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A HYBRID MVO-BMO TECHNIQUE FOR PLUG-IN ELECTRIC VEHICLE CHARGING OPTIMIZATION

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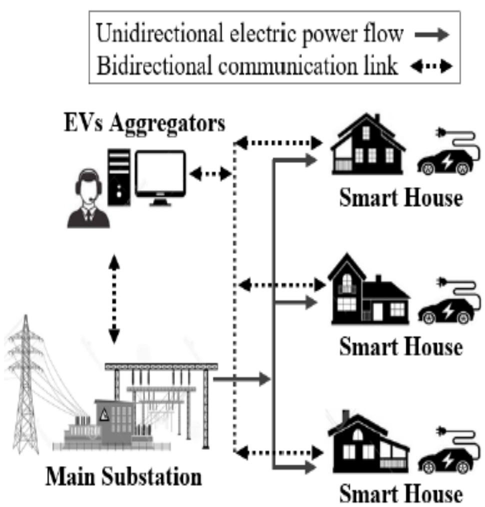
Graphical abstract



Abstract

The electric vehicle (EV) market is expanding rapidly around the world due to technological advancements, decreasing cost of batteries, and supportive government regulations. It is both a challenge and an opportunity for distribution utilities to manage the additional power demand from EVs. Effective and optimal EV charging scheduling strategies are essential to avoid the adverse effects of large EV penetration in the power grid system. This paper proposes an optimal plug-in electric vehicle (PEV) charging scheduling in a distribution grid system using a hybrid algorithm approach that combines a multiverse optimizer (MVO) and also a barnacle mating optimizer (BMO) termed as HMVO-BMO. The optimization model is developed with the objective to minimize the grid power loss, considering overnight home charging. Random arrival times of PEVs are considered and charging is scheduled based on available power demand on the distribution grid. The proposed methodology is demonstrated on the IEEE 33-bus system with different PEV penetration levels. Comparisons are made between three optimization algorithm approaches, namely the standard MVO and BMO, and the proposed HMVO-BMO algorithms. The simulation results demonstrated that the proposed hybrid technique can achieve better and efficient results in terms of system power loss.

Keywords: Electric vehicle, smart charging, hybrid MVO-BMO, distribution system, minimum power loss

Abstrak

Pasaran kenderaan elektrik (EV) berkembang pesat di seluruh dunia disebabkan oleh kemajuan teknologi, kos bateri yang berkurangan dan sokongan kerajaan. Ia merupakan satu cabaran dan peluang untuk pihak utiliti menguruskan permintaan kuasa tambahan daripada EV. Strategi penjadualan pengecasan EV yang berkesan dan optimum adalah penting untuk mengelakkan kesan buruk daripada penembusan EV yang besar dalam sistem grid kuasa. Kertas kerja ini mencadangkan penjadualan pengecasan kenderaan elektrik plug-in (PEV) yang optimum dalam sistem grid pengedaran menggunakan pendekatan algoritma hibrid yang menggabungkan pengoptimum berbilang ayat (MVO) dan juga pengoptimum mengawan teritip (BMO) yang dinamakan HMVO-BMO. Model pengoptimuman dibangunkan dengan objektif untuk meminimumkan kehilangan kuasa grid, dengan mengambil kira pengecasan rumah semalaman. Masa ketibaan rawak PEV dipertimbangkan dan pengecasan dijadualkan berdasarkan permintaan kuasa yang tersedia pada grid pengedaran. Metodologi yang dicadangkan ditunjukkan pada sistem bas IEEE 33 dengan tahap penembusan PEV yang berbeza. Perbandingan dibuat antara tiga pendekatan algoritma pengoptimuman, iaitu standard MVO dan BMO, dan algoritma HMVO-BMO yang dicadangkan. Keputusan simulasi menunjukkan bahawa teknik hibrid yang dicadangkan boleh mencapai hasil yang lebih baik dan cekap dari segi kehilangan kuasa sistem.

Kata kunci: Kenderaan elektrik, pengecasan pintar, hybrid MVO-BMO, sistem pengedaran, kehilangan kuasa minima

1.0 INTRODUCTION

Traditional internal combustion engine (ICE)-based transportation is reported to be one of the top emission sectors, contributing to 37% of the total CO2 emissions in 2021 [1]. Plug-in electric vehicle (PEV) technology introduces a more environmentally friendly and sustainable transportation option with its distinct advantages of being independent of fossil fuel resources and having zero emissions while driving. The adoption rate of PEVs has seen a substantial increase in recent years due to its efficient charging and battery technology, as well as government support for PEV research and incentives for PEV buyers. To accommodate large-scale PEV charging demand, an organized and sophisticated PEV charging infrastructure is essential to avoid overloading and adverse impacts on the power grid network. Among the significant impacts of the uncontrolled PEV charging process are voltage drops, line ampacity violations, transformer overloading, and aging, increased grid peak load demand, and power line losses [2, 3, 4].

Residential electrical loads can be divided into two general categories namely PEV charging load and non-PEV household load. Non-PEV household loads can include daily electricity usage from common appliances such as air conditioners, rice cookers, microwaves, refrigerators, etc. Currently, a significant proportion of PEV charging has been reported to take place at residences [5]. In line with the increasing demand for PEV charging loads on the distribution network, the widespread adoption of PEVs may increase the severity and frequency of impacts on network stability and performance. Without any charging controls, PEVs are charged regardless of the power grid status. They will start charging once plugged into the power grid and finish when their charging needs are met or they are disconnected from the power grid [4]. Since a PEV charging load demand is typically greater than the average non-PEV household load demand [6], this uncontrolled PEV charging condition is likely to increase the non-PEV peak load profile without any limitations. Overloading in a distribution network can result in equipment failures and even worse, it can lead to power outages. Thus, robust PEV charging management is essential to serve the required PEV charging demand.

