater energy values than consumer x_5, a consumer must be randomly picked to be its meal from among them all. For instance, consumer x_6 is chosen as a Carnivorous.

$$x_i(t+1) = x_i(t) + C\left(x_i(t) - x_j(t)\right):\ i \in [3,\ldots,n];\ j = randi([2i–1]) \quad \ldots (17)$$

Omnivore: It has more energy than a producer will be consumed if one is selected at random to be an omnivore. For example, consumer x_7, who is chosen at random to be an omnivore, would eat producer x_1. From consumers x_2 to x_6, each of whom has more energy than x_7, one is selected at random. An omnivore's eating behavior may be expressed

$$x_i(t+1) = x_i(t) + C(r_2(x_i(t) - x_1(t)) + (1 - r_2\left(x_i(t) - x_j(t)\right):\ i \in [3,\ldots,n];\ j = randi([2i–1]) \quad \ldots (18)$$

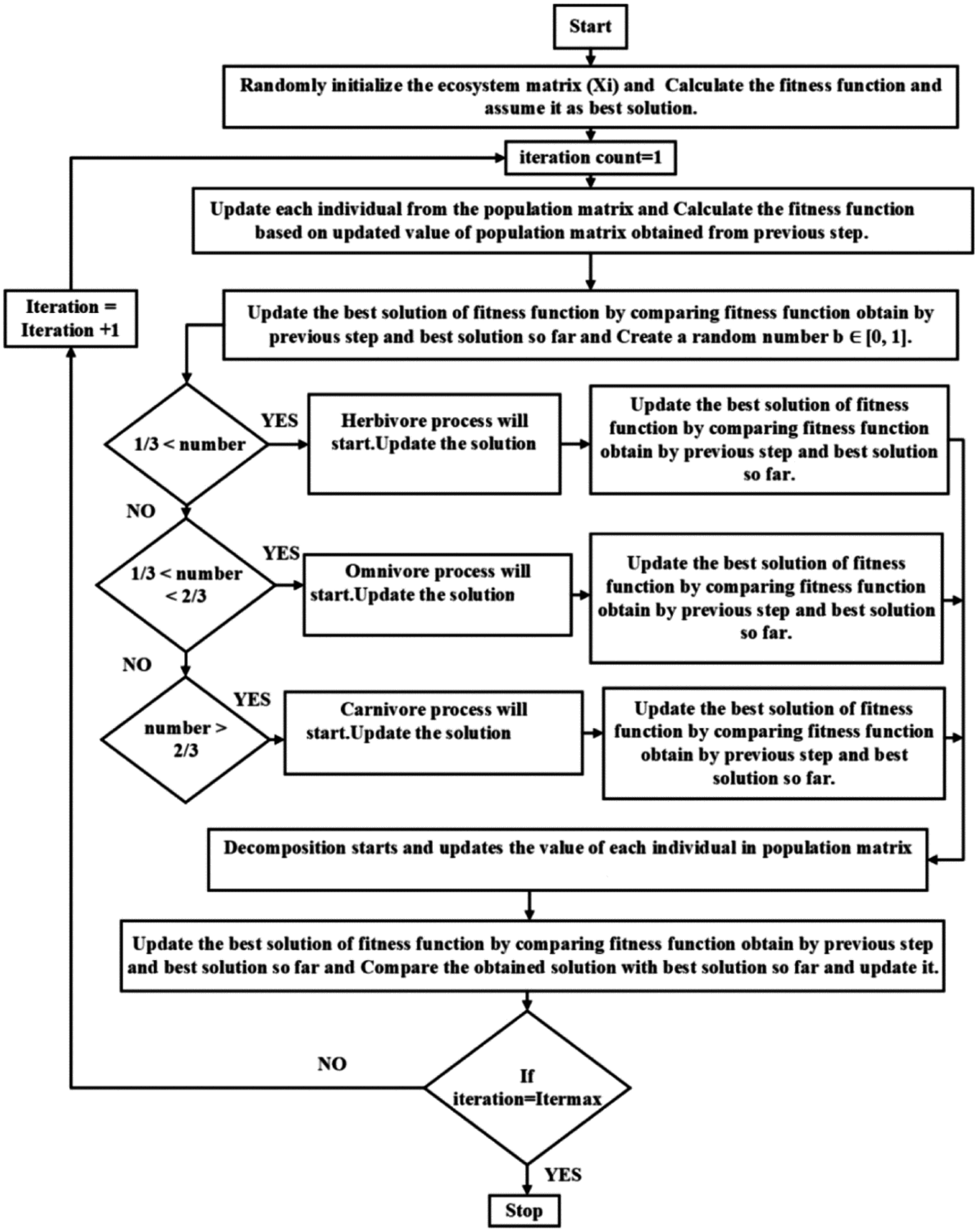

Fig. 1 — The AEO solution's process flow diagram for the WSPEV DEED issue

where, C is consumption factor derived from a normal distribution. r_2 ranges from 0 to 1. Because of these setup choices, the setting of the i^{th} individuals x_i may become dependent on the placement of the decomposer x_n.

Decomposition Operator: The decomposer x_n breaks down the remains of other individuals to enrich the environment. This process allows the population to escape local optima by relating the position of all individuals to the decomposer's state.

$$x_i(t+1) = x_n(t) + D \times (3 \times r_3 \times x_n(t) - x_i(t)) \quad \ldots (19)$$

EO Method Implemented in WSPEV DEED Problem

The generalized flowchart of AEO algorithm is given in Fig. 1. To implement AEO for the WSPEV-DEED problem, the following logic is applied:

Step 1: Define objective functions (cost & emission) with constraints; include time-dependent load demand and RES availability.

Step 2: Generate initial population (particles) representing generator outputs, RES, and PEV profiles within limits to ensure diversity.

Step 3: Evaluate fitness; apply penalties for constraint violations (e.g., power imbalance, generator limits).

Step 4: Simulate energy assimilation—better solutions gain more energy, enhancing survival and competitiveness.

Step 5: Reproduce via selection of high-fitness parents; apply crossover and mutation to maintain diversity and avoid stagnation.

Step 6: Preserve elite solutions in the next generation.

Step 7: Monitor convergence; stop when improvement falls below a threshold.

Step 8: Extract final solutions, ensuring feasibility, and evaluate cost and emission reduction.

Step 9: Validate results against benchmarks/other algorithms and perform sensitivity analysis.

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Algorithm 1: AEO for WSPEV DEED

