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RESEARCH ARTICLE

A Dynamic Optimal Scheduling Strategy for Multi-Charging Scenarios of Plug-in-Electric Vehicles Over a Smart Grid

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ABSTRACT Green transportation has become our top priority due to the depletion of the earth's natural resources and rising pollutant emission levels. Plug-in electric vehicles (PEVs) are seen as a solution to the problem because they are more cost and environment friendly. Due to rapid industrialization and government incentives for zero-emission transportation, a significant challenge is also constituted in power grids by the self-interested nature of PEVs, with the asymmetry of information between the charging power demand and supply sides. In this paper, we propose an optimal strategy in industrial energy management system, based on evolutionary computing, to characterize different charging situations. The proposed approach considers stochastic, off-peak, peak, and electric power research institute charging scenarios for attaining the vehicle-to-grid capacity in terms of optimal cost and demand. An extensive scheduling of charging cases is studied in order to avoid power outages or scenarios in which there is a significant supply-demand mismatch. Furthermore, the proposed scheme model also reduces the greenhouse gases emission from generation side to build a sustainable generation infrastructure, which maximizes the utility of fuel-based energy production in the presence of certain nonlinear constraints. The simulation analysis demonstrates that PEVs can be charged and discharged in a systematic manner. The participation of transferable load through the proposed methodology can significantly reduce the economic costs, pollutant impacts, efficiency, and security of power grid operation.

INDEX TERMS Energy emission dispatch (EED), industrial energy management system (IEMS), plug-in electric vehicle (PEV), plug-in electric vehicle charging coordination (PEVCC), vehicle-to-grid (V2G), valve-point loading effect (VLE).

I. INTRODUCTION

A. BACKGROUND

The world-wide industrial expansions on global scale gave birth to the continuous demand of electricity, and scientists around the globe are finding new tools for the power demand and supply adjustment to achieve the energy gap demands [1], [2], [3], [4], [5], [6], [7], [8]. The primary objective of energy emission dispatches (EEDs) is to find the best combination of thermal units to minimise air pollutants and the total cost of generation of electricity [9], [10], [11], [12], [13], [14], [15], [16]. The attainment of lowest cost of a reliable energy supply to a power system can be a really complicated task due to the increase of complex new load types such as plug-in-electric vehicles (PEVs) and green energy charging stations, which depend heavily on grid control [17]. Another important aspect of the world order is that energy is not the primarily concern. The increasing carbon and other gaseous oxides emissions of

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power generation utilities are affecting the earth's atmosphere dramatically, and emission regulatory authorities are forcing the power generation companies to limit their emission to an acceptable level. According to US environmental protection agency, 50% of emissions of greenhouse gases is caused by the electricity production and transportation alone [18]. These agencies are also encouraging industries to switch the users on green energy with lower or zero emission by providing tax free rebates and other financial benefits to protect the environment [19]. In the future, it is expected that PEVs will dominate all other means of transportation industries due to zero carbon foot prints and easy maintenance as compared to combustion engines. The distribution of charging infrastructure is unquestionably one of the most essential areas of studying the mechanics and applications of traditional EVs recharging, whether for PEVs or exchange recharging techniques. Some recent research focused on developing charging technologies for EVs, including rapid inductive recharging (RIR), short mileage capacity, and extended charging periods. Fathollahi et al. [20], [21] developed a statistical technique for the positioning and navigation of commercial EVs. Taking into account variables such as EVs energy potential, fuelling facility construction costs, power setbacks, and energy hubs' power dissipation, the proposed method has successfully mapped the location of IRR infrastructure and the scheduling of EVs. Majhi et al. [22] developed a combined optimization technique for identifying an economical approach for the optimal distribution of RIR infrastructure on a large transport grid while maintaining a satisfactory SOC. However, due to the nature of their use, many commercial and domestic PEVs are charged at frequent intervals. This results in an abrupt increase in the demand for electricity on the energy generating hubs. To contemplate this situation, a viable solution is needed to avoid energy mismatch of energy integrated systems [23].

B. RELATED WORK

The primary concern of the EEDs is to improve the use of energy supplies in the power grid [7], [24], [25], [26], [27], [28], [29], [30]. In the past, several techniques have been used to reduce the overall cost of fuel-based production units and for delivering high-quality electricity to customers, while EEDs are the most cost-effective and best possible options [31]. In recent years, car manufacturers and federal financial institutions have preferred the adoption of PEVs because they have low oxides emission, better torque, energy saving and easy maintenance [32], [33], [34], [35]. However, a substantial percentage of PEVs will cause massive instability in the operation of power grids [36], [37]. Due to inherent autonomy of PEVs, an efficient charging model of all PEVs in a given urban area is presented in [38] and [39]. After government legislation of PEVs charging, a voltage control model has been proposed to reduce power system voltage fluctuations while ignoring the power losses in the optimization goal [40], [41]. The charging nature of PEVs as load in grid network system reflects it as the highly non-convex and non-differential task.

Electricity and transportation industries are the largest emitters of greenhouse gases on earth. Primarily, solar and wind integration in the electricity industry can reduce these harmful emissions [42]. The emission reductions may be further aided by grid-enables vehicles (GVs), which are PEVs with a V2G feature. PEVs have been used as loads, energy sources, and energy storage in a smart power system with renewable energy sources [43]. In the past decade, scientists have considered many PEVs penetrations in the conventional power grid systems [44]. Abdullah et al. [45] studied the risks and obstacles that come from charging and discharging PEVs as well as their potentials as a way to integrate renewable energy sources. Qiao et al. [46] developed an adaptive structure of PEVs and wind farms that utilises the charging and discharging of PEVs to mitigate the wind energy penalty costs associated with exceeded and underrated wind energy availability. Behera et al. [47] used fuzzy decision approach, based on constriction particle swarm to solve the dynamic EEDs and attained feasible greenhouse gases emission rate by integrating renewable energy sources and PEVs. Flower pollination meta-heuristic optimization algorithm is used in [48] to tackle the complex dynamic EEDs subject to traditional and charging constraints of PEVs. However, the charging constraint model has considered the conventional capacity limit on power generation, and practically, the charging of PEVs is truly stochastic in nature [49], [50], [51].

Hong et al. [52] suggested the power systems concept to manage the charging behaviour of all PEVs in a single urban area due to their intrinsically autonomous properties. On the basis of V2G technology, Wei et al. [53] suggested that PEVs may be employed as a tiny transportable power plant. They initially introduced the EEDs model for unit commitment with PEVs and then utilized particle swarm optimization for power mismatch constraints. Wu et al. [54] presented an hierarchical approach for scheduling PEVs as industrial loads. The model, on the other hand, does not take into account the limits imposed by the EVs or the spinning reserves.

To elude the problem, Liu et al. [55] analyzed the pricing model and dispatching scheme for PEVs-storage participation in the alternate service model and proposed an optimal allocation strategy for PEVs-storage with the goal of economic dispatch. The study can be found to effectively improve PEVs reaction to ancillary service market participation and to increase the hub revenue. Babaei et al. [56] used data mining approach for the uncertain load management of PEVs over power network, considering a convex optimization model. In [57], the authors solved a combined EEDs problem by using a back tracking search algorithm. Li et al. [58] suggested an improved sailfish optimizer for strategic planning scheme to ensure flexibility in the programming of power systems and addressed random wind power effectively while reducing the operating costs and pollutant emission.

Numerous methods have been used as effective optimization tools and have become widespread in the search for the optimal solution to the EEDs problem [59], [60]. However, the implementation of an appropriate multi-objective economic emission dispatch system is still an intensively studied topic that requires additional effort to balance the power grid network energy flow in order to support the rapid development of PEVs [61], [62], [63], commercial flying drones, and other dynamic loads of energy storage devices [64], [65], [66]. The authors in [67] presented a combined grid stability and cross emissions reduction model for the energy dispatch by considering PEVs to attain the lowest grid operational cost. The presented model can reduce the operational cost and emissions of energy hubs by relocating the transferable electrical loads, such as PEVs, to time intervals when generation costs are low. In [68], the challenging dilemma of electricity grid security due to uncertain load demand was investigated. The authors have used a reinforcement learning model to meet the energy demand of PEVs with varying users in various places while concurrently boosting energy security.

