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Original Article

Dynamic Economic Load Dispatch for Grids with Hybrid Energy Systems and Plug-in EVs

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Abstract *- This research examines the performance of a power system network with the inclusion of Plug-in Electric Vehicles (PEVs) that use Vehicle-to-Grid (V2G) and Renewable Energy Sources (RES) for the Dynamic Economic Load Dispatch (DELD) problem. The V2G support and RES integration make the conventional thermal plant into a more robust power system, solved by using a nature-inspired optimization called the Mother Optimization Algorithm (MOA). The simulation results show that the integrated system with MOA reduces fuel cost and power losses over 24 hours by stabilizing optimal power generation and renewable outputs. Due to the PEVs, the emissions are reduced in the environment in a substantial manner. This multi-objective problem provides sustainable and eco-friendly power system operation conditions with the integration of various energy sources.*

Keywords *- Plug-in Electric Vehicles, Vehicle-to-Grid, Renewable Energy Sources, Dynamic Economic Load Dispatch, Mother Optimization Algorithm.*

1. Introduction

The power system, which deals with the integration of generation, transmission, and distribution to supply energy to the consumer in an economical manner. In this regard, considering the Economic Load, Dispatch (ELD) is considered for fixed demand over a period of time, Dynamic ELD (DELD) is considered for 24-hours varying power demand. In order to meet the consumers' power requirement, the latest trend incorporates the Renewable Energy Sources (RES) and Plug-in Electric Vehicles (PEVs) in modern power systems. Due to the uncertainty in the renewable power outputs, the DELD problem becomes more robust and nonlinear in practice. By considering the valve-point effect, unstable power demand, and the PEVs' charging and discharging patterns [1-4], the necessity of optimizing the power system operation arises. For the reliable operation of a power system, the multi-objective research problem needs to be solved with the help of optimization methods to reduce fuel cost, emissions, and power losses. Researchers are steadily using metaheuristic and nature-inspired approaches to deal with these problems. Hybrid vehicles provide a conciliation between fuel costs and contaminants [1], while Teaching-Learning-Based Optimization (TLBO) resolves non-convex ELD problems 2]. Effects of valve points [3], improvements to PSO [4], and adaptable techniques such as the Plant Propagation Algorithm (APPA) [5] have been investigated. Recently made. Some examples of algorithms include the Ant Lion Optimizer (ALO) and Flower Pollination Algorithm (FPA) [6, 7]. Hybrid methods like Gaining-Sharing Knowledge Using Differential Evolution (DE) [8] and stochastic models with Wind power [9] expand the solution space. These tests illustrate that metaheuristic methods may deal with complicated issues in dispatch. DELD is used to manage situations that change throughout time. Nonlinear costs with valve-point effects are effective with TLBO [3]. Grey Wolf Optimization (GWO) method evaluated on integration of wind-thermal-solar systems power dispatch as a multi-objective problem. The DELD problem, subject to various constraints, has been addressed using several optimization techniques [4, 5, 10-15], all aimed at minimizing fuel cost and emissions. Putting renewable energy and plug-in electric automobiles into dispatch models has been given top priority. [16] evaluated the incorporation of RES with PEVs in ecological and ED, whereas [17] observed dynamic bacterial foraging in conjunction with RES integration. Literature confers the optimization of RES in conjunction with PEVs to enrich grid stability and cost [18]. The Mother Optimization Algorithm (MOA) is a likely metaheuristic for engineering optimization problems since it is robust, supple, and converges [19]. The current literature fails to address the complex and unpredictable interactions between the integration of renewable energy sources and the optimization of plug-in electric vehicle dispatch in real-time dynamic scenarios, despite progress in this area. Forming optimization outlines for DELD in amalgam energy systems that are both cost-effective and reliable is a big challenge, especially when it comes to the problem's multi-objective, non-convex, and stochastic quantities.

This paper examines an MOA-based DELD system to deal with the changes in solar energy, load profiles, and PEVs' capacity to charge and discharge in both directions. MOA uses its strong exploration and convergence characteristics. To lower emissions and generation costs while making the system more reliable and flexible in real-world, yet unexpected, operating conditions, present hybrid power systems require better optimization methodologies.

2. Problem Formulation

This section explains the mathematical problem in detail.