PEV charging can be classified based on voltage and power level. It has four categories: Level 1, Level 2, Level 3/DC Fast Charging, and Tesla Supercharging [3, 7]. Level 1 and Level 2 are known as slow but economic EV charging mode. Level 1 is practically carried out at night time, when EVs are parked at home. This charging mode is capable to charge most EVs available on the market, taking 8-12 hours to fully charge a PEV using a 120-volt outlet. Level 2 charging utilizes a 240-volt outlet, similar to what is used for a clothes dryer or oven, and can charge an EV in 4-8 hours, depending on the vehicle's battery size and charging capacity. While Level 1 and 2 type of chargers utilize single-phase system, Level 3 chargers are using three-phase system for fast charging scheme. Level 3/DC Fast Charging uses a 480-volt direct current (DC) power source and can rapidly charge a PEV to 80% in just 30-60 minutes. However, these charging stations are not as widely available as Level 1 and Level 2 options, and are usually found at public charging stations or facilities owned by some EV manufacturers. Tesla Supercharging is a proprietary charging network designed specifically for Tesla vehicles. Home charging is typically operated at Level 1 and Level 2 options using the standard charging port and connector based on the SAE Electric Vehicle Conductive Charge Coupler Standard (SAE J1772) [8].

Smart PEV charging control can be implemented based on different aspects and perspectives [3]. There are two main approaches for PEV charging scheduling, namely centralized and decentralized charging which has been extensively discussed in the literature [9]. Both charging schemes are controlled by an agent called an aggregator. An aggregator is an intermediary between PEV customers and the distribution system operator (DSO), which collect necessary data from these two parties and optimally fulfills the dynamic PEV charging demand without compromising network stability [10]. The aggregator plays a key role in scheduling the EV charging process to ensure mutual benefits for both the DSO and PEV customers. Control algorithms are designed and implemented in the aggregator based on control objectives, and network constraints [11]. The centralized approach is able to provide full support of ancillary services and systematically scheduled charging for large-scale PEV populations. However, it has a higher computational complexity due to the handling of large amounts of data [12]. According to [13], this approach requires numerous conditions to schedule charging loads, leading to limited flexibility. [13] also proposed a method to reduce the computational complexity in a centralized PEV charging control framework based on a two-stage hierarchical optimization structure.

In a decentralized or distributed charging control system, individual PEV customers have decision-making power regarding their charging. This empowers customers, but it may not result in an optimal solution for the distribution network as the aggregators cannot directly control the charging activities. They can only influence the customers' charging behavior by offering incentives through dynamic electricity pricing schemes [14]. The decentralized scheme is appropriate for low levels of PEV penetration and has limited communication infrastructure needs. However, it has no communication links to the overall network, and thus, the safety margins to maintain operating limits are limited. Also, the reliance on local information prevents the attainment of system-wide optimality [12]. Both centralized and decentralized charging schemes have been developed in previous studies [13, 14], each chosen based on their respective advantages in achieving the desired study objectives. This study implemented a centralized charging scheme to leverage its promising potential of dynamic energy management.

Ongoing research on PEV charging has been conducted worldwide to find the best approach and solution. Different optimization techniques have been proposed in previous studies to achieve various objectives such as reduced charging time, waiting time, reducing power system stress, energy losses, voltage deviations, and the total cost on both sides: the grid operators and the PEV [15]. The quadratic and dynamic programming approaches, presented in [16], are among the first methods for coordinating PEV charging in order to minimize power losses. Trends in recent years have shown an increase in the application of metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), Gravitational Search Algorithm (GSA) and many more because of their advantages over traditional methods [17]. The implemented optimization methods are not only to achieve the desired objective function but also to meet the constraints involving the operation of the network topology, limitations of PEV battery, and also the degree of PEV owners' satisfaction.

The study in [18] presented optimal scheduling of PEV charging based on metaheuristic methods to minimize power loss and voltage deviation with the inclusion of time-of-use (ToU) electrical tariff to minimize the charging cost in residential distribution system. Optimization of EVs charging scheduling in [19] uses GA to reduce the EV owners' energy arbitrage benefit loss and the distribution network power loss. The work conducted in [20] introduced a smart charging algorithm based on Evolutionary Programming (EP) optimization to determine cost saving on the EV owner's part by varying the charging rate. Authors in [21] also introduced a smart charging scheduling algorithm for multiple PEVs incorporating a Differential Evolutionary (DE) optimization technique to find out the optimal total daily cost. Real-time EV charging scheduling was proposed in [22]. This work uses an improved dynamic multi-objective PSO algorithm that requires fewer iterations and has higher computational complexity. EV charging time prediction model based on a machine learning algorithm was developed in [23] and its parameters were optimized using three metaheuristic algorithms namely GWO, PSO, and GA.

While most researchers focus on optimization using a single algorithm solution, some use hybrid techniques which combine two or more algorithms in order to achieve the same objective function. Optimization solution based on the hybrid algorithm has been proven to achieve better results and outperform other competing algorithms. A study in [24] proposed a hybrid technique that combines a Harris Hawk Optimization (HHO) algorithm and an exponential weighted moving average (EWMA) to schedule the EV charging points and select the optimal charging stations. A novel Grey Sail Fish Optimization (GSFO) which is an integration of Grey Wolf Optimizer (GWO) and Sail Fish Optimization (SFO) has been developed in [25] to optimize EV charging schedules. Compared to existing methods, the proposed hybrid algorithm has proven to produce better performance for a large number of vehicles.

Hence, this study proposes a novel hybrid algorithm technique called Hybrid Multiverse Optimizer - Barnacle Mating Optimizer (HMVO-BMO) for a centralized PEV charging scheduling scheme. To the best of the authors' knowledge, this specific technique has not been previously documented in any published research. The objective of this study is to achieve minimum power loss in a residential distribution system (RDS). Results are evaluated by comparing the proposed system using the hybrid algorithm as well as its two basic algorithms.

2.0 METHODOLOGY

This section elaborates on the proposed methodology that includes the system models and assumptions made for this study, problem formulations related to the objective function and constraints applied, details on PEV charging strategies, optimization algorithm structures, and the proposed hybrid algorithm framework.