Nonetheless, avoiding local minima is a major challenge when solving optimization problems with strict constraints. The researchers in [69] came up with a hybrid optimization scheme, namely GSA-PSO, in order to improve the global search performance. Additionally, some recent works have presented the state-of-the-art ways to solve the hard optimal energy dispatch problem while taking PEVs into consideration [70], [71], [72], [73].

C. RESEARCH OBJECTIVE AND CONTRIBUTION

This work proposes a new paradigm to address the economic emission model, contemplating unsteady load management of PEVs. The developed framework provides the optimum solution of cost and emission while delivering a unified strategy for achieving a more precise and stable dispatch with the addition of PEVs as additional loads. One of the most difficult problems in power system control is to schedule the active powers from all engaged thermal power stations in such a manner that the generation costs and emissions are minimized to the maximum possible extent while satisfying all associated constraints. In addition, the EEDs for a single connected load for a fixed time while meeting restriction such as capacity generation limitations is referred to as static EEDs. The EEDs for a loading condition of 24 hours while taking ramp constraints into account is referred to as dynamic EEDs, which is a more appropriate and pragmatic dispatch requirement. An astute soft computing paradigm is proposed and applied to solve the dynamic EEDs with traditional convex and nonlinear constraints such as valve-point effect, prohibited operating regions, internal network losses. A new constrained model of PEVs with energy storage and multi-charging mechanism is also incorporated as an unsteady load. CEED with consideration for PEVs is an important power system optimization task. This research assists energy operators and policymakers in developing cost-effective generation schedules that take into account the power demand of charging PEVs. In addition, by establishing an optimal generation merit order, the strategy will help reduce the environmental emissions of power plants. The following are, however, the most important contributions made by this study:

1) Compared to [74] (see also [75], [76], [77], and [78]) for vehicle-to-grid (V2G) system in unbalanced power distribution systems, a new approach for dynamically managing the EEDs problem has been developed. In this case, the approach is based on evolutionary computing, which seeks out the most optimal solution to the problem.
2) The approach also improves the operation of EEDs by including unanticipated PEVs loads with a defined probability distribution of several charging scenarios over the course of a 24-hour period. While addressing the inclusion of PEVs in the problem, this approach also optimises the operation of EEDs, lowering the overall energy costs and greenhouse gases emission while meeting limitations such as VLEs, ramp rates and generation demand, respectively, [79], [80], [81], [82] and [46].
3) In contrast to the previous EEDs model in [74], two highly nonlinear real-world constraints, namely, forbidden operating regions and spinning reserve of thermal power plants are also inducted in the model to enhance the practicality of the proposed system.
4) The proposed iterative algorithm for the combined energy emission dispatch (CEED) problem in the presence of high-dimensional, non-protuberant and uncertain characteristics attains excellent optimization performance and less computational cost. It also demonstrates the better convergence and execution time when compared to current advanced algorithms [74] (see also [83] and [84]).
5) Five test systems ranging from small-scale to large-scales were used to assess versatility of the proposed algorithm for CEED in various PEVs charging scenarios such as EPRI, peak, off-peak and stochastic [85], [86], [87].

The objective of this study is to propose a low emission energy dispatch model for IEMS to minimize the daily operational cost of energy grids by considering dynamic power demand for conventional grid loads and PEVs charging load under various charging scenarios such as EPRI, stochastic, peak and off-peak. The dynamic CEED problem is a complex task in IEMS due to its strict system level constraints, and modeling the problem with PEVs charging scenarios make it highly multidimensional problem. The penetration of these charging scenarios in energy grid not only increases the operational cost of energy production but it also affects the power and emission profiles of generation and grid stability. In light of the CEED model characteristics including PEVs load, an effective intelligent optimization framework can be developed that ensures convergence in terms of speed and accuracy compared to [74] (see also [75], [76], [77], and [78]). The proposed framework will also ensure the reduction in operation cost and emissions while effectively satisfying the CEED constraints and PEVs charging scenarios.

D. ABBREVIATIONS AND ACRONYMS

Nomenclature

E_{ed}	Emission dispatch.
F_{fd}	Fuel cost dispatch.
F_{gc}	Global cost.
W_s	Scaling weights.
CEED	Combined energy emission dispatch.
DE	Differential evolution.
DEED	Dynamic economic emission dispatch.
e-TLBO	Elitist teaching-learning-based optimization.
EBWO	Efficient black widow optimization algorithm.
EED	Economic emission dispatch.
ELD	Economic load dispatch.
EP	Evolutionary programming.
EPA	Environmental protection agency.
m-TLBO	Modified teaching-learning-based optimization.
MAFRL	Multi-agent fuzzy reinforcement learning.
PEM	Plug-in electric mobility.
PEVCC	Plug-in electric vehicle charging coordination.
PEVs	Plug in electric vehicles.
PS	Pattern search optimization.
PSO	Particle swarm optimization.
PSO-CF	Particle swarm optimization constriction factor.
SA	Simulated annealing.
SL-TLBO	Self learning teaching-learning-based optimization.
SOC	State-of-charge.
TLBO	Teaching-learning-based optimization.
w-PSO	Weighted particle swarm optimization.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. CEED PROBLEM FORMULATION

The goal of CEED is to find a balance between power generating plants cost and gaseous emissions. It is a bi-objective task that combines the economic and environmental objective of power delivery into a single optimization problem. The goal of the CEED remedy is to bring the price of fuel down to a more affordable level and to reduce fossil fuel-related emissions for electricity producing units while addressing a variety of convex and non-convex constraints. F_{fd} and E_{ed} are the acronyms for these two objectives. Ultimately, the CEED issue has been treated as a single problem in the following manner:

$$\min(F_{gc}) = W_s(F_{fd}) + (1 - W_s)(E_{ed}). \tag{1}$$

In (1), F_{gc} denotes the global cost to be minimize, W_s is the scaling weight having random value between 0 and 1, and F_{fd}, E_{ed} are fuel cost dispatch and environmental dispatch respectively.

1) COST DISPATCH MODELLING

The goal of cost dispatch is to reduce the cost of fossil fuels used by thermal plants while ensuring that the system limitations are not violated. The mathematical representation of cost dispatch model is as follows:

$$\begin{aligned} F_{fd} &= \sum\nolimits_{\tau=1}^{t} \sum\nolimits_{k=1}^{NU} F_k(P_{k,\tau}) \\ &= \sum\nolimits_{\tau=1}^{t} \sum\nolimits_{k=1}^{NU} (a_k + b_k P_{k,\tau} + c_k P_{k,\tau}^2), \end{aligned} \tag{2}$$

where $P_{k,\tau}$ is the generation power of k^{th} generator at time instant τ. a_k, b_k and c_k are the cost coefficients of k^{th} generators. NU is the number of operating units.

2) VALVE-POINT LOADING EFFECT MODELLING

A thermal plant has special mechanized operation of valve opening for steam under increase in load condition for synchronization of generated power and load demand. This valve opening operation introduces sinusoidal ripples on output cost curve. The expression (2) can be modified for VLE non-convex constraint as follows:

$$\begin{aligned} F_{fd} &= \sum\nolimits_{\tau=1}^{t} \sum\nolimits_{k=1}^{NU} (a_k + b_k P_{k,\tau} + c_k P_{k,\tau}^2) \\ &\quad + \left| e_k \sin\left(f_k(P_{k,\min} - P_{k,\tau})\right)\right|, \end{aligned} \tag{3}$$

where e_k and f_k are the vale-point loading effect coefficients causing rippling effect on output cost curve.