Input: System Parameters (N, T, w), AEO Parameters ($N_{pop}$, $T_{max}$)
Output: Optimized Power Dispatch Schedule
Initialize Ecosystem Population $X_i$ within constraints
Calculate Fitness $J_i$ for each individual i
While $t < T_{max}$
    Update Weighting Factor (a) and Consumption Factor (C)
    Production Phase
    Update Producer $x_1$ via random interaction and boundary limits
    Consumption Phase
    For i = 2 to $N_{pop}$
        If rand < 1/3: Update $x_i$ via Herbivore logic
        Else if 1/3 < rand < 2/3: Update $x_i$ via Carnivore logic
        Else: Update $x_i$ via Omnivore logic
    End For
    Decomposition Phase
    Update all individuals $x_i$ relative to Best Solution
    Constraint Verification
    Apply Penalty to any individual violating Balance or SoC limits
    Update t = t + 1
End While
Return Best Solution (Min Cost & Emission)
```

Results and Discussion

Comprehensive numerical simulations were carried out on test systems with 10 and 20 thermal generators connected to stochastic RES and PEV fleets to assess the technical performance and practical feasibility of the proposed WSPEV DEED framework. These computational experiments were conducted in MATLAB 2021a on a machine with an Intel Core i5 processor and 4 GB of RAM and a 24, hour dispatch horizon was used. The dispatch horizon is set to 24 hours to capture daily load and generation cycles. The profiles include real-time solar and wind patterns to model the stochastic nature and intermittency of green energy. The operational data of the thermal units and the real, time solar and wind profiles were taken from the Renewable.ninja database.[46] Solar and wind capacities were set at 2 MW and 40 MW, respectively. The PEV part was developed based on the features of a Nissan Leaf with a 24 kWh battery capacity and an energy consumption of 0.15 kWh/km.[47] To provide confidence in the results and to lessen the effect of random changes, the AEO algorithm was run 50 times independently, with each trial having 5,000 iterations. The management of reliability and uncertainty was done by giving the reserve upward and downward weighting factors the value of 0.5.[48] The operation of the wind turbine was based on the standard cut, in, rated, and cut, out wind speed limits.

Case Study 1: Multi-Objective Dispatch of a 10-Unit Thermal System Integrated with RES and PEVs via AEO

The section proposes the AEO method solution for DELD problem with integrate RES and PEVs. To charge scheduling for PEVs, off-peak periods such as 22:00–06:00 h, 15:00–16:00 h, and from 18:00 h onwards have been considered. This is also programmed so that in peak demand, the PEVs charge between 08:00 to 14:00 and 19:00 to 21:00. Solar units are available from 06:00 to 18:00. Maximum production for solar units occurs at 14:00 with a capacity of 29.30 MW. Wind units are expected to reach up to 27.59 MW at 04:00. The AEO algorithm delivers a fuel cost of 2,259,905.91 $/day and an emission of 258,227.86 Tonne/day as shown in Table 1. This translates into a saving of 8,872.15 Tonne/day emission relative to the level of emissions. Annually, 50,000 PEVs are expected to save 106,465.80 Tonne/day of emissions. Moreover, the thermal system attains a cost saving of 32,410.80