2.1. Economic Dispatch Model

The objective is to economically distribute the net power demand among the online participating generators while simultaneously satisfying the essential constraints. The Economic Dispatch problem is expressed in the following way:

$$Cost_{Thermal} = \sum_{i=1}^{NG}(a_i + b_i P_{Gi}(t) + c_i P_{Gi}^2(t)) \quad (1)$$

In this context, ai, bi,and ci represent the fuel cost indices for unit i. PGi(t) denotes the power generated by unit i at hour t, and CostThermal refers to the net cost of generation for the system. NG shows the total number of thermal units running, and TC is improved with the following limits.

Equality Bound

$$\sum_{i=1}^{NG} P_{Gi}(t) = P_D(t) + P_L(t) \quad (2)$$

$$Where \begin{cases} P_D(t): power\ demandat\ hourt \\ P_L(t): transmission\ loss\ at\ hourt \end{cases}$$

$$P_L(t) = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_{Gi}^T(t) B_{ij} P_{Gi}(t) \quad (3)$$

$$WhereB_{ij}: Losscoefficient$$

In-Equality Bound

$$PGi_{Gi,max_{Gi,min}} \quad (4)$$

Where

$$\begin{cases} P\ lim\ i^{th}{}_{Gi,min} \\ P\ lim\ i^{th}{}_{Gi,max} \{ \end{cases}$$

2.2. Wind Energy

Over- and underestimation costs are integrated by weighting the traditional cost function, as Equation 5.

$$WEC = \sum_{i=1}^{M} C_{\omega i}(\omega_i) + \sum_{i=1}^{M} C_{p,\omega i}(\omega_{i,av} - \omega_i) + \sum_{i=1}^{M} C_{r,\omega i}(\omega_i - \omega_{i,av}) \quad (5)$$

C_{wi}(wi) denotes the cost as a function of the wind's velocity contour. Equation (6) uses the Weibull probability distribution equation f w (w) of wind energy, which has been referenced in [4].

$$C_{\omega i}(\omega_i) = f_\omega(\omega)(\omega_i) \quad (6)$$

A wind energy generator's estimated power is represented by w_i. If all the supplied wind power is not used, the underestimation cost is$C_{p,\omega i}(\omega_{i,av} - \omega_i)$. The penalty reserve cost, also known as the overestimation cost, is calculated as$C_{r,\omega i}(\omega_i - \omega_{i,av})$. This occurs when the real or available wind power falls short of the scheduled wind power.