3) ENVIRONMENTAL DISPATCH MODELLING

The environmental power dispatch objective is to reduce emissions levels of air contaminants such as nitrogen oxides (NO_X), carbon oxide (CO_X) and sulphur oxides (SO_X) at possible optimum level. The total emission of a thermal power plants can be expressed as a quadratic polynomial as shown below.

$$\begin{aligned} E_{ed} &= \sum\nolimits_{\tau=1}^{t} \sum\nolimits_{k=1}^{NU} [(A_k + B_k P_{k,\tau} + C_k P_{k,\tau}^2)] \\ &\quad + \eta_k \exp(\delta_k P_{k,\tau}), \end{aligned} \tag{4}$$

where A_k, B_k, C_k, η_k and δ_k are the emission coefficients.

B. CONSTRAINTS MODELLING

Both economic and emission dispatch models possess several system associated constraints that need to be satisfied in entire dispatch operation. These are due to machines manufacturing and operational limitations. Mathematical representation of these constraints are as follow.

1) GENERATION CAPACITY AND RAMP-RATE LIMITATIONS

To ensure optimal dispatch, each thermal power generator must maintain an active power output within its own power limit range, which is typically between its upper and lower power capacities. Power units are subject to ramp-up/ramp-down restrictions to reduce unintended power output oscillations between two adjacent instances. Mathematically, they can be represented as follow.

$$\begin{aligned} &P_{k,\tau}^{\min} \leq P_{k,\tau} \leq P_{k,\tau}^{\max}, \\ &P_{k,\tau} - P_{k,\tau-1} \leq RU_k, \\ &P_{k,\tau-1} - P_{k,\tau} \geq RD_k. \end{aligned} \tag{5}$$

2) LOAD DEMAND

Each interval's total generated power must be sufficient to meet the energy demand for a specified time period. In this study, the three types of loads, namely the demand load $P_{D,\tau}$, PEVs load $P_{PEV,\tau}$, and overall power system losses $P_{losses,\tau}$ for time instance τ are considered.

$$\sum\nolimits_{k=1}^{NU} P_{k,\tau} = P_{D,\tau} + P_{EV,\tau} + P_{losses,\tau}. \tag{6}$$

3) FORBIDDEN OPERATION REGIONS (FOR)

Thermal power plants also include some mechanical operations, such as the regulation of steam valves and the vibration of the turbine shaft. Using these mechanisms, the machines are able to operate within certain operating limitation regions. When these regions are violated, serious system contingencies can occur. Mathematically it can be represented as follows.

$$\begin{aligned} P_k^{\min} &\leq P_k \leq P_{k,1}^{D}, \\ P_{k,\tau-1}^{U} &\leq P_k \leq P_{k,\tau}^{D}, \\ P_{k,nz}^{U} &\leq P_k \leq P_k^{\max}, \\ \tau &= 2, \ldots, nz. \end{aligned} \tag{7}$$

4) SPINNING RESERVE

The symbol S_k represents the k^{th} spinning reserves (SRs) contribution, $S_{R,full}$ reflects the full SRs criterion, S_k represents the maximum SRs contribution for k^{th} unit. Mathematically, SRs can be modeled as

$$\sum\nolimits_{k=1}^{NU} S_k \geq S_{R,full}. \tag{8}$$

III. PEVs POWER DEMAND AND CHARGING SCENARIO

PEVs are recognised as the unconventional electric loads due to their manufacturing hardware circuit complexities, as compared to the traditional domestic and industrial loads. The use of synchronous charging for household purposes with a capacity of 0.02 MW and fast charging for industrial purposes with a capacity of 0.2 MW (turbochargers) can be accounted, which are primarily used by PEVs. This will cause substantial rising spikes in the daily system demand load curve. By appropriate scheduling of thermal power stations and PEVs, these cascading effects on the daily demand curve are preventable. Four different charging cases are examined and taken from [79] and [88]. The detailed charging mechanisms for PEVs are as follow.

A. ERPI CHARGING CHARACTERISTICS FOR PEVs

To assess and examine the effect of PEVs owner behaviour on the energy grids, an EPRI charging profile is selected [79]. EPRI is a non-profit research organization founded in 1972, and it is one of the leading global organizations supporting energy production planning and research on power operation. EPRI compiles a profile of PEVs charging schemes by taking into account the environmental aspects and assesses greenhouse gases emission. The charging profile probability distribution for PEVs by ERPI is provided in Table 1, and it is found that more then sixty percent of energy is consumed in seven hours of time slot [89].

TABLE 1. EPRI charging scenarios of EVs.

Time	Probabilities					
01:00-06:00	0.1	0.1	0.095	0.07	0.05	0.03
07:00-12:00	0.01	0.003	0.003	0.013	2.1	0.021
13:00-18:00	0.021	0.021	0.021	0.01	0.005	0.005
19:00-24:00	0.016	0.036	0.054	0.095	0.1	0.1

B. OFF-PEAK CHARGING CHARACTERISTICS FOR PEVs

Based on the expected consumption of lithium-ion powered automobiles, this method examines charging instances of off-peak. The probability-based allocation for each 60 minutes during the off-peak period is shown in Table 2. This configuration achieves 3 recharge stages of lithium-ion batteries by providing around 18.5% of the power between 23:00 and 02:00 hours, approximately 9% of the power between 02:00 and 04:00 hours, and any leftover power until 06:00 hours. This is an ideal situation because, in addition to the eight hours allowed for charging, electric vehicles are not permitted to be charged during other hours [90].

TABLE 2. Off-Peak charging scenarios of EVs.

Time	Probabilities					
01:00-06:00	0.185	0.185	0.09	0.09	0.04	0.04
07:00-12:00	0	0	0	0	0	0
13:00-18:00	0	0	0	0	0	0
19:00-24:00	0	0	0	0	0.185	0.185

C. PEAK CHARGING CHARACTERISTICS FOR PEVs

This profile is continuous recharging of lithium-ion powered automobiles, having 3 loading rates for the power sources of electric vehicles during peak hours. Table 3 presents the probabilistic distribution at peak hour. It is a serious case comparison to prior situations, since electric vehicles require energy between 13^{th} and 20^{th} peak hours. The rate of charge and times for this case are in-line with [91].

D. STOCHASTIC CHARGING CHARACTERISTICS FOR PEVs

The stochastic charging profile of PEVs is used by enabling charging uncertainties. We consider quick or instant charging of an immediate vehicle at an irregular time frame of all

TABLE 3. Peak charging scenarios of EVs.

Time	Probabilities					
01:00-06:00	0	0	0	0	0	0
07:00-12:00	0	0	0	0	0	0
13:00-18:00	0.185	0.185	0.185	0.185	0.09	0.09
19:00-24:00	0.04	0.04	0	0	0	0

day long in the stochastic charging scenario of PEVs. By a margin of 5%, the random probability distribution shows the normal distribution exactly. There are probabilities for the stochastic charge scenario, presented in Table 4 for every hour of the schedule. In all periods, the probability distribution ranges from 1.1 to 9.7 percent for the stochastic charging profile, where state-of-charge (SOC) changes randomly. This research proposes a stochastic charging characteristic to account for PEVs owner behaviour uncertainties. The profiles are adopted from [79] to demonstrate the performance of proposed method under uncertain charging scenarios. More explicit results on uncertain behaviour of drivers can be seen in the work [92]. It is pertinent to mention here that the selected stochastic profile is assumed to be Gaussian as compared to [92].

Figure 1 shows the rates of load demands for each of the four situations. These models take into account the identical proportion of demand in balance for load power $P_{EV,\tau}$. The research problem becomes more complicated and multidimensional by considering the presented scenarios [79].

TABLE 4. Stochastic charging scenarios of EVs.

Time	Probabilities					
01:00-06:00	0.057	0.049	0.048	0.024	0.026	0.097
07:00-12:00	0.087	0.048	0.011	0.032	0.021	0.057
13:00-18:00	3.8	2.2	0.021	0.061	0.032	0.022
19:00-24:00	0.028	0.022	0.055	0.025	0.035	0.082

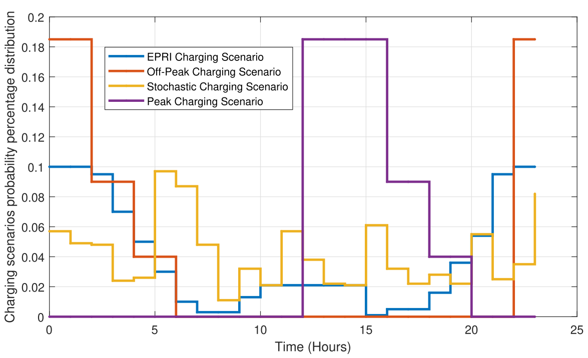

FIGURE 1. Distribution curves for various charging scenarios.