Table 1 — Display of all units' and PEVs' output power as determined by the AEO algorithm in Test System 1

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	Solar output (MW)	Wind output (MW)	PEV (MW)	Fuel cost ($)	Emission (Tonne)
1	75.01	58.45	124.16	126.67	173.65	175.11	92.02	163.01	72.54	53.27	0.00	7.47	−85.37	59947.72	4629.54
2	74.43	119.76	85.97	115.10	222.89	184.10	168.22	122.43	50.32	42.12	0.00	8.08	−83.42	63825.13	5231.43
3	136.61	125.96	148.35	77.70	199.78	183.59	128.99	160.98	110.64	48.72	0.00	3.56	−66.88	72597.18	5727.65
4	106.89	139.01	83.29	119.86	221.29	256.07	191.72	163.29	117.66	54.20	0.00	8.49	−55.77	77870.14	7217.85
5	150.09	128.90	177.62	161.61	224.69	249.68	110.25	201.74	79.79	48.76	0.00	1.11	−54.25	82533.74	8122.16
6	155.66	138.25	169.19	189.77	282.85	253.82	159.41	143.80	122.37	51.00	0.01	0.54	−38.66	89982.35	9294.15
7	155.92	122.07	192.45	190.90	255.14	224.68	212.01	178.18	96.25	50.47	1.22	7.54	15.16	89221.02	9700.46
8	162.54	218.15	199.47	185.21	258.54	193.08	225.64	214.04	41.11	52.98	2.20	6.41	16.64	95648.48	10880.36
9	159.70	261.77	287.03	213.48	274.10	224.95	182.47	131.87	101.64	51.82	2.52	6.18	26.46	106178.26	12748.14
10	200.75	226.99	204.67	252.20	333.56	254.79	210.85	142.64	87.64	53.69	2.66	3.79	47.76	109452.36	13530.62
11	185.79	204.65	282.59	207.87	279.67	226.18	241.71	226.09	144.96	40.40	2.52	3.86	59.73	111471.26	14624.41
12	150.70	216.55	206.45	293.69	315.91	254.61	207.23	261.93	119.64	46.68	2.57	4.00	47.05	111866.16	15569.02
13	197.94	232.78	215.48	243.71	314.30	300.41	203.74	170.54	101.17	41.73	2.21	3.72	44.28	112057.66	14167.75
14	213.82	223.01	264.75	115.20	310.80	260.32	157.41	189.20	99.18	54.81	0.68	5.59	29.22	106172.01	12353.57
15	169.45	173.47	219.92	195.98	268.91	205.06	191.27	201.99	142.80	46.12	0.91	5.98	−45.86	98779.58	11028.66
16	124.01	150.04	204.15	181.24	266.37	238.21	202.46	117.45	84.91	49.34	0.00	5.53	−69.69	86427.97	9239.92
17	148.52	134.51	193.01	160.78	242.61	165.46	158.52	164.13	120.31	51.28	0.00	4.45	−63.59	83538.19	7839.97
18	173.10	125.87	207.21	225.85	272.31	211.50	209.69	129.30	74.33	53.16	0.00	4.18	−58.49	90649.07	10163.31
19	149.37	106.52	184.95	180.62	273.98	266.78	207.45	246.84	87.43	49.24	0.00	3.99	18.83	91614.22	11113.89
20	196.14	232.68	186.97	165.30	322.98	304.31	250.15	170.74	54.26	48.49	0.00	1.70	38.28	106542.89	13240.07
21	182.83	210.22	191.35	278.79	293.10	251.80	203.52	80.18	142.65	51.89	0.00	6.36	31.32	105558.63	12663.73
22	144.51	190.55	214.01	171.01	176.16	193.49	144.01	211.37	126.68	54.12	0.00	5.53	−3.43	89502.31	8804.15
23	135.89	146.23	175.55	132.16	169.82	130.15	171.10	194.65	96.48	48.90	0.00	5.30	−74.22	76420.30	6672.40
24	93.04	128.92	133.80	156.93	191.78	148.71	129.95	164.50	78.42	51.88	0.00	4.93	−98.86	69111.57	5563.13