2.1 System Models

2.1.1 Network Topology

Figure 1 shows an IEEE 33-bus RDS used to evaluate the performance of the proposed PEV charging scheduling and optimization. This network consists of 33 buses and 32 lines. It has a voltage level of 12.66kV, a load size of 3.715MW, and 2.3MVar. The maximum and minimum voltage limits for all buses are considered at ±10%. 32 buses except bus 1 are connected to low voltage (LV) 415V residential feeders. Each residential feeder is assumed to have a maximum of 8 nodes representing houses with populated PEVs. The line and load data of the system are given in [26].

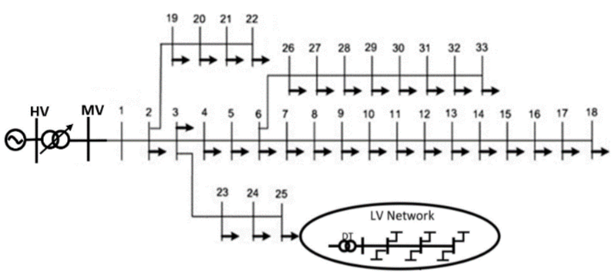


Figure 1 The test network of IEEE 33-bus radial distribution system with 32 buses connected to LV 415V residential feeders

2.1.2 Residential Daily Load Profiles

In this study, the PEV charging load is considered a controllable load while all other household loads are classified as fixed loads. The daily power load profile of a typical Malaysian residential, as depicted in Figure 2, is employed to model the domestic load variations for each household within a 24-hour period, excluding PEV charging. The maximum power consumption of a house is assumed to be on average 2kW with a power factor of 0.9 [27]. The off-peak period is from 9 am to 6 pm, when most people are not at home, as reflected in the load profile. After 6 pm, there is a sudden increase in demand that reaches a maximum at 8 pm, then gradually decreases until midnight. Malaysia is a hot country and consumers often use air conditioners until late at night, high demand continues until midnight.

2.1.3 PEV Charging Profiles and Assumptions

PEV charging profile includes battery capacity (kWh), battery remaining capacity (kW) or SoC, and constant charging demand (kW). In this study, each of the PEVs has a lithium-ion type battery with a capacity of 16kWh. This battery requires approximately 4 hours to be fully charged with its 4kW single-phase onboard charger [3]. However, considering the optimum battery life expectancy, it is recommended to utilize only 80%±10% of the battery capacity [29]. In this regard, each PEV will take up to 2.5 hours to fully charge its battery from 20% initial SoC. All PEVs are charged at a 4kW constant power. Every PEV is assigned its charging schedule based on the 24-hour residential load given in Figure 2 and under constraints of feeder bus voltage magnitude and the transformer capacity. During peak load, the number of PEVs that will be charged is probably smaller. Charging of each PEV will occur continuously or periodically depending on the available load demand at a certain time interval within the defined time period. Users are assumed to target a full charge every time they require to drive their PEV [30].

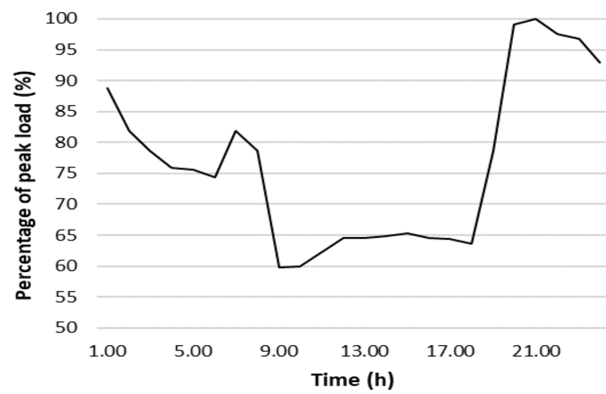


Figure 2 Residential daily load profiles in percentage [28]

2.2 Problem Formulation

A PEV charging scheduling with metaheuristic algorithm approaches is proposed and presented in this study which aims to accommodate all PEV charging requests and at the same time achieve minimum power losses of the test RDS. The developed algorithm is formulated considering a set of system constraints and an objective function aimed to achieve a near-optimal solution.

2.2.1 System Constraints

System constraints are subjected to the following voltage magnitude and power demand for each charging time interval. The voltage magnitude constraints of the distribution system are set within the lower limit, V_{min}, and upper limit, V_{max} ranges corresponding to the grid voltage regulation set by the utilities. The voltage magnitude limits in this study is set at 10% with V_{min} = 0.9pu and V_{max} = 1.1pu of 1-hour rms value [31];

$$V_{\min} \leq V_i(t) \leq V_{\max} \qquad \text{for } i = 1,........,n \tag{1}$$

where i and n are the node number and the total number of nodes, respectively. In order to avoid overload conditions caused by PEV charging, the amount of power consumption at a given time interval must be set not to exceed the maximum demand of the RDS.

$$P_{total}(t) = \sum_{i=1}^{n} (P_{load,i}(t) + P_{PEV,i}) \le P_{\max}(t) \quad (2)$$

$$t = \Delta t, 2\Delta t, ... \quad (3)$$

where $P_{total}(t)$ is the total power consumption at time interval t within the 24-hour period, $P_{load,i}(t)$ is the base load power at time interval t, $P_{PEV,i}$ is the consumed power from PEV at node i and $P_{max}(t)$ is the maximum load demand level that would normally occur without any PEVs during a day. In this study, $P_{total}(t)$ is set at 3715kW corresponding to the load size of the test RDS.

2.2.2 *Objective Function*

In terms of energy management, the strategy of PEV charging scheduling can reduce power losses, with proper planning and optimization techniques. The minimization of power losses is one of the desired goals from the perspective of a DSO and is formulated as in Equations 4 and 5.

$$f_{\min} = P_{totalloss}(t) = \sum_{i=1}^{n-1} P_{loss,ij}(t) \quad (4)$$

$$P_{loss,ij}(t) = R_{ij}(|V_j - V_i||Y_{ij}|)^2 \quad (5)$$

The total power loss, $P_{totalloss}(t)$ is considered at time interval t and $P_{loss,ij}(t)$ is the power loss of the line section between nodes i and j. V_i and V_j are the voltages at node i and j, while R_{ij} and Y_{ij} are resistance and admittance of the line section between nodes i and j.