IV. METHODOLOGY FOR OPTIMAL SCHEDULING OF PEVCC

The presented methodology resolves the PEVCC problem by defining an optimal schedule for energy exchange between the batteries of PEVs and the energy grids. Additionally, an economically viable operation for the EEDs is attained, and operational limitations are satisfied. The optimal charging scheduling must minimize the energy costs by avoiding battery discharge on PEVs and by minimizing power loss in EDDs. V. Hayyolalam and A. Pourhaji Kazem [93] proposed a new evolutionary optimization algorithm based on the mating rituals of black widow spiders, which has been applied in many different advanced industrial research problems due to its convenience of use, adaptivity and speed. The efficient black widow optimization (EBWO) is influenced by the black widow spider's unusual sexual dimorphism. This methodology includes a unique stage known as cannibalism. As a result of this phase, the circle excludes species with poor fitness which further leads to early convergence. For the purpose of determining the effectiveness of the proposed method in finding optimal solutions, the EBWO algorithm is evaluated on five different test systems. The EBWO algorithm performs admirably during the exploitation and exploration processes because it ensures rapid convergence and avoids local optimum issues. Furthermore, it should be noted that EBWO has the ability to strike a fine line among exploitation and exploration. In other words, it has the capability of scanning a large area in search of the best optimal solutions. As a result, EBWO is an excellent choice for solving a variety of optimization problems involving a multiple local optima [93].

A. LIFESTYLE STAGES OF BLACK WIDOW

Black widows are atrocious arachnids known for their hourglass-shaped logo on their abdomens, which can be found all over the world in places that are moderate in temperature. The brief life cycle of balck widow is as follow.

1) BLACK WIDOW SPIDER MATTING PROCESS

Black widow spiders are most dangerous to insects and male black widows. After mating, females will sometimes devour their mates. This behaviour is referred to as "black mating" and gives the insect its name. In contrast to other species, black widows have a generally solitary lifestyle throughout the year except for this violent mating behavior. By reducing the attractiveness of females' webs to rivals, the first male enters the web. Females devour males during or immediately after mating and then transfer eggs to their egg blister. Sibling cannibalism is committed by the offspring immediately after hatching. They do, however, spend some time on their mother's webs, where they can eat her. Fit and strong [94] are guaranteed to live through this cycle. The optimal solution is the one that achieves the global optimum of the targeted function.

2) REPRODUCTION AND CANNIBALISM

Sex cannibalism is known to occur among invertebrates, such as tarantulas, arachnids, and praying mantises. It is an enthralling natural phenomenon to observe. By adjusting their approach in response to these factors, males are able to reduce their risk of being killed. It is one of very few significant species where the male actively participates in sexual cannibalism with the female. During mating, the female usually eats the male in two-thirds of the cases. Non-consumed males die shortly after mating from their injuries.

3) SELF-DEVOURING IN SIBLINGS

As soon as their eggs are laid, spider lings can begin to hatch. They can then emerge from the egg blister after about 11 days, though cooler weather can probably slow their development and delaying emergence for months. In the egg sac, they feed on the yolk and moult once after hatching. During the first few days or weeks of life on the prenatal web, sibling cannibalism is most common. They are then carried away by the wind. Cannibalistic behavior is caused by several factors, the most obvious being contest among predation related species and the potential for alternative food sources during periods of low prey availability. Un-selective sibling cannibalism's precise effect on parental fitness may have an influence on the development of parenting practices procreative strategies. Cannibalism lowers the amount of survivor spider lings; however, if survivors have improved body condition, it may also increase parental fitness. It would be expected that cannibalism rates would rise in proportion to family size if cannibalism follows the same patterns as other forms of cannibalism, especially if the potential cannibal is in poor health. Additionally, in some instances, unfertilized spider lings consume their mother slowly. In a matter of weeks, she deteriorates to the point where she can no longer move and is completely devoured.

B. LOGICAL STEPS FOR EBWO

A re-adjustment of the variables in the traditional EDP optimization problem with PEVs acting as an additional unsteady load is required in order to solve the optimization problem successfully. The main structured variable is referred as widow in EBWO, chromosome in genetic algorithms, and particle position in swarm optimization. Each problem variable depicts as widow and fitness of each variable depends on predefined fitness function. EBWO proceeds in the following sequence of logical steps.

1) INITIAL POPULATION

A widow of $1 \times W_{var}$ dimensional array represents the solution to a multi-dimensional EEDs optimization problem considering PEVs as additional load with all associated constraints. Furthermore, the following describes the definition of this array:

$$Widow = [Q_1, Q_2, \ldots, Q_{Wvar}]. \tag{9}$$

A floating-point number is used to represent each value associated with the variable $(Q_1, Q_2, \ldots\ldots..Q_{Wvar})$. A widow's fitness level is determined by applying the fitness function f at $(Q_1, Q_2, \ldots\ldots..Q_{Wvar})$. The expression for fitness can be expressed as follow.

$$Fitness = f(Widow) = f(Q_1, Q_2, \ldots, Q_{Wvar}). \tag{10}$$

The optimization process begins with a starting population of spiders in order to generate a feasible widow matrix of size $Wpop \times Wvar$ that can be used to solve the optimization problem. Next, sets of family members are chosen at random to perform the procreative step of mating, during which the female black widow consumes the male black widow, and the process is repeated.

2) PROCREATIVE

Mating occurs in parallel amongst the pairs, just as nature dictates, with each pair breeding within its own web and without the interference of the others. In the real world, each mating produces approximately thousand eggs, but some of the stronger spider babies survive. For breeding purposes, an array termed alpha must be formed as long as the widow array consists random numbers. After that, descendants are created by employing σ and the following equation, in which m_1 and m_2 are parents and Q_1 and Q_2 are offspring.

$$\begin{cases} m_1 = \sigma \times Q_1 + (1-\sigma) \times Q_2, \\ m_2 = \sigma \times Q_2 + (1-\sigma) \times Q_1. \end{cases} \tag{11}$$

Following this, the babies and their mothers are incorporated into an array and classified according to fitness value. Now, depending on the canabolism rate, the best participants are incorporated into the newly produced population, and all pairs should adhere to the procedure.

3) CANNIBALISM

Cannibalism is a mechanism for population control or for ensuring a participant's genetic contribution. In the life cycle of Black Widow spider, we have three types of cannibalism as follow.

i) First case of sexual cannibalism is when the lady spider widow consumes her companion male.
ii) Sibling cannibalism in which stronger spider lings consume their weaker siblings.
iii) Spider lings consume their materfamilias.

4) MUTATION

Individuals from the population are randomly selected which are mutepop individuals. Each of the selected solutions swaps two variables as depicted in Figure 2, and mutation rate is used to calculate mutepop. The shared solutions are further evaluated in accordance with the specified value in Table 1 to generate the new improved mutated optimal population.

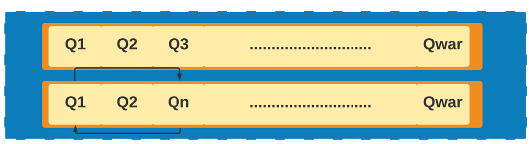

FIGURE 2. Mutation process for survived population.

5) EBWO CONVERGENCE

Similar to other meta-heuristic approaches, three stopping conditions are considered as follow.

i) A pre-configured iteration count.
ii) Maintaining a constant fitness value for the best widow over a number of iterations.
iii) Attaining the prescribed level of precision.