$/day and an annual saving of 388,929.60 $/year from the further operational cost savings to be realized through the transport sector. The output power in visual form for all units and PEVs in Test System 1, as optimized by the AEO algorithm as shown in Fig. 2. The compromise graph for Test System 1, which was obtained using the AEO method, is also shown in Fig. 3. A comparison of results for Test System 1 are shown in Table 2.

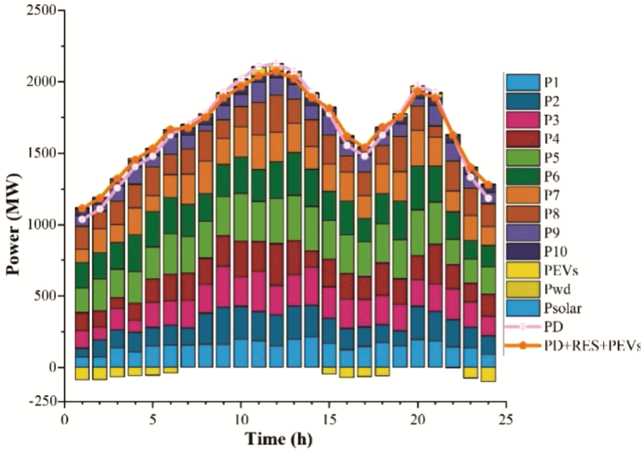

Fig. 2 — Display of all units' and PEVs' output power as determined by the AEO algorithm in Test System 1

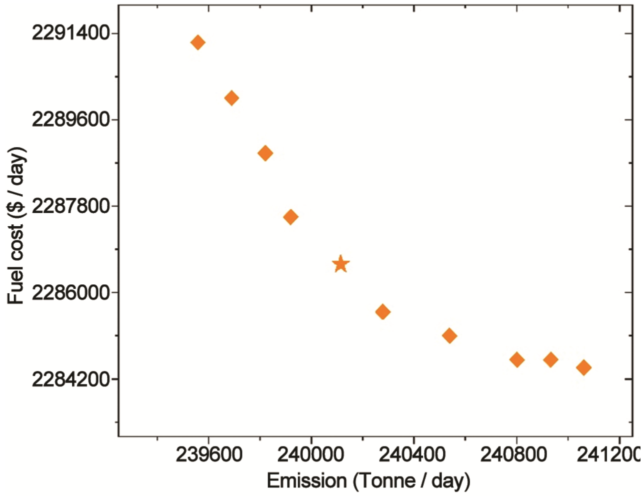

Fig. 3 — Pareto optimal front of the AEO algorithm for Test System 1, illustrating the non-dominated trade-off between total generation cost and atmospheric emissions

Case Study 2: Scalability Analysis using a 20-Unit Thermal System with Stochastic RES and PEV Penetration

A solution to the DEELD problem, including RES and PEVs, has been implemented with Test System 2 of AEO. PEVs charging is scheduled at 24:00–07:00, which are the non-peak hours and 08:00–23:00 as peak hours. The peak value of 51.78 MW is recorded at 14:00. This output power peaks at 19:00, with an amount of 73.96 MW when accounting for wind units. Emission is found at 96,672.22 Tonnes and generated for 1,356,594.42 $. This led to the cut down of 3,076,165.55 Tonnes, or 8,416.07 Tonne/year, in their emission as shown in Fig. 4. A comparison of these outcomes with those of other optimization algorithms, highlighting the AEO algorithm's better performance in terms of minimizing costs and reducing emissions as shown in Table 3. A Comparative performance analysis of the AEO algorithm and benchmark metaheuristics for Test System 2, focusing on total operational

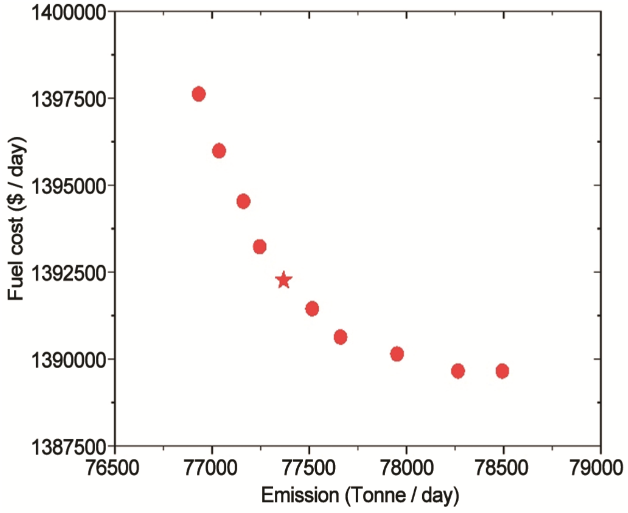

Fig. 4 — Pareto optimal front of the AEO algorithm for Test System 2, illustrating the non-dominated trade-off between total generation cost and atmospheric emissions

Table 2 — Comparative performance metrics for Test System 1: AEO vs. literature–based Metaheuristics

Optimization objective	Metric	AEO	SaMODE LS	SaMODE	MOEA/D	2lb-MOPSO	NSGA-II	SPEA2
Economic priority	FC ($\times 10^6$ \$ /day)	2.25	2.39	2.46	2.48	2.45	2.5	2.51
(Minimize fuel cost)	FM ($\times 10^5$ Tonne/day)	2.58	2.78	2.82	2.77	2.91	2.68	2.64
Environmental priority	FC ($\times 10^6$ \$ /day)	2.32	2.5	2.58	2.59	2.6	2.52	2.53
(Minimize emissions)	FM ($\times 10^5$ Tonne/day)	2.41	2.51	2.55	2.53	2.52	2.63	2.63
Best compromise	FC ($\times 10^6$ \$ /day)	2.3	2.43	2.5	2.51	2.5	2.51	2.51
(Weighted solution)	FM ($\times 10^5$ Tonne/day)	2.42	2.6	2.62	2.61	2.64	2.66	2.64

Table 3 — Display of all units' and PEVs' output power as determined by the AEO algorithm in Test System 2

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	T11 (MW)	T12 (MW)
1	160.25	88.76	76.18	106.28	128.41	76.92	188.80	89.80	159.29	107.60	196.59	175.60
2	166.32	122.64	45.68	96.51	146.15	28.22	123.84	85.08	147.61	103.55	191.16	166.63
3	168.24	117.28	19.18	114.10	120.32	71.68	99.42	69.32	140.07	84.28	178.41	191.34