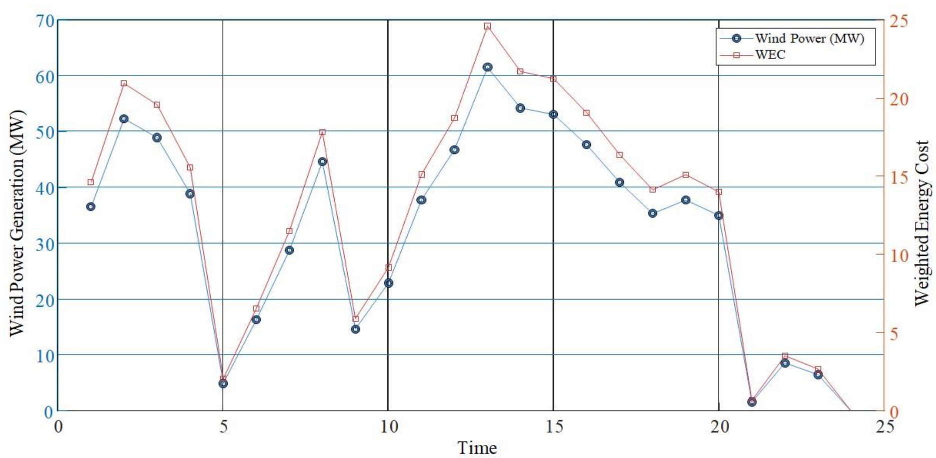

Fig. 1 Hourly wind power generation vs. Cost

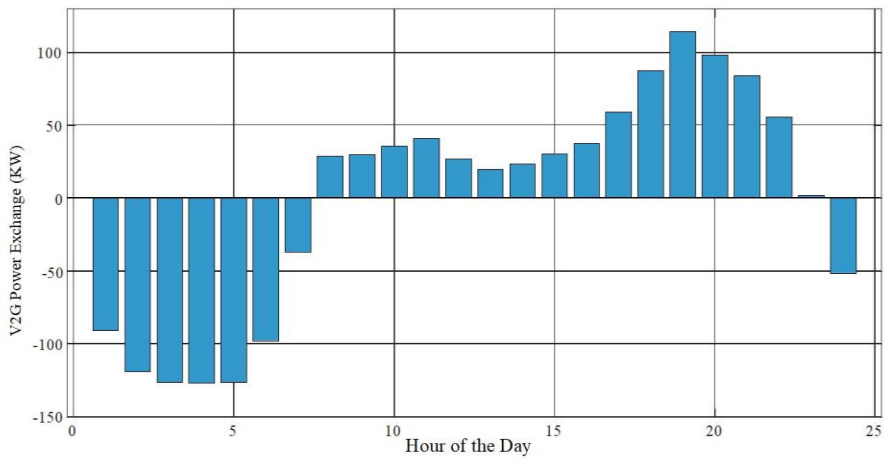

Fig. 2 Hourly Vehicle-to-Grid (V2G) power exchange

Figure 1 displays the results of computing the hourly Wind Energy Cost (WEC) over a 24-hour period using scheduled and estimated available wind power, which is used in this paper. Assuming a 20% increase over the scheduled power, the penalty for under- and overestimation is 2 times the cost coefficient p and 3 times the cost coefficient r, respectively.

The Weibull distribution is used to represent the ambiguity in wind power generation, where A=10 and B=2 are the scale and shape parameters, respectively. Wind generation and related costs fluctuate throughout the day, as shown in the graph. Figure 1 shows the results of calculating the hourly WEC over a 24-hour period, based on both planned and predicted wind power availability.

2.3. Mathematical Model for PEV

Whether PEVs are being used as loads or sources, the power from the distributed generators needs to be enough to meet the load demand, D(t).

Power demand is set in this way: when PEVs supply power, equation (7) is used, and when they draw power, equation (8) is used.

$$\sum_{i=1}^{N} P_i\,(t) + \sum_{j=1}^{N_{PEV}(t)} \eta P_j^{PEV}(t)(\psi_{pre} - \psi_{dep})\, P_{wind}(t) = D(t) + P_{loss}(t) \tag{7}$$

$$\sum_{i=1}^{N} P_i\,(t) + P_{wind}(t) = D(t) + P_{loss}(t) \sum_{j=1}^{N_{PEV}(t)} \eta P_j^{PEV}(t)(\psi_{pre} - \psi_{dep}) \tag{8}$$

For hour t, $P_{wind(t)}$ denotes the power produced by wind, and $_{Ploss(t)}$ denotes the power loss. The total number of PEV associates to the grid at hour t is denoted by $N_{PEV}(t)$, the generation of the j-th PEV at hour t is denoted by$P_j^{PEV}(t)$, the charging state of the PEVs' batteries is denoted by ψ pre, the net efficiency of the system is denoted by η, and N max PEV is the total quantity of PEVs used during the entire period, represented by N max PEV.

$$\sum_{j=1}^{T} N_{PEV}\,(t) = N_{PEV}^{max} \tag{9}$$

Figure 2 displays the power exchange between the V2G and the grid during a 24-hour period. A positive value indicates energy delivered to the grid, while a negative value indicates energy drawn for charging, which is used in this paper. Power exchanged when charging and discharging is affected by efficiency (0.9). A power flow metric that tracks the number of active PEVs varies hourly. Peak charging occurs in the morning, and peak discharge occurs in the evening, according to the plot.

2.4. Mathematical Model for Emission Dispatch

A promising definition of this issue is to determine the optimum solution that minimizes the overall amount of emissions, as termed by Eq. (10).

$$TE = \sum_{i=1}^{N} (\alpha_i + \beta_i P_{Gi}(t) + \gamma_i P_{Gi}^2(t)) \tag{10}$$

Then, TE is the total thermal unit emissions, while αi, βi, and γi are the coefficients of greenhouse gas emissions from the ith generating unit.