6) PARAMETER CONFIGURATION

The parameters must be adjusted appropriately to enhance the algorithm's success in finding gain advantages. Efficient parameter tuning provides the ability to jump out of any local optimum with greater chances of success while making a comparison between exploitation and exploration. It includes the rate of reproduction (RP), the rate of cannibalism (RC), and the rate of mutation (RM). The norms for these characteristics that were chosen for this article are tabulated in Table 5. RP is the procreating percentage, which indicates the number of individuals participating in reproduction. RC eliminates the inadequate individuals from the available population. Setting the appropriate value for this parameter ensures that the exploitation stage performs well by transferring search agents. RM decides the proportion of individuals who participate in mutation. Maintaining a more delicate balance between exploitation and exploration with the precise value for this parameter is beneficial. This factor can be used to handle the transition of search agents from the global to the local level, as well as to direct them toward the most optimal solution possible. The diagrammatic representation in the form of flowchart for PEVCC is depicted in Figure 3 which shows the step-by-step working of EBWO to solve the optimal scheduling of PEVCC. As a starting point for the proposed EBWO, a population of spiders, each of which demonstrates an optimal solution, is leveraged in-line with the parameter values as indicated in Table 1. As a first phase, these spiders hook up and attempt to produce a new generation that will update the population and randomly select two genes according to the specified procedure of cannibalism and mutation. Again, the population is updated in line with the parameter values, and the process continues until the stopping requirement is fulfilled (that is, all constraints are satisfied and the global optimal point is found). In this work, an evolutionary computing-based approach is presented to solve the complex, nonlinear practical problem in industrial operation of utilities. Compared to [74], the EBWO approach's versatility in dealing with wide range of constraints has also been demonstrated. Furthermore, the CEED model is re-designed by induction of two more practical real-world constraints, namely SRs and FOR. The performance and reliability of presented approach has been evaluated using several charging scenarios for PEVs on economic dispatch, and the results are compared with [74], [79], [80], and [95], and the references therein.

TABLE 5. Controlling parameter setting.

Parameter	Value
Rate of reproduction (RP)	0.61
Rate of cannibalism (RC)	0.42
Rate of mutation (RM)	0.44

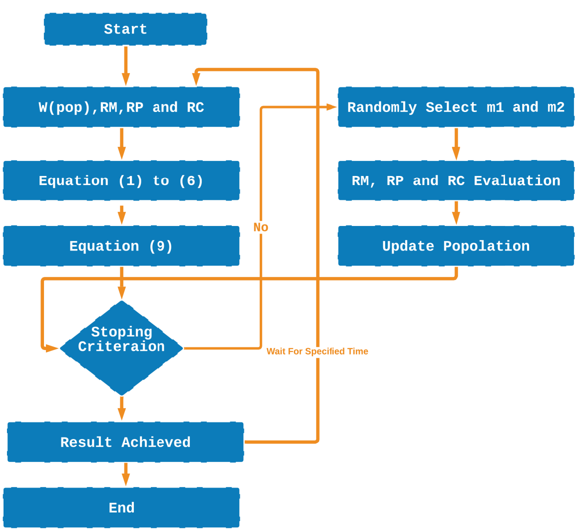

FIGURE 3. Flowchart for dynamic optimal scheduling of PEVCC.

V. TEST AND RESULTS

In this section, we apply EBWO to the benchmark test systems of PEVCC by taking PEVs into account. As the optimal solutions for test systems are known in literature, achieving a specified level of accuracy demonstrates the proposed technique's superiority over other state-of-the-art heuristic techniques. The benchmark test systems of PEVCC that consider PEVs charging under various scenarios make the model high-dimensional and complicated. The constraints causing the complexity of the problem have a direct impact on energy grid stability, daily operational costs, and environmental implications. The reason for choosing EBWO for this complex optimization problem with contiguous constrained restrictions is that it has a very superior efficiency in intelligently identifying the global optimal cost with a high degree of precision and rapid convergence.

Five case studies have been performed to showcase the effectiveness and feasibility of designed scheme for real-world power system applications. The EBWO was simulated for the dynamic CEED responses and the optimised cost of fuel for charging fleet of plug-in electric vehicles under various scenarios was compared to advanced heuristic approaches. The required time analysis was carried out on a Lenovo notebook equipped with an Intel celeron (R) N2940 CPU running at 1.83GHz and 4.0 GB of RAM, with MATLAB version R2017b. The experimental layout of case studies is depicted in Figure 4 which consists of three linked blocks. The first block is problem formulation block where two highly conflicted objective functions along with the system constraints are modeled into single objective function with the help of scaling weights. The second block represents the working strategy of EBWO along with algorithm parametric values, and it will generate the best optimal values of given problem by satisfying the all constraints and fed it to energized load line represented in block three. All dynamic loads are considered for attaining optimal fuel cost price and emission under system constraints such as valve-point loading effect, transmission losses with additional dynamic load of PEVs charging. The brief system description of case studies is as follow.

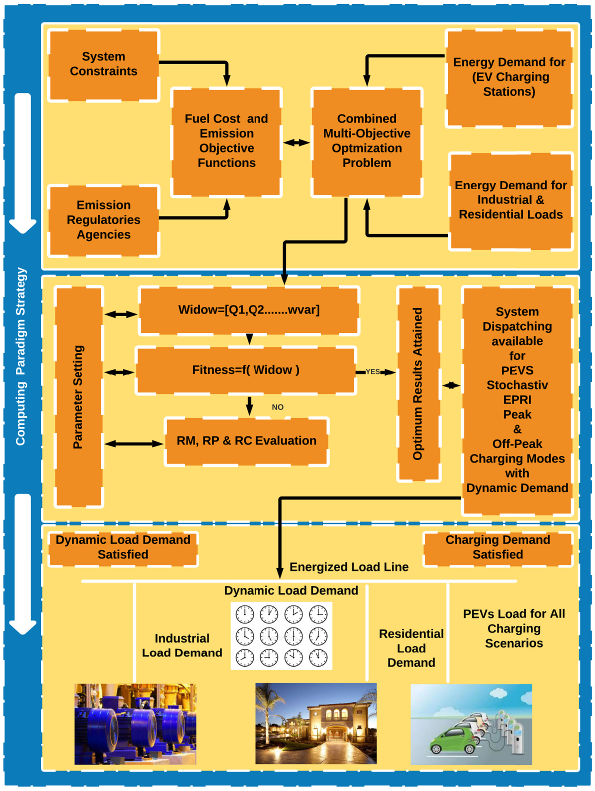

FIGURE 4. Experimental layout of the formulated problem, algorithm, and charging load of PEVs with other loads.

i) Case Study-I: Five units test system with VLEs and transmission losses without considering charging scenario of PEVs.
ii) Case Study-II: Five units test system with VLEs and transmission losses by considering four charging scenario of PEVs.
iii) Case Study-III: Five units test system of dynamic emission dispatch, VLEs and transmission losses by considering charging scenario of PEVs.
iv) Case Study-IV: CEED model with VLEs and transmission losses by considering charging scenario of PEVs.
v) Case Study-V: Large-scale system with 15 units of dynamic economic dispatch by VLEs and transmission losses.

Five case studies have been conducted to demonstrate the feasibility of the proposed EBWO algorithm. There is a 5-unit EEDs system, constrained by equations (3)-(6), for demand presented in Appendix B taking into account PEV charging scenarios. The results of these case studies are compared to other advanced methods, including PSO, SA, TLBO, EP, and other hybrid schemes. EBWO outperformed in terms of achieving the best global optimal with stable convergence, as demonstrated by the results. In addition, the effectiveness of the proposed EBWO is not restricted to smaller test systems, as demonstrated by Case Study V. This case study focuses on a 15-unit system with rigid system constraints. The numerical simulations demonstrate that the proposed EBWO achieves a global optimum solution regardless of a large search space in a shorter amount of time than other advanced hybrid methods reported in the literature, including SL-TLBO, w-PSO, PSO-CF, DE, e-TLBO, m-TLBO, and MAFRL.

A. CASE STUDY-I

The cost coefficient data for dynamic economic dispatch of five units is taken from [96]. The EBWO approach is capable of generating powers of all committed units optimally for 24 hours, as illustrated in Figure 5. The result is compared to the previously used approaches and is shown in Table 6 and Figure 6. The statics obtained through EBWO has a lower fuel dispatch cost than several other techniques such as SA, PS, EP, PSO, SL-TLBO, and MAFRL [74] reported in the literature.