4	183.20	121.17	75.33	83.75	110.76	87.37	148.73	60.66	146.46	74.38	163.47	180.78
5	165.65	60.39	83.04	125.16	136.26	83.77	66.29	103.15	163.37	114.88	162.26	165.80
6	193.61	105.73	80.87	38.69	138.21	112.33	136.24	74.92	112.47	30.95	181.30	193.43
7	189.81	90.23	33.51	106.93	133.46	54.69	139.21	106.78	158.50	42.85	168.42	219.91
8	200.16	95.05	75.81	101.88	171.45	28.37	119.62	171.47	175.87	92.73	187.15	186.14
9	205.80	122.62	91.96	105.41	151.52	20.81	183.02	154.44	160.92	87.30	190.55	205.09
10	198.57	109.90	73.59	115.29	133.50	90.10	74.64	67.58	172.26	122.66	163.56	196.19
11	199.63	62.73	48.71	142.63	129.76	81.49	148.00	133.98	168.18	14.31	178.21	221.88
12	192.22	71.23	46.85	141.15	90.24	4.48	179.06	139.71	134.40	151.03	179.38	196.84
13	175.14	94.06	81.17	50.02	173.32	106.88	129.23	73.80	164.85	84.21	181.49	185.16
14	177.19	128.52	59.07	135.58	147.99	86.98	89.10	84.71	112.05	132.29	191.65	195.27
15	206.76	123.06	100.95	140.89	95.89	53.46	148.17	102.19	208.52	141.81	201.56	207.03
16	192.62	114.50	112.31	34.53	186.63	93.21	59.67	122.79	217.29	127.71	201.95	222.25
17	229.01	63.77	78.61	141.57	175.89	96.30	192.11	134.04	183.50	163.02	225.04	238.27
18	218.01	33.29	94.69	123.03	167.94	150.60	170.85	83.47	204.83	188.07	221.35	203.90
19	189.91	137.91	103.93	62.51	181.90	96.41	180.08	46.33	193.11	163.10	202.33	198.03
20	187.32	131.43	116.88	142.88	178.31	33.72	183.10	97.55	179.12	100.33	196.65	213.18
21	197.89	50.60	109.92	131.84	165.17	34.06	195.73	81.52	201.45	104.74	224.93	212.13
22	175.76	104.25	92.62	69.57	125.71	157.75	172.42	130.63	135.72	87.64	182.48	194.86
23	201.98	112.98	83.21	139.38	187.62	64.29	167.01	115.59	190.80	88.64	203.63	210.53
24	184.67	82.25	71.81	110.19	129.72	57.28	149.33	85.66	114.00	191.54	187.58	218.84

T13 (MW)	T14 (MW)	T15 (MW)	T16 (MW)	T17 (MW)	T18 (MW)	T19 (MW)	T20 (MW)	Solar Output (MW)	Wind Output (MW)	PEV (MW)	Fuel cost ($)	Emission (Tonne)
135.62	88.15	25.85	24.26	20.56	19.54	54.24	40.05	0.00	19.74	−177.89	50478.45	251.24
113.49	160.50	22.15	21.10	20.45	39.60	37.12	48.09	0.00	12.16	−173.85	48980.08	234.55
153.07	98.49	16.56	24.55	23.81	49.96	51.50	41.92	0.00	9.93	−139.29	47872.31	233.31
92.74	73.96	26.63	21.20	19.47	37.20	63.07	33.98	0.00	6.01	−116.25	47328.52	228.07
160.46	22.49	13.47	21.35	22.89	27.14	61.34	55.58	0.00	2.40	−113.00	47789.43	219.66
90.94	156.69	21.44	28.72	25.74	37.61	64.07	39.88	0.00	1.20	−80.54	48504.60	258.21
160.56	141.54	34.84	26.60	22.25	26.76	33.65	31.29	0.70	1.20	31.57	49566.69	281.23
128.08	122.78	32.13	23.73	26.74	63.58	43.30	53.63	4.98	1.89	34.67	53255.66	310.12
163.90	36.70	21.85	31.37	31.07	38.35	42.60	33.96	10.19	1.64	55.15	52763.05	329.79
140.51	163.71	15.76	35.24	33.63	48.66	37.16	52.21	16.62	0.43	99.54	52139.10	292.12
120.27	152.10	30.33	25.53	18.87	38.13	76.38	41.65	18.92	0.29	124.41	51809.73	321.80

(Contd.)

Table 3 — Display of all units' and PEVs' output power as determined by the AEO algorithm in Test System 2 (*Contd.*)

Time	T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	T6 (MW)	T7 (MW)	T8 (MW)	T9 (MW)	T10 (MW)	T11 (MW)	T12 (MW)