3. Mother Optimization Algorithm

The Mother Optimization Algorithm (MOA), proposed by Hatamlou and Ghaemi in 2022 [19], is a metaheuristic inspired by the nurturing role of a mother. In MOA, every solution is treated like a child that steadily grows, directed through steps of mentorship, training, and correction until it develops to its full potential. A key strength of MOA lies in how it carefully balances the search for new possibilities between exploration-seeking out uncharted options-and exploitation-refining the best candidates. The MOA progresses in an iterative fashion: it starts with a group of prospective solutions, evaluates their performance, and progressively homes in on the most promising ones.

$$X_i^{new} = X_i + r_1 * (X_{best} - |X_i|) \tag{11}$$

The finest solution within the current population is denoted as Xbest, while represents a uniformly distributed random number. During the training phase, each ‘child’ picks up and improves by interacting with a randomly picked peer, gaining awareness through this interchange.

$$X_i^{new} = X_i + r_2 * \left(X_j - X_i\right), X_j \neq X_i \quad (12)$$

$Wherer_2 \in (0,1) and X_j \neq X_i$

After this, the processes of reinforcement and correction take place. At this stage, the fitness of a child’s updated position in the search space is assessed. If the new position proves better than the previous one, it is preserved and encouraged, driving the solution toward improvement. Positive reinforcement, in turn, strengthens and secures these beneficial advancements. Should the new location fail to enhance fitness, the algorithm implements a regulated stochastic perturbation to amend the solution.

This interlude stimulates the youth to inspect other search realms, possibly shirking local optima and sighting superior solutions. This combination of rewarding successful actions and corrective research for unproductive ones maintains the search process by leveraging effective solutions and investigating novel alternatives.

$$X_i^{new} = X_i + r_3 * randn(D) \quad (13)$$

$Wherer_3 \in (0,1 and randn(D)$ is a D-dimensional random vector from a normal distribution.

MOA Parameters and Their Mapping to the ELD Problem are represented in Table 1.

Table 1. Typical parameter values of MOA

Parameter	Description	Typical Range	ELD Mapping
PopSize	Number of candidates	30-100	Different generator dispatch combinations
MaxIter	Maximum iterations	100-1000	Iterative cost optimization cycles
r_1, r_2, r_3	Random coefficients	[0, 1]	Guide exploration and learning
D	Dimension of the problem	Depends on system	Number of generators
X_min, X_max	Variable bounds	Problem-specific	Generator limits: PG_{imin}, PG_{imax}

4. Results and Discussion

This study uses the Mother Optimization Algorithm (MOA) in MATLAB to tackle the economic and emission dispatch problem of a system consisting of 20 steam power units. The MOA algorithm is applied to calculate the actual power loss. System emission, cost, and loss coefficient data are taken from [4]. In this case, it is assumed that there will be 120,000 Plug-in Electric Vehicles (PEVs), as reported in [4]. The Wind Farm (WF) is considered to have a capacity of 61.5 MW. A Conventional Vehicle (CV) emits approximately 5,340,000 g of Green House Gases (GHGs) per year, based on an average emission rate of 445 g per mile. Therefore, replacing 120,000 CVs with PEVs is expected to reduce emissions by about 6,408,000 tons annually [5, 10]. Wind speed data are obtained from [8]. Additional system parameters include: a 24-hour scheduling horizon, an average annual travel distance of 12,000 miles per PEV, and a daily energy requirement of 8.22 kWh. On average, each CV is assumed to emit 445 g of pollutants per mile [9]. In this study, MOA is employed for multi-objective optimization. The data from the load over 24 hours displays how the power offerings from thermal power, wind power, and V2G systems vary, as shown in Table 2 and the related image. The primary source, thermal power, is quite constant throughout the day. V2G reveals charging (negative values) and discharging (positive values) performance, substantially impacting the entire power profile, while wind power shows trivial vacillations. There are times when V2G surges supply by adding more power to the grid, and other times when it declines net readiness by drawing power, as shown in Figure 3. A dynamic total power curve is formed by the shared effect of these sources, which underlines the function of renewables and EVs in regulating the supply and demand for energy.