2.3 PEV Charging Strategy

Different PEV charging strategies will have different impacts on the test distribution system. The following sub-sections will discuss in detail the two methods of PEV charging carried out in this study which is the uncontrolled and optimized PEV charging.

2.3.1 *Uncontrolled Charging*

There are two possible situations for uncontrolled PEV charging. PEVs are instantly charged at full charging power when plugged in during the early evening peak hours or will start charging after a fixed start delay period set by PEV users. Upon plugging in, the charging unit automatically captures the PEV data, including the time of arrival, battery capacity, the SoC at the time of arrival, and the charging rate power. Meanwhile, users can define their estimated departure time and desired SoC at the time of departure through a user interface integrated into the charging unit. For simulation purposes, all PEV users are assumed to require a full charge during departure, regardless of the departure time [30]. The detailed simulation procedure of the uncontrolled PEV charging scheme is presented in a flowchart as shown in Figure 3.

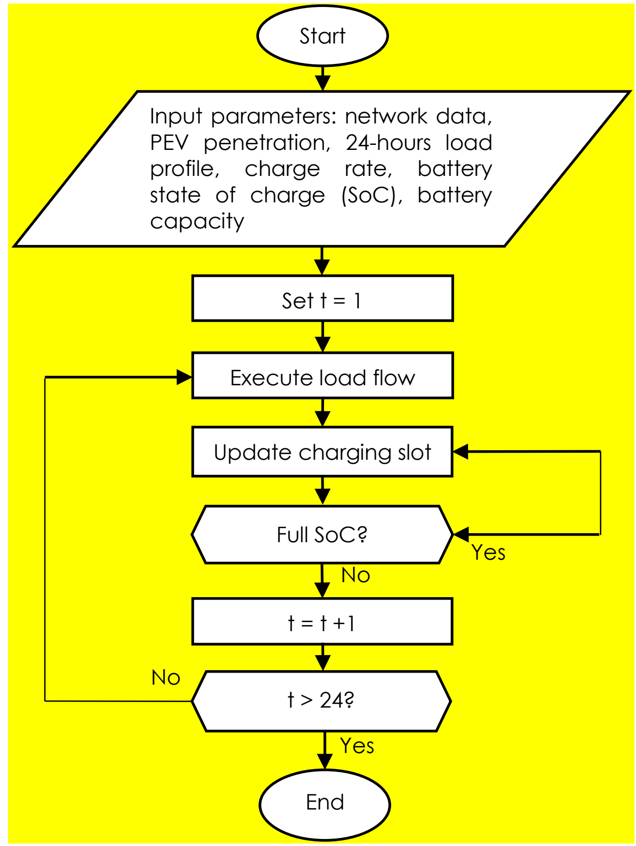


Figure 3 Procedures of the uncontrolled PEV charging

2.3.2 *Proposed PEV Charging Scheduling*

Residential overnight PEV charging from 7 pm to 7 am i.e. a 12 hours period is proposed taking into account the availability of PEV users at home after working hours and returning to their workplaces the next morning. Random PEV arrivals are considered. From the collected data for the PEVs as well as the latest network status, a smart PEV charging scheduling strategy in a distribution grid system with minimum power loss is established. The proposed scheduling framework is shown in Figure 4. The simulation program is developed using MATLAB script files.

There are four different PEV penetration levels being considered which are 0%, 25%, 50%, 63%, and 88% [18]. 0% also indicates that there are no PEVs being plugged and charged in the system and this serves as the reference case. At each time interval, the total charging power of PEVs that are plugged in is initially calculated so as not to exceed the maximum demand limit of the RDS. Each PEV request to charge within a time interval will be initiated as soon as possible based on the power demand available.