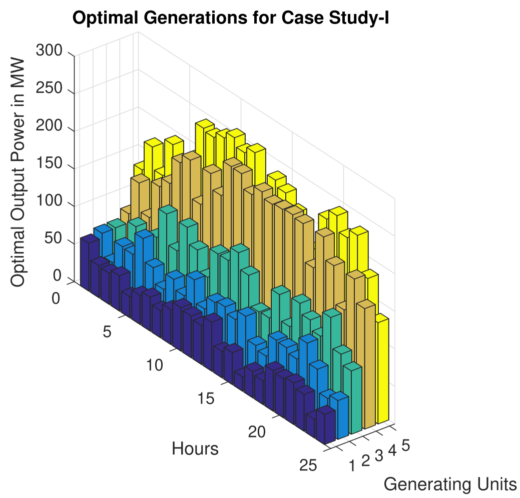

FIGURE 5. Best dynamic generation of all committed units for Case Study-I.

TABLE 6. Fuel dispatch cost ($/day) comparison for Case Study-I.

Approach	Fuel Cost ($/day)	Approach	Fuel Cost ($/day)
SA	4.7356e4	PSO	4.4253e4
PS	4.6530e4	SL-TLBO	4.4119e4
EP	4.6777e4	MAFRL	4.3647e4
-	-	EBWO	34884

B. CASE STUDY-II

This case study takes into account all charging load profiles such as ERPI, off-peak, stochastic and peak for PEVs,

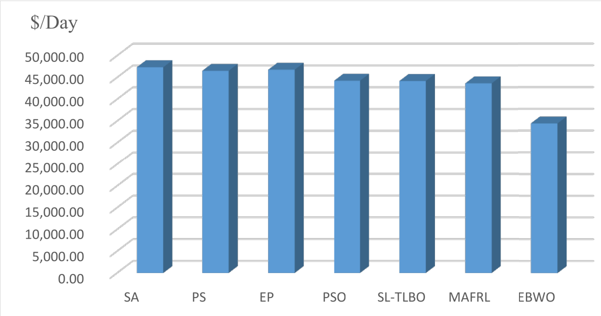

FIGURE 6. Fuel dispatch cost ($/day) comparison for dynamic ELD without PEVs for Case Study-I.

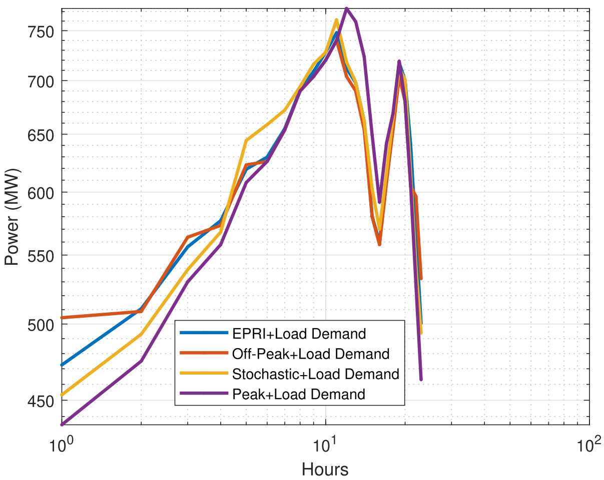

FIGURE 7. Load profiles for charging PEVs in a 5-unit system.

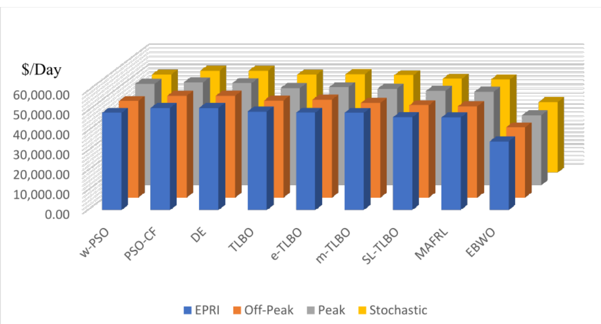

FIGURE 8. Fuel dispatch cost ($/day) comparison for dynamic ELD with PEVs for Case Study-II.

as well as a 5-unit system for the dynamic ELD problem. The 5-unit system is used to simulate 3×10^3 multiple kinds of PEVs to account for the load imposed by PEVs on entire grid. There are three different types of PEVs: low-hybrid PEVs with 15 kWh storage capacity, middle-hybrid PEVs with 25 kWh storage range, and pure hybrid PEVs with 40 kWh storage range. These are proportioned at 45, 25, and 30 percent, respectively, with all PEVs are assumed to have a 50 percent SOC. The cumulative power demand of PEVs for charging the batteries under various charging scenarios from power delivery grids for 24-hours is computed as follow: $P_{EV,\tau} = 30 \times 1000 \times (15 \times 45\% + 25 \times 25\% + 40 \times 30\%) \times 0.5 = 375$ MW. Figure 7 illustrates the charging load profiles for the PEVs strategy. It is clear from the plot that the demand for electricity increases all through EPRI and peak charging, which occurs among 12:00 and 05:00. During the hours of 06:00–09:00, a new sub-peak can be observed in the stochastic charging profile as indicated by the yellow line. Table 7 and Figure 8 show a comparison of the results obtained using different techniques. When it comes to charging profiles, the EBWO significantly outperforms all of the other methods. Additionally, as shown in Figure 8, EBWO has been compared for the charging duration of all PEVs, and it has been found that the lowest production cost is attained during the EPRI charging slot, with 35,219.00 dollars per day being the lowest. The highest cost of production is noticed during the off-peak charging slot, with a daily cost of 38,415 dollars. The cost of operation during the peak charging slot is 37,735.73 dollars per day, which is higher than the cost of dispatch during the stochastic charging intervals (37,488.004 dollars per day).

TABLE 7. Fuel cost ($/day) comparison for PEVs and dynamic economic dispatch Case Study-II.

Approach	EPRI	Off-Peak
w-PSO	49,004.13	48,587.97
PSO-CF	51,482.18	51,231.77
DE	51,457.32	51,238.97
TLBO	49,649.47	48,884.45
e-TLBO	49,049.49	49,306.12
m-TLBO	48,974.99	47,656.89
SL-TLBO	46,770.71	46,508.86
MAFRL	46,640.80	45,915.95
EBWO	35,219.00	38,415.29
Approach	**Peak**	**Stochastic**
w-PSO	50,875.78	49,333.11
PSO-CF	51,682.02	49,333.11
DE	51,310.22	51,292.57
TLBO	48,775.31	51,283.18
e-TLBO	49,270.68	49,292.38
m-TLBO	48,459.70	49,549.59
SL-TLBO	47,367.17	48,970.59
MAFRL	46,940.24	47,158.86
EBWO	37,735.73	37,488.004

C. CASE STUDY-III

Rather than considering economic dispatch, dynamic EEDs is taken into consideration for this case study. The PEVs charging scenarios from Figure 7 are used again here, with the same system restrictions and SOC. With all four charging loads scenarios, dynamic environmental dispatch was evaluated, and comparisons were made with the recently applied approaches such as weighted particle swarm, constriction factor particle swarm, teaching learning-based, dragon fly, elitist teaching learning-based, modified teaching learning-based, self learning teaching learning-based and multi-agent fuzzy reinforcement learning optimizations. Table 8 and Figure 9 demonstrate the results of the comparative analysis. When using EBWO, it can be seen in Figure 9 that the stochastic charging profile emits less air pollution (17265.91 lb/Day), whereas the maximum air pollution (18662.20 lb/Day) is produced by the peak charging profile.