Table 2. 24-Hour economic load dispatch using MOA for a 20-unit thermal system (K = 0.7295)

Hour	PT (MW)	P_{wind} (MW)	V2G (MW)	Hour	PT (MW)	P_{wind} (MW)	V2G (MW)
1	1854	36.54	-90.53	13	1926	61.5	19.97
2	1785	52.33	-119.05	14	2076	54.23	23.54
3	2028	48.93	-126.18	15	2029	53.1	30.67
4	1778	38.89	-126.74	16	2046	47.66	37.8
5	1778	4.94	-126.18	17	2118	40.93	59.19
6	1858	16.32	-97.66	18	2174	35.33	87.71
7	1956	28.73	-37.06	19	2192	37.76	114.44
8	2016	44.58	28.89	20	2196	35	98.4
9	2017	14.65	30.06	21	2200	1.59	84.14

10	1971	22.91	36.02	22	2145	8.6	55.62
11	1992	37.78	41.36	23	2054	6.49	2.15
12	1965	46.78	27.1	24	2007	0	-51.32

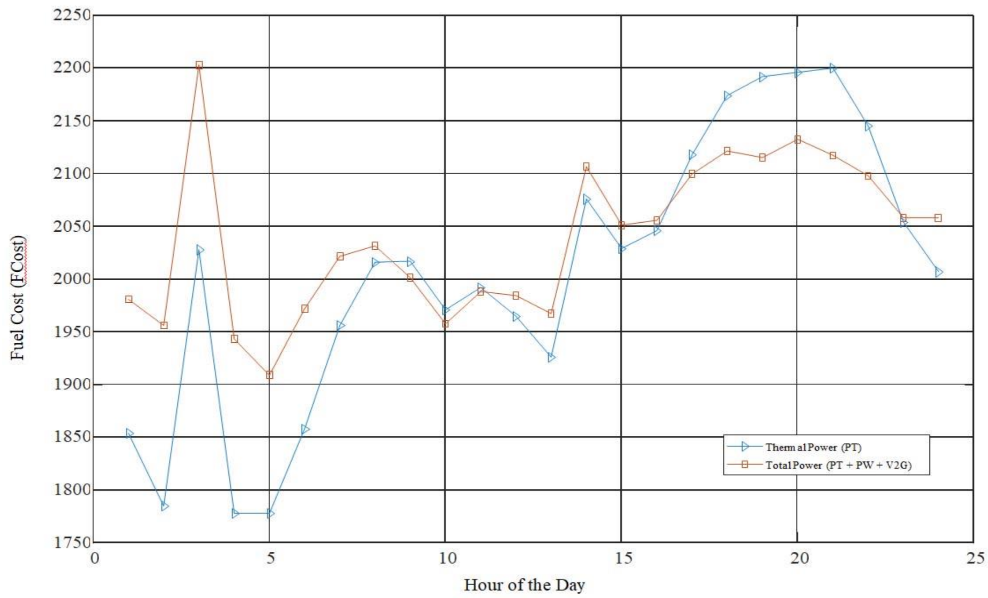

Fig. 3 Power profiles for case 1 (thermal only) and case 2 (thermal + wind + V2G)

4.1. Case 1: without PEVs and RES

In order to find the best DELD, the MOA is run on a thermal power system with 20 units, excluding PEVs and RESs. Table 2 provides the generating schedule that corresponds to a scaling factor of K=0.7295. The method was performed 10 times independently at this value of K in order to get the best possible outcome. A comprehensive Economic Load Dispatch (ELD) study covering 24 hours is included in Table 3.

The goal is to maximize power demand while simultaneously optimizing fuel cost and pollution levels. Reflecting the environmental impact of power generation, the total fuel cost for the day was 1,227,422.8 \$/hr, and the total emissions reached 454,706.96 kg/ton. With a total of 22.9536 MW loss in transmission during the day, the loss percentage was quite modest when compared to the total energy produced. Power generation peaked at 2344.2 MW at Hour 19, during peak load, and dropped to a minimum of 1687.6 MW at Hour 4 due to demand fluctuations. The corresponding ranges for fuel costs and emissions were 44,635.84-57,130.70 and 13,617.33-22,795.18 kg, respectively. Power dispatch approaches may be tested on this dataset, which displays how well the system stability competence and ecological effect.

4.2. Case 2: with PEVs and RES

The operative load demand is lower in Case 2, which associates wind power with Vehicle-to-Grid (V2G) expertise, as is associated with Case 1. This shifts the liability to conservative power plants and decreases fuel ingestion, resulting in condensed fuel costs over the 24-hour period (Table 3). Emissions are also reduced due to lower fossil fuel generation, emphasizing the environmental benefits of renewable energy and smart grid solutions.