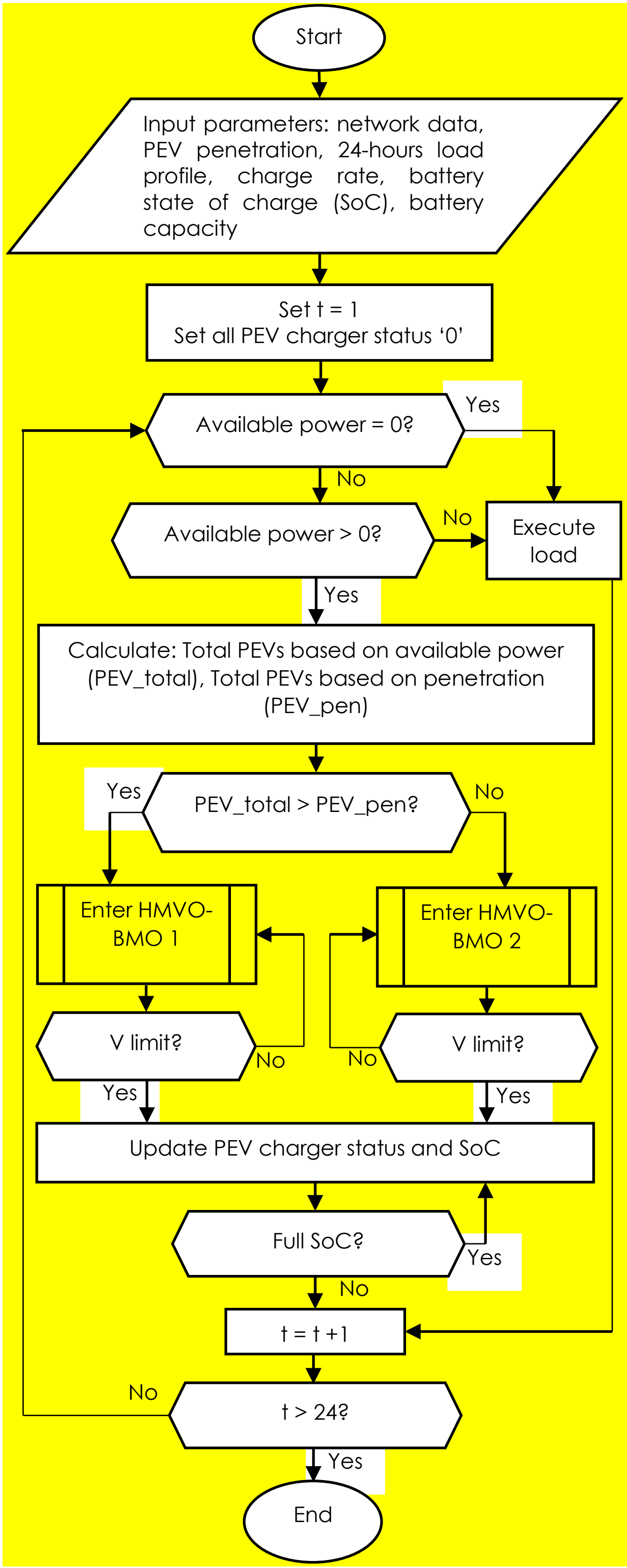


Figure 4 The proposed PEV charging scheduling framework

The first PEV to start charging is also programmed to finish earlier than the PEV that starts charging after. In order to assess the steady-state operation of the distribution system, a load flow analysis is performed using the Newton-Raphson method.

2.4 Optimization Algorithms

Two newly developed metaheuristic optimization algorithms namely Multiverse Optimizer (MVO) and Barnacle Mating Optimizer (BMO) are proposed in order to solve the PEV charging scheduling problem. Additionally, a new hybrid algorithm based on these two algorithm principles is developed. The detailed structure of all algorithms is provided in the following sub-sections.

2.4.1 Multiverse Optimizer (MVO)

MVO is a population-based algorithm based on the concept of the multiverse theory. As implied by the name, Seyedali Mirjalili [32] introduced this approach for solving numerical optimization issues in 2015. In particular, the MVO algorithm is inspired by the three main concepts of the multiverse theory: white holes, black holes, and wormholes. White holes and black holes are used as exploration agents in the search area. On the other hand, wormholes are utilized for exploitation in the local area, which is accomplished after the exploration stage to identify the optimal global solution. The conceptual model of the MVO algorithm is shown in Figure 5.

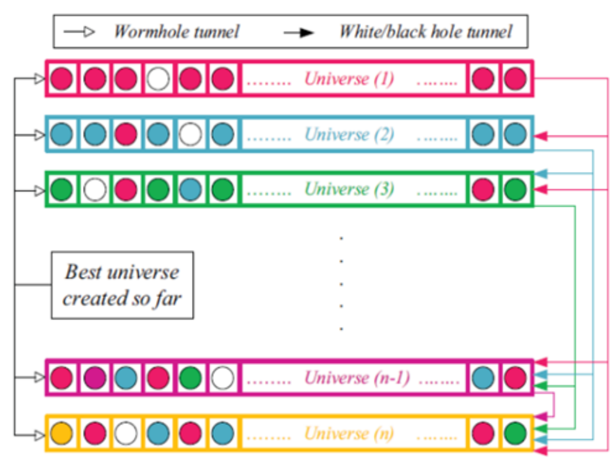


Figure 5 MVO conceptual model [31]

The inflation rate or fitness value determines the objective function for each search agent, where every object and universe within the search agent represents a variable and a potential solution. Universes with high inflation rates may attempt to exchange objects with universes that have low inflation rates. However, for a low inflation rate universe to remain stable, it must receive objects from high inflation rate universes. These steps are repeated in an iterative optimization process and adjusted based on the inflation rates.

The main mathematical model of MVO algorithm is described in Equation 6

$$X_i^j = \begin{Bmatrix} X_k^j, & r_1 < NI(U_i) \\ X_i^j, & r_1 \geq NI(U_i) \end{Bmatrix} \quad (6)$$

where X_i^j represents the j^{th} object of the i^{th} universe, X_k^j represents the j^{th} object of the k^{th} universe which is selected by a roulette wheel mechanism, r_1 is a random value in the range of 0 to 1, *NI* is the normalized inflation rate, and U_i is the i^{th} universe.

The selection of best universe can be derived using the roulette wheel mechanism as in Equation 7

$$X_i^j = \begin{cases} \begin{cases} \left(X_j + TDR \times (ub - lb) \times r_4 + lb\right), & r_3 < 0.5 \\ \left(X_j - TDR \times (ub - lb) \times r_4 + lb\right), & r_3 \geq 0.5 \end{cases}, & r_2 < WEP \\ X_i^j, & r_2 \geq WEP \end{cases} \quad (7)$$

where X_j represents the j^{th} parameter of the best universe obtained, *ub* and *lb* represent the upper and lower bounds, r_2, r_3, and r_4 are random values in the range of 0 to 1, *TDR* and *WEP* are abbreviations for Travel Distance Rate and Wormhole Existence Probability, respectively and both are coefficients. The coefficient WEP is employed to enhance exploitation and TDR is employed to enhance exploitation around the best solution so far. The adaptive formula for both coefficients is given in Equations 8 and 9.

$$WEP = \min + t \times \left(\frac{\max - \min}{T_{\max}}\right) \quad (8)$$

$$TDR = 1 - \frac{t^{(1/p)}}{T_{\max}{}^{(1/p)}} \quad (9)$$

where *t* is the current iteration, T_{max} is the maximum iterations, min and max are the minimum and maximum values of the controlled variables, and *p* represents the exploitation accuracy over the iterations. Higher value of *p* means better exploitation accuracy and faster local search.

The optimization procedure of MVO algorithm starts by creating a set of universes with random numbers. During each iteration, every universe undergoes random theoretical transfer in its variables through wormholes towards the best universe. This process is repeated for a pre-defined maximum number of iterations.