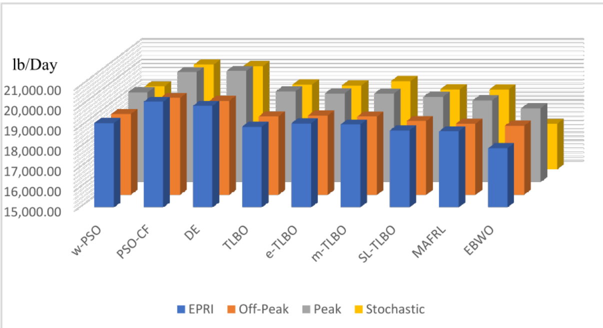

FIGURE 9. Emission dispatch (lb/day) comparison for PEVs and dynamic economic dispatch Case Study-III.

TABLE 8. Emission dispatch (lb/day) comparison for PEVs and dynamic emission dispatch Case Study-III.

Approach	EPRI	Off-Peak
w-PSO	19,189.83	18,998.30
PSO-CF	20,232.49	19,794.18
DE	20,030.88	19,658.45
TLBO	19,002.82	18,887.37
e-TLBO	19,170.59	18,930.36
m-TLBO	19,112.78	18,879.95
SL-TLBO	18,820.78	18,659.24
MAFRL	18,770.84	18,524.80
EBWO	17,070.321	18,354.06
Approach	**Peak**	**Stochastic**
w-PSO	19,443.99	19,112.25
PSO-CF	20,440.12	20,183.56
DE	20,493.63	20,109.08
TLBO	19,483.80	19,195.84
e-TLBO	19,390.75	19,154.89
m-TLBO	19,379.09	19,369.38
SL-TLBO	19,227.18	18,963.69
MAFRL	19,050.75	18,955.54
EBWO	18,851.50	17,874.00

D. CASE STUDY-IV

The CEED model is taken into consideration for this case study, and the PEVs charging scenarios in the case study are also considered with the same system constraints and SOC as in the case study-III. EBWO was used to evaluate dynamic CEED for all four charging loads of PEVs and to compare them to the previously applied techniques such as weighted particle swarm, constriction factor particle swarm, teaching learning-based, dragon fly, elitist teaching learning-based, modified teaching learning-based, self learning teaching learning-based and multi-agent fuzzy reinforcement learning. Table 9 and Figure 10 contain the comparison results. As illustrated in Figure 10, peak charging profile emits 24,934.20 lb/day of pollution, while off-peak charging profile emits 23,178.20 lb/day.

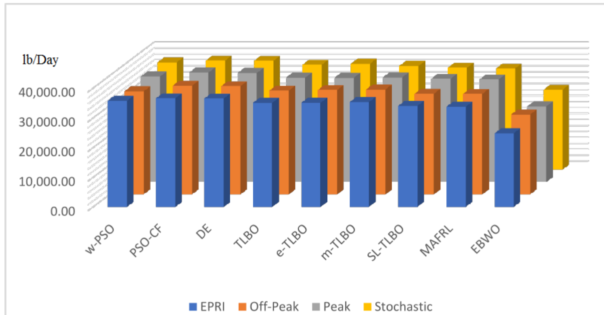

FIGURE 10. Emission dispatch (lb/Day) comparison for PEVs and dynamic EEDs Case Study-IV.

TABLE 9. Emission cost (lb/Day) comparison for PEVs and combine dynamic EED Case Study-IV.

Approach	EPRI	Off-Peak
w-PSO	35,785.15	34,705.22
PSO-CF	36,611.46	36,601.88
DE	36,534.69	36,421.38
TLBO	35,037.04	34,959.16
e-TLBO	35,064.55	35,167.21
m-TLBO	35,300.92	35,355.49
SL-TLBO	33,998.31	33,924.62
MAFRL	33,740.25	33,875.60
EBWO	24771.00	23178.20
Approach	**Peak**	**Stochastic**
w-PSO	35,514.07	36,022.33
PSO-CF	36,814.66	36,632.76
DE	36,657.76	36,581.62
TLBO	35,112.58	35,269.76
e-TLBO	35,048.14	35,654.87
m-TLBO	35,162.68	34,857.65
SL-TLBO	34,731.92	34,245.83
MAFRL	34,525.45	33,990.87
EBWO	24934.20	23997.24

E. CASE STUDY-V

To further validate the effectiveness of the proposed scheme, a large-scale 15-unit EED task with several charging situations for PEVs is performed over a large time period. In comparison to the previous studies, this case is highly multi-dimensional and complicated. The dispatch cost coefficient data for thermal generators is taken from [97], and the total load demand of power is accounted as 60960 MW. Previous to this case study, a system of five units considered 120 variables that was compact in size. In order to solve the dynamic EED problem, fifteen units are combined to form a complex system with 360 variables. Multiple charging loads for PEVs are taken into account in this case, as well as a fifteen units system for the dynamic ELD problem. For the purpose of allowing PEV loads, a simulation of 90,000 various varieties of PEVs with a fifteen units system is considered. Similar to the five units system, these PEVs are classified into three distinct groups. The state of charge (SOC) of the rechargeable batteries for PEVs is assumed to be 50%. The additional charging load requirement for a twenty-four-hour period is calculated as follows: $P_{EV,\tau} = 90\text{K} \times (15 \times 45\% + 25 \times 25\% + 40 \times 30\%) \times 0.5 = 1125$ mega-watt. The charging load demand profile of PEVs is depicted in Figure 11. The plot clearly demonstrates that the demand for energy rises during peak charging scenario. The results of this study are compared to other existing techniques in Table 10 and Figure 12.

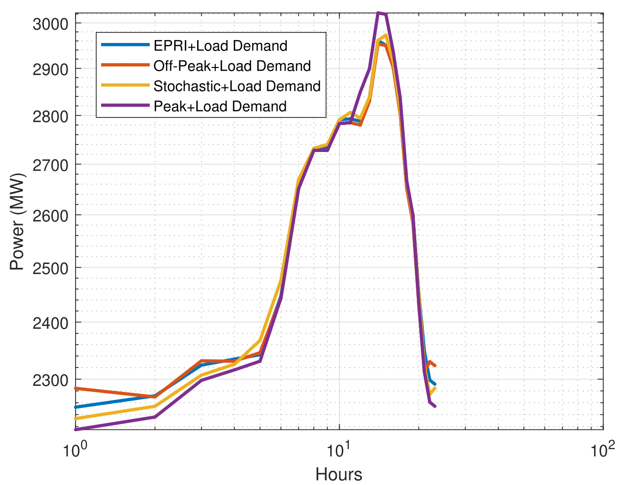

FIGURE 11. Load profiles for charging PEVs in a fifteen-unit system.

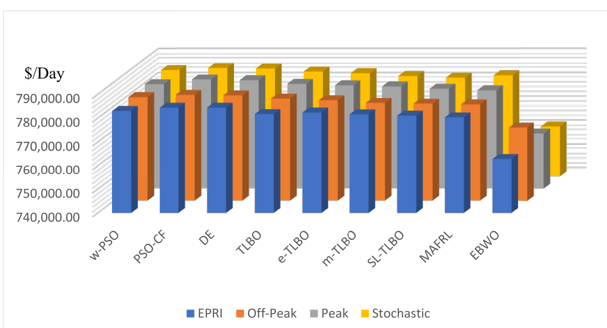

FIGURE 12. Fuel dispatch cost ($/day) comparison for PEVs and combine dynamic EED of 15 units.

While charging under the EPRI scenario, charging during off-peak hours, and charging under stochastic conditions, the EBWO outperforms all other methods. Additionally, with fuel dispatch cost of 767,110.42 dollars per day during the stochastic charging interval, EBWO has the lowest operating dispatch cost. The highest cost of the system is noticed during the off-peak charging interval with a daily cost of 776,850.23 dollars. The dispatch cost of operation during the EPRI charging interval is 767,260.08 dollars per day, which is higher than the cost of operation during the peak charging slot (766,050.11 dollars per day). According to Figure 13, there are detailed solutions for optimal power generation under multiple charging scenarios using the EBWO for a fifteen units complex system. EBWO has not only achieved the lower operating costs for fuel, but it has also dealt with complex non-convex system constraints while maintaining smooth delivery of the PEVs load power demand during the charging periods.

TABLE 10. Fuel dispatch cost ($/day) comparison of PEVs for 15-unit system with combine dynamic EED Case Study-V.