Also, through periods of high load, Case 2 shrinks grid stress by reducing the need for extreme thermal unit generation, making extreme demand dealing more effective. Power losses may be reduced by conveying energy closer to demand sites or by rationing it back from vehicles, obligations to the rationalized generation of wind power, and the bidirectional nature of V2G. Associating Case 2 with the predictable dispatch shown in Case 1, Figure 4 shows that the latter improves operative efficiency and grid tractability while also optimizing resource use.

The regular system enactment over 24 hours in Case 1 shows a total fuel cost of 1,227,422.8 units, emissions of 454,706.96 kg, and losses of 22.95 MW. The generation diverges between 1,687.6 MW and 2,344.2 MW. As a result of dispersed generation and enhanced load balancing using V2G, fuel costs in Case 2 drop to 1,201,523.2 units and losses to 14.81 MW. The mixture of wind energy with V2G capability brings about weighty benefits, such as a straighter hourly generation outline with fewer peaks and a minor rise in emissions to 461,158.53 kg. Case 2 emphasises the need to unite RES and V2G technology into ELD, as it reduces fuel expenses and transmission losses while preserving competitive ecological effectiveness.

Table 3. MOA hourly metrics: fuel cost, emissions, losses, and generation for Case 1 vs. Case 2

	CASE 1				CASE 2			
HR	F_{Cost}	**Emission**	P_{Loss}	P_{Gen}	F_{Cost}	**Emission**	P_{Loss}	P_{Gen}
1	46762.164	15368.914	0.7349	1800.7	48803.739	17503.416	0.8419	1908.8
2	45218.069	14098.872	0.655	1718.7	47738.861	16197.535	0.787	1852.5
3	49600.15	18542.241	0.8839	1950.9	52554.369	22612.356	1.0331	2106.3
4	44635.84	13617.326	0.6257	1687.6	48006.058	16526.881	0.8008	1866.7
5	44823.561	13769.935	0.635	1697.6	48638.009	17296.049	0.8332	1900.1
6	46328.504	15016.186	0.7124	1777.7	49397.949	18271.866	0.8731	1940.2
7	49543.238	18465.688	0.8809	1947.9	49872.084	18902.221	0.8983	1965.2
8	52224.964	22154.773	1.0175	2089	49458.449	18352.295	0.8764	1943.4
9	51710.09	21407.434	0.9939	2062	50023.195	19100.374	0.9063	1973.2
10	51100.935	20578.829	0.9641	2030	48881.034	17601.192	0.8459	1912.9
11	51881.62	21640.999	1.0015	2071	48896.002	17620.192	0.8467	1913.7
12	51234.109	20769.447	0.9714	2037	48484.258	17106.361	0.8253	1891.9
13	48349.478	16942.233	0.8184	1884.8	47602.956	16079.137	0.7797	1845.3
14	51405.382	21006.794	0.9801	2046	50515.914	19762.091	0.9325	1999.2
15	52683.351	22795.182	1.0374	2113	49509.662	18420.693	0.8791	1946.1
16	53027.593	19800.165	1.054	2131.1	49800.15	18808.689	0.8946	1961.4
17	54697.083	20680.158	1.1317	2218.1	50889.444	20279.677	0.9526	2018.8
18	56221.101	20406.264	1.199	2297.2	51518.851	21139.611	0.99	2051.90
19	57130.699	20852.846	1.235	2344.2	51306.416	20873.668	0.98	2040.80
20	56859.635	17484.663	1.223	2330.2	51740.577	21448.151	1.00	2063.60
21	56018.148	19500.124	1.191	2286.7	52726.739	22946.511	1.04	2115.30
22	54523.918	19983.672	1.1231	2209.1	52087.199	21972.602	1.01	2081.80
23	51729.144	19210.762	0.9947	2063	51412.235	21008.236	0.98	2046.30
24	49713.993	20613.454	0.89	1956.9	51659.031	21328.725	0.99	2059.30
TOTAL	1227422.8	454706.96	22.9536		1201523.2	461158.53	14.8065	