2.4.2 Barnacle Mating Optimizer (BMO)

BMO is a new bio-inspired meta-heuristic algorithm proposed by [33] that mimics the special mating behavior of barnacles. Barnacles are known as micro-organisms having reproductions of mostly hermaphrodites meaning that they have both male and female reproduction organs. They reproduce through a process called broadcast spawning. Through random movements, barnacles search for a partner and once found, they release their sperm into the cavity of their partner's mantle, which is known as natural intercourse. Alternatively, if the sperm released into the seawater fertilizes the eggs of another barnacle, this is known as sperm mating.

Similar to other optimization problems, the first step of the process is initialization. The random initial population can be presented in a matrix form of control variables as defined in Equation 10

$$X = \begin{pmatrix} X_1^1 & \cdots & X_1^{\dim} \\ \vdots & \ddots & \vdots \\ X_n^1 & \cdots & X_n^{\dim} \end{pmatrix}, X_j^i \in [lb_i, ub_i] \quad (10)$$

where *n* denotes the population size or number of barnacles and dim is the number of control variables. Each barnacles of X_i^j is subjected to the upper bound, *ub* and lower bound, *lb* of the i^{th} variable. The initial population is evaluated based on the fitness value and then the sorting process is carried out to obtain the best solution. The selection process of two barnacles is done randomly based on the length of their penises, *pl*. This process is defined in Equations 11 and 12

$$b_D = rand(n) \quad (11)$$

$$b_M = rand(n) \quad (12)$$

in which b_D and b_M define the mated parents that are located within *pl*. For simplification, it is assumed that each barnacle can only be fertilized by one other barnacle only at a time. If the selected parents are out of the range *pl*, the new off-springs are produced using the sperm casting process.

Differs from other evolution-based algorithms, the BMO reproduction process of new offsprings is based on the principle of Hardy-Weinberg [34], which is given in Equations 13 and 14.

$$X_{j\_new}^i = pX_{b_D}^i + qX_{b_M}^i \qquad for\ k \leq pl \quad (13)$$

$$X_{j\_new}^i = rand()\ \text{x}\ X_{b_M}^i \qquad for\ k > pl \quad (14)$$

where *p* is the normally distributed pseudo-random value between 0 and 1, *q* = (1 - *p*), *rand*() indicates a random number in the range of [0,1], X^i_{bD} and X^i_{bM} are the selected parents using Equations 11 and 12, and $k = |b_D - b_M|$. It can be observed from these equations that *p* and *q* denote the proportion of characteristic inheritance from the respective parental barnacles. The equations also demonstrate that BMO algorithm includes both the exploitation process (Equation 13) and the exploration process (Equation 14). Each new offspring is assessed and combined with its parents to control the solution matrix expansion from the population size. Then the sorting process is performed to select the 50% top solution that fits the population size, and the poor results are eliminated.

2.4.3 Hybrid MVO-BMO Algorithm

Hybrid algorithms are commonly employed to achieve high-quality solutions for specific problems by integrating various search strategies from two or more methodologies within the solution space. A new hybrid approach termed as HMVO-BMO algorithm is developed to address the shortcomings of the basic MVO and BMO algorithms and improved the optimal value of the fitness function. The optimal solution is achieved by combining the best strengths of both MVO and BMO in the exploration phase. The final iterative solution from the MVO is made into a good-quality initial population for the BMO. A flowchart of the proposed HMVO-BMO is shown in Figure 6.

3.0 RESULTS AND DISCUSSION

The performance of the proposed optimized PEV charging system using MVO, BMO, and HMVO-BMO methods was compared using the IEEE 33-bus RDS as detailed in sub-section 2.1.1. The distribution network with uncontrolled PEV charging and RDS with optimized PEV charging scheduling was considered as the case studies. Four PEV penetration levels were considered, that is 25% (64 PEVs), 50% (128 PEVs), 63% (160 PEVs), and 88% (224 PEVs). The PEV charging time period spanned from 19:00h until 07:00h with a time interval of 30 minutes, i.e., Δt = 0.5h. The given PEV number by penetration level is the total number of PEVs available for charging in the network at each time interval. The impact of each PEV charging schedule is evaluated in terms of load demand, system losses, and voltage profile.

3.1 Uncontrolled Charging

For this case study, all 32 load buses were accommodated with the same number of PEVs according to the level of penetration. The impact of uncontrolled or random PEV charging on the tested RDS network is shown in Figures 7, 8, and 9. This charging process leads to overloading, increase power loss, and low bus voltage that increases the stress of the RDS.

Figure 7 represents the total system power consumption. It was observed that at all penetration levels, the RDS was overloaded beyond its maximum load capacity of 3715kW. In the initial time interval, the RDS was overloaded during 88% PEV penetration level only. Starting from 19:30h, overload conditions were also observed at PEV penetration levels of 50% and 63%. Meanwhile, the 25% PEV penetration level starts to overload the RDS at 20:00h as the load is approaching peak value around this hour. This overload condition ended at 23:30h for 88% PEV penetration level and at 00:00h for the remaining PEV penetration levels.

The total system power loss in Figure 8 shows that the RDS experienced an excessive power loss even at a low PEV penetration level of 25%. The highest power loss of 307.26kW can be observed at 21:00h for 88% PEV penetration level. The voltage profiles at the system's weakest feeder which is bus 18 are shown in Figure 9. It can be observed that at every level of PEV penetration, there were violations of the voltage constraints established for the tested RDS network.