182.58	94.62	29.53	26.54	20.27	50.49	45.29	42.92	17.94	1.34	98.05	51609.64	295.98
188.82	103.84	35.93	18.38	22.88	26.02	61.86	42.53	17.84	6.45	92.22	51238.59	277.65
161.62	119.64	29.16	26.26	20.11	32.84	56.18	46.08	18.28	14.62	60.93	51848.23	279.22
147.72	85.45	37.24	22.94	35.29	53.49	57.65	34.47	15.82	21.41	−95.56	55187.58	375.19
167.85	142.52	38.73	5.91	19.57	79.69	78.42	59.28	10.14	23.88	−145.15	56857.96	421.42
164.32	17.60	43.31	21.66	36.03	39.48	48.13	36.58	4.78	26.17	−132.49	57660.78	473.13
144.20	119.57	29.65	31.29	29.56	66.81	59.51	59.09	1.15	28.26	−121.90	59163.29	434.66
204.09	119.51	21.11	28.87	26.69	53.46	55.68	50.42	0.00	28.08	39.24	57473.78	390.40
171.60	25.35	36.69	16.76	21.88	66.21	69.58	64.73	0.00	24.39	79.75	55858.47	393.39
169.63	109.66	27.60	21.61	30.05	37.17	62.74	47.50	0.00	15.90	65.31	55432.99	388.42
152.54	179.94	30.56	23.62	28.23	58.03	63.22	44.74	0.00	13.52	−7.18	55452.01	312.67
54.65	99.98	33.71	31.94	30.14	70.61	70.27	44.15	0.00	19.38	−154.67	55164.50	389.62
80.30	156.62	37.96	27.68	27.35	55.38	74.59	54.46	0.00	23.88	−206.01	53119.86	344.96

cost and global emission minimization is shown in Table 4.

Table 4 — Comparative performance analysis of the AEO algorithm and benchmark metaheuristics for Test System 2, focusing on total operational cost and global emission minimization

Methods	Total cost ($/Day)	Total emission (Tonne)
AEO (Proposed)	1,356,594.77	96,672.55
SaMODE-LS	1,374,141.78	99,562.76
SaMODE	1,374,512.67	99,987.21
MOEA/D	1,374,951.56	101,524.34
2lb-MOPSO	1,386,785.45	101,452.44
NSGA-II	1,397,552.34	102,785.77
SPEA2	1,408,415.33	103,485.45

Conclusions

The WSPEV-DEELD framework, optimized via the AEO algorithm, establishes a robust paradigm for balancing economic efficiency with environmental sustainability in modern power systems. By successfully synthesizing thermal generation with the stochastic nature of RES and the bi-directional energy flow of PEVs, this research proves that ecosystem-inspired metaheuristics can navigate the complexities of real-world dispatch more effectively than traditional methods. While the study demonstrates high scalability across 10-unit and 20-unit systems, a notable limitation remains the exclusion of battery degradation costs and the geographical specificity of the renewable datasets used. Consequently, this model serves as a practical decision-support tool for grid operators managing the transition to green energy and V2G integration. Future research will focus on expanding the framework to encompass mega-scale multi-area grids and integrating real-time market pricing to further enhance the adaptability and economic viability of the proposed optimization strategy.

Conflicts of Interest

The authors affirm that they have no known financial or interpersonal conflicts that would have seemed to have an impact on the study.

Ethics Approval

This article does not contain any studies with human participants or animals.

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