Approach	EPRI	Off-Peak
w-PSO	783,004.14	783,650.51
PSO-CF	784,391.24	784,532.96
DE	784,354.55	784,313.52
TLBO	781,644.49	783,002.47
e-TLBO	782,323.93	782,320.70
m-TLBO	781,562.91	781,179.19
SL-TLBO	781,001.23	780,862.82
MAFRL	780,288.72	780,544.82
EBWO	767260.08	776850.23
Approach	**Peak**	**Stochastic**
w-PSO	783,863.93	784,610.33
PSO-CF	785,851.62	785,491.74
DE	785,512.30	785,273.31
TLBO	784,004.33	783,962.29
e-TLBO	783,383.72	783,280.51
m-TLBO	782,922.74	782,138.87
SL-TLBO	781,961.91	781,459.24
MAFRL	781,315.65	782,415
EBWO	766050.11	767110.42

TABLE 11. Cost and emission coefficients with ramp-rate limitations for Case Studies I–IV.

Unit No.	P_k^{min}	P_k^{max}	a_k	b_k	c_k	RU
1	10	75	25	2.0	0.0080	30
2	20	125	60	1.8	0.0030	30
3	30	175	100	2.1	0.0012	40
4	40	250	120	2.0	0.0010	50
5	50	300	40	1.8	0.0015	50
Unit No.	η_k	δ_k	A_k	B_k	C_k	**RD**
1	100	0.042	80	-0.805	0.0180	30
2	140	0.040	50	-0.555	0.0150	30
3	160	0.038	60	-1.355	0.0105	40
4	180	0.037	45	-0.600	0.0180	50
5	200	0.035	30	-0.555	0.0120	50

TABLE 12. Dynamic load for 24-hours for Case Studies I–IV.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load	410	435	475	530	558	608	626	654	690	704	720	740
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	704	690	654	580	558	608	654	704	680	605	527	463

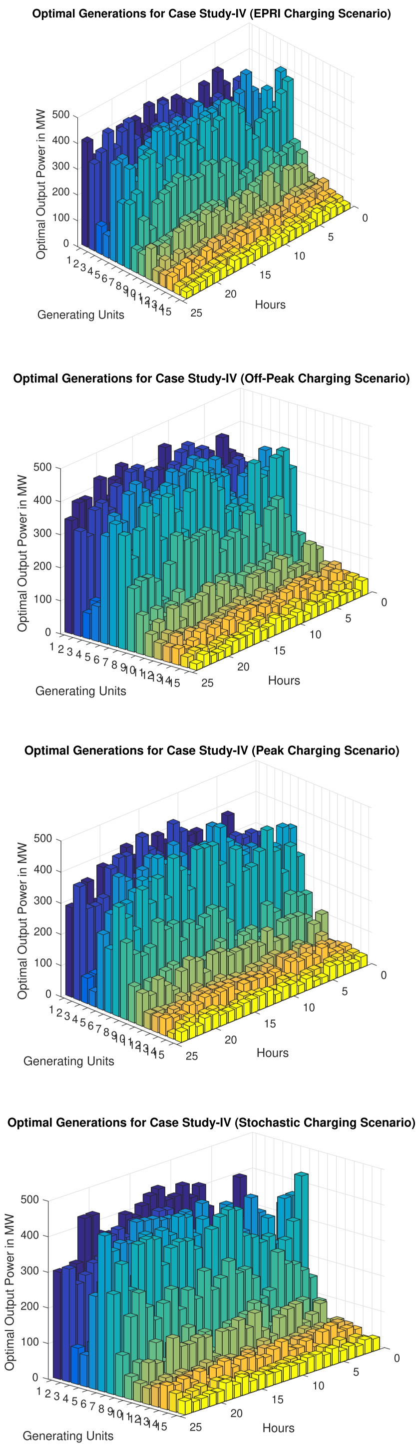

FIGURE 13. Optimal generations of Case study-V for all charging scenarios.

Comparative investigations of experimental outcomes for eleven well-known approaches, namely, SA, PS, EP, PSO,

TABLE 13. Cost and emission coefficients with ramp-rate limitations for Case Study V.

Unit No.	P_k^{min}	P_k^{max}	a_k	b_k	c_k	RU	RD
1	150	455	671	10.1	0.000299	80	120
2	150	455	574	10.2	0.000183	80	120
3	20	130	374	8.8	0.001126	130	130
4	20	130	374	8.8	0.001126	130	130
5	150	470	461	10.4	0.000205	80	120
6	135	460	630	10.1	0.000301	80	120
7	135	465	548	9.8	0.000364	80	120
8	60	300	227	11.2	0.000338	65	100
9	25	162	173	11.2	0.000807	60	100
10	25	160	175	10.7	0.001203	60	100
11	20	80	186	10.2	0.003586	80	80
12	20	80	230	9.9	0.005513	80	80
13	25	85	225	13.1	0.000371	80	80
14	15	55	309	12.1	0.001929	55	55
15	15	55	323	12.2	0.004447	55	55

SL-TLBO, w-PSO, PSO-CF, DE, e-TLBO, m-TLBO and MAFRL-EBWO were conducted in distinct case studies, each with complicated system limitations. Four different charging scenarios of EPRI, off-peak, peak, and stochastic were included in Tables 6 to 10. The results show that in each case study, EBWO has outperformed the other approaches for better cost values. EBWO has also attained the global optimal point with faster convergence during the iterative process regardless of search space.

VI. CONCLUSION AND FUTURE WORK

In this paper, an evolutionary computation-based method, namely EBWO, has been considered to solve the optimal charging coordination of PEVs in energy hubs for various charging strategies, such as EPRI, peak, stochastic, and off-peak, of PEVs by considering a dynamic load. Each scenario is confined by complex energy dispatch system limitations such as generation capacity, load demand, valve-point loading effects, ramp-rate limitations and forbidden operating regions. Additionally, a more complex multi-objective model has also been investigated to examine the environmental effects and emission costs of power plants. Furthermore, four complex charging scenarios for PEVs by taking into account the driver behavior and energy grid peak and off-peak hours are investigated. The proposed scheme determines the optimal charging schedules, optimal cost and optimal emissions in order to avoid operational concerns associated with uncontrolled PEVs charging in IEMS such as grid security and stability. There was no PEVs energy curtailment in any of the scenarios studied herein with regard to system load imbalance, and the charging schedules were able to meet the operational constraints. For the purpose

TABLE 14. Dynamic load for 24-hours for Case Study V.

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load	2236	2215	2226	2236	2298	2316	2331	2443	2657	2728	2783	2785
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	2780	2830	2953	2950	2902	2803	2651	2584	2432	2312	2261	2254

of calculating the effectiveness of the proposed method, evaluations were carried out on small-scale 5-generator systems and large-scale 15-generator systems with a variety of charging scenarios for PEVs. Simulation results showed that the proposed EBWO approach can be an alternate technique for solving both small-scale and large-scale energy/emission dispatch problems, and it outperforms a number of existing techniques in terms of cost function optimization and convergence time. Additionally, the proposed EBWO approach is superior to the other approaches used and has achieved the global minima for all test functions, whereas PSO, SA, TLBO, EP and other hybrid schemes may result in local optimum for high-dimensional space and have low convergence rates during the iterative process. However, this study does not examine the ecologically friendly energy sources, such as wind turbines, solar-powered energy cells, and green-fuel automobiles. This investigation could be expanded to include machine learning-based recharging protocols, battery health management solutions, incentive-based charging frameworks, and sustainable energy-based facilities for charging EVs. Future studies can investigate the effectiveness of the design for multi-powered networks using RETScreen® software. A real-time analysis of the financial management, site feasibility, and risks of integrating renewable energy resources into traditional energy hubs can be provided in upcoming research.

APPENDIX A
See Table 11.

APPENDIX B
See Table 12.

APPENDIX C
See Table 13.

APPENDIX D
See Table 14.

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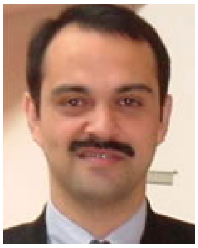

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