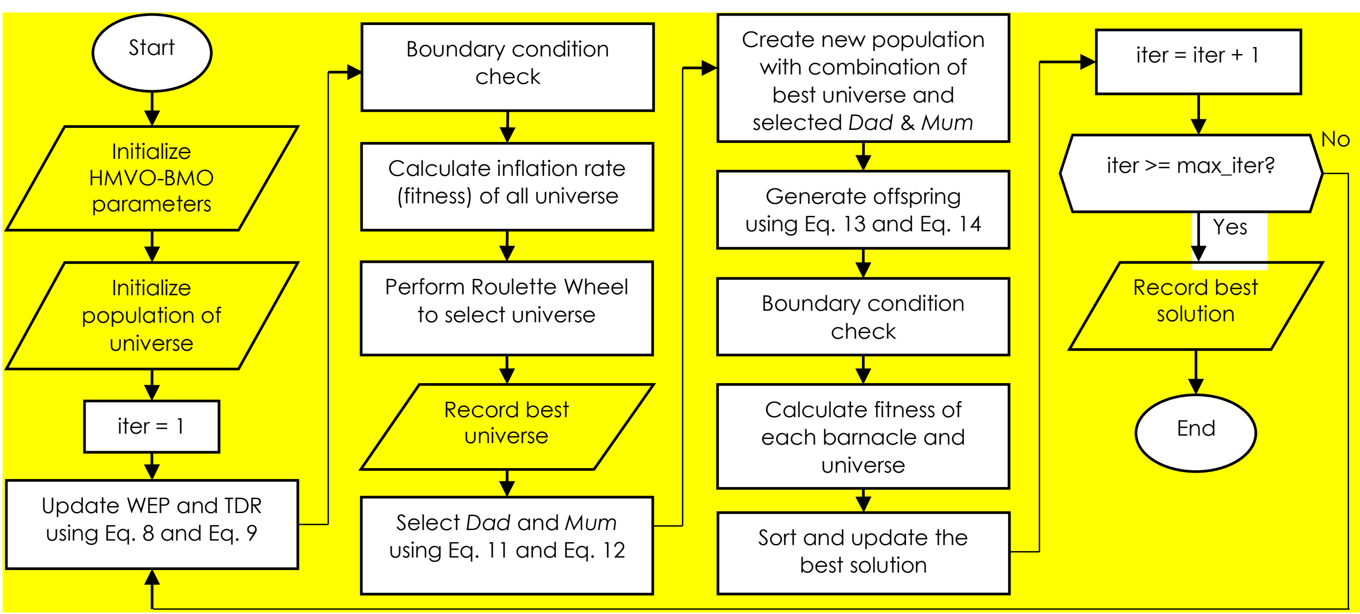


Figure 6 Flowchart of the proposed HMVO-BMO algorithm

The worst voltage drop was recorded at 88% PEV penetration with a magnitude of 0.879 p.u. at 21:00h. For other PEV penetrations of 25%, 50%, and 63%, the voltage at the weakest node was 0.897 p.u., 0.890 p.u. and 0.887 p.u., respectively at the same hour.