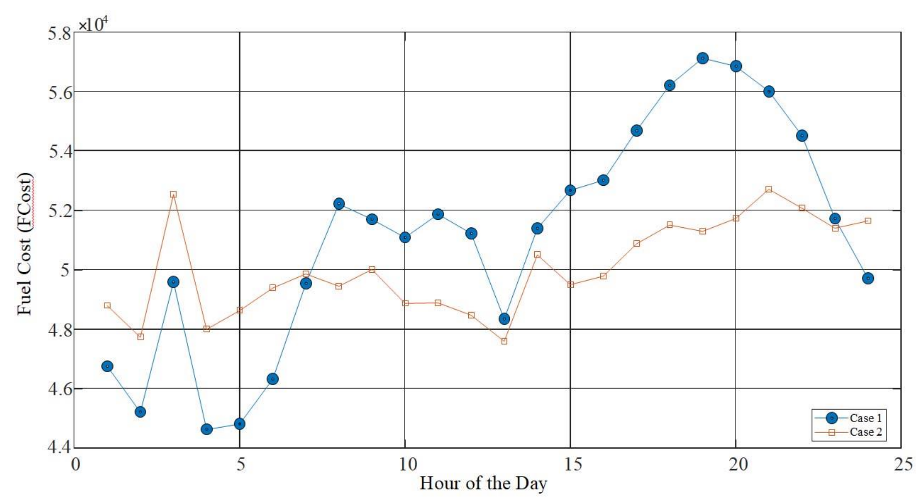

Fig. 4 Hourly fuel cost comparison for Case 1 and Case 2 with MOA

Table 4. Comparison results of MOA and PSO [30] for Case 1 and Case 2.

Parameter	Algorithm	Case 1	Case 2
Total Fuel Cost ($)	MOA	12,27,422.80	1,201,523.2 (↓ 2.1%)
	PSO [30]	12,30,170.79	1,220,052.57 (↓ 1%)
Total Emissions (Tons)	MOA	4,54,706.96	461158.53 (↑ slight)
	PSO [30]	12,12,452.13	896,441.02 tons (↓ 26%)
Transmission Loss (MW)	MOA	22.95	14.81 (↓ 35%)
	PSO [30]	69.77	76.28 (slightly higher)

Table 4 compares the proposed Mother Optimization Algorithm (MOA) with Particle Swarm Optimization (PSO) [18] for Case 1 and Case 2 in a 20-unit system that includes wind and PEV integration. In Case 2, MOA shrinks the overall fuel cost by 2.1%, which is further than PSO's 1% shrinkage. This indicates that MOA is superior at reducing costs.

MOA's emissions go up a diminutive because of V2G diminuendos, but PSO's emissions go down by 26%. This is the trade-off between equivalent money and keeping the environment. For Case 2, MOA notches transmission losses by a lot (↓ 35%), where PSO just makes them a tiny bit mediocre. The enriched enactment of MOA is due to its human-inspired exploration and exploitation procedures, which preserve a balance concerning global search and local tweak, avoiding early convergence in non-convex resolution spaces.

Its adaptive examination technique deviates the updates to solutions based on how well the population is exploited, which makes it easy to deal with fluctuating loads, renewable intermittency, and stochastic PEV performance. MOA may improve many intentions at the same time, which means it is able to subordinate fuel costs, contaminants, and transmission losses all at the same time. This leads to a more sensible operative enactment. MOA is more sturdy, reliable, and adjustable than PSO and other customary metaheuristics when operating in unidentified situations. This makes it a good fit for existing DELD concerns in power systems that are involved in renewable energy and have PEVs integrated into them.

5. Conclusion

The current research examined the DELD problem contained in the situation of a modern power system that includes thermal power plants, RESs, and PEVs integrated into the system. The Mother Optimization Algorithm was used to assess the system's performance in two circumstances: without and with the absorption of V2G and RES technology. The findings specify that operative efficiency is considerably improved when RES and V2G technologies are used in combination. This alteration led to a decline in transmission losses surpassing 35% and a diminution in fuel costs from 1,227,422.8 \$/hr to 1,201,523.2 \$/hr. The benefits of distributed and bidirectional energy pours in smart grid technologies, as presented by these enrichments, are considerable. PEVs have a net positive ecological effect since they reduce millions of tons of greenhouse gas emissions yearly. Finally, the power system networks are becoming more robust, eco-friendly, and cost-effective with the integration of EVs and RESs to the DELD problem.

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