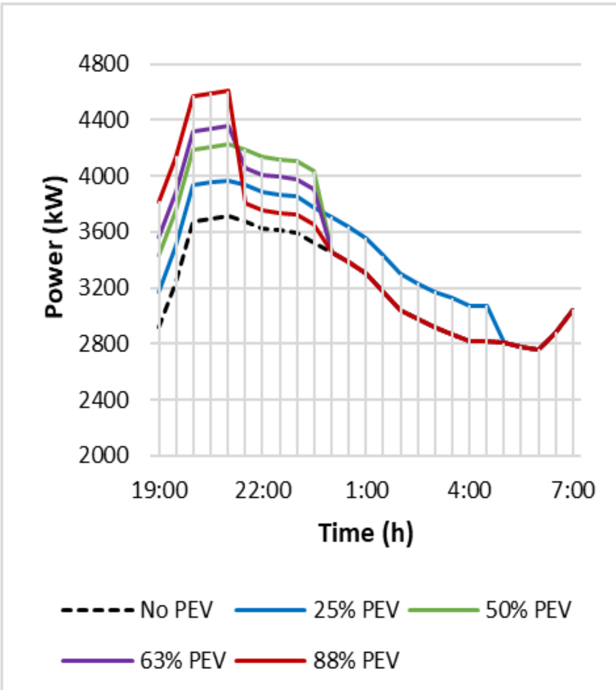


Figure 7 Impact of uncontrolled charging on total power consumption

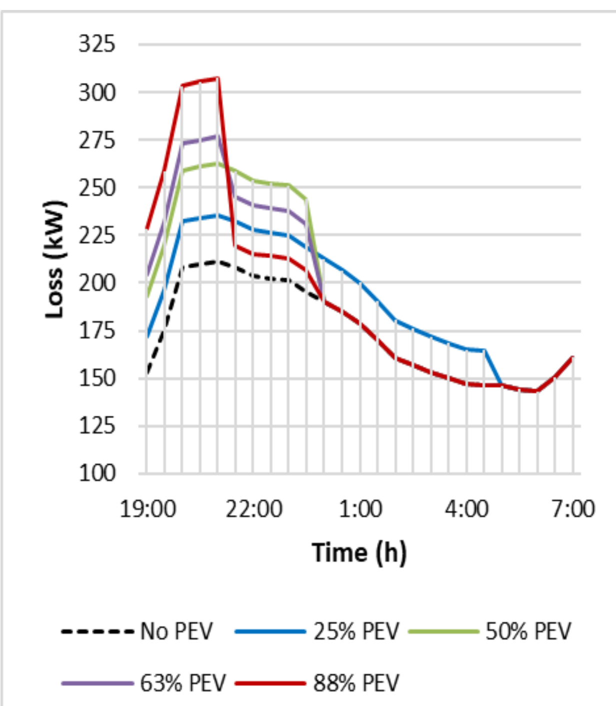


Figure 8 Impact of uncontrolled charging on total power loss

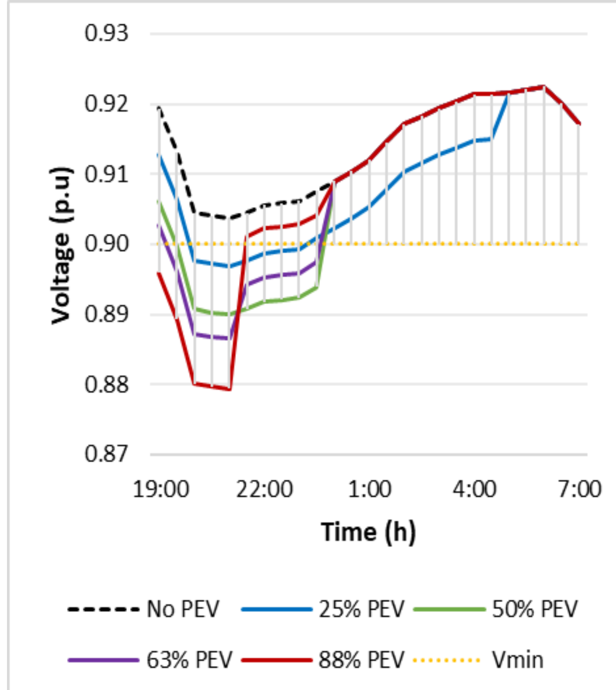


Figure 9 Impact of uncontrolled charging on weakest feeder voltage

3.2 Proposed PEV Charging Scheduling

An optimal PEV charging scheduling was developed to eliminate the adverse impacts of uncontrolled PEV charging. Based on the level of PEV penetration, the number of PEVs allowed to charge in each time interval depends on the power demand available on the RDS when residential load is taken into account. Figure 10 until 12 present the results of total system power consumption, total system power loss, and voltages of the weakest feeder, respectively using the proposed PEV charging scheduling with the HMVO-BMO optimization algorithm.

From Figure 10, it can be observed that at all PEV penetrations, the RDS maximum demand level is not violated. The optimization process will initiate under two conditions: either when there is an inadequate power demand to meet the charging requirements for PEVs, or when the system constraints are violated after considering the PEV charging load. It was observed that the optimization process initiates at 19:00h for 88% PEV penetration level, and at 19:30h for 50% and 63% PEV penetration levels. While for PEV penetration levels of 25%, the optimization process initiates at 20:00h. This process could prevent the occurrence of overload conditions caused by uncontrolled charging, while optimizing the power loss during each time interval. The optimization process ends at 00:00h for PEV penetration level of 25%, and at 01:30h for 50% penetration level. Similarly, at PEV penetration levels of 63% and 88%, the optimization process continues until 02:00h whereby nearly all 8 PEVs per bus are fully charged. This duration excludes 21:00h since at this time interval, the base load from residential has already reached its maximum level. The obtained curves of system power consumption are similar to Figure 10 for optimization using the basic MVO and BMO algorithms.

Figure 11 shows a significant reduction in power loss compared to uncoordinated charging at all levels of PEV penetration. The total power loss reduction for a 12-hour time period compared to uncontrolled charging for penetration levels of 25%, 50%, 63% and 88% is 81.21kW, 152.49kW, 161.39kW, and 174.68kW, respectively. The highest power loss recorded was 213.18kW occurs at 01:30h during 50% PEV penetration level. The voltages of bus 18, which is the weakest feeder of the test RDS are shown in Figure 12. After the application of the proposed HMVO-BMO, it was found that for all PEV penetration levels, the voltage values were within the established limitations.

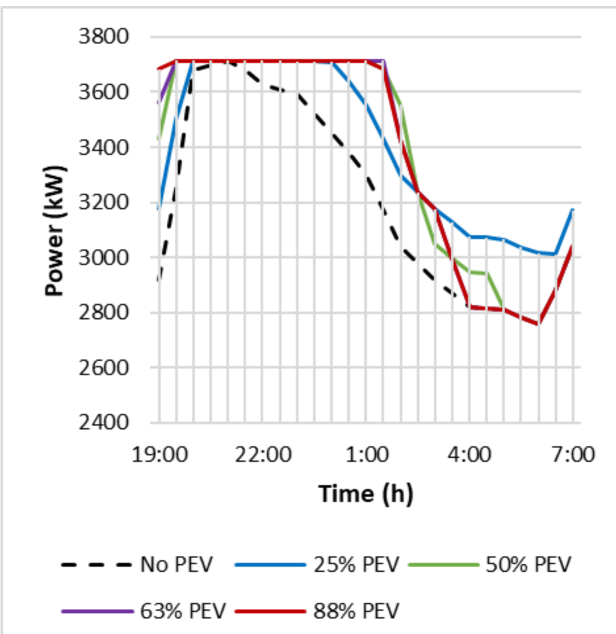


Figure 10 Impact of PEV charging scheduling with HMVO-BMO algorithm on total power consumption

3.3 Power Loss Analysis Comparing Three Optimization Methods

The RDS power loss based on different optimization methods and different PEV penetration levels is observed and compared. The recorded total system power loss in 12 hours for uncontrolled PEV charging and optimized PEV charging using the MVO, BMO, and the proposed HMVO-BMO algorithms are shown in Table 1. In this table, it can be observed that the best results for minimum system power loss were found using the HMVO-BMO methodology. It is noted that there was small difference in power loss between the three methodologies as the optimization involves the best configuration of network buses to charge PEVs over a time interval. There was a difference involving only one bus number and lower power loss results were obtained.

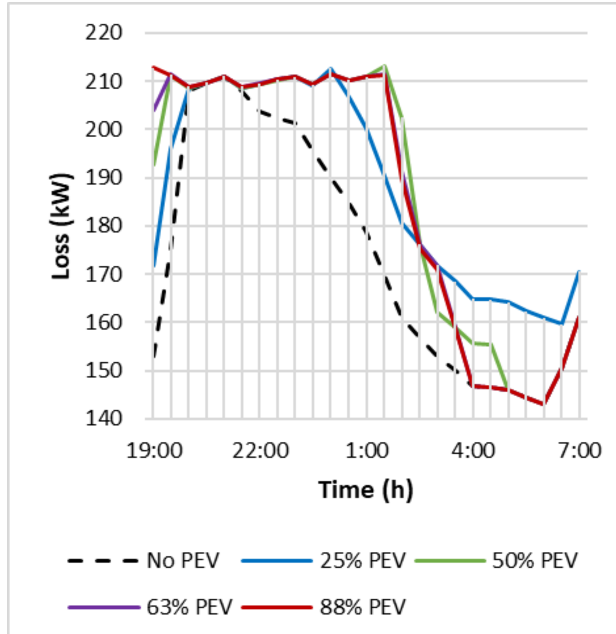


Figure 11 Impact of PEV charging scheduling with HMVO-BMO algorithm on total power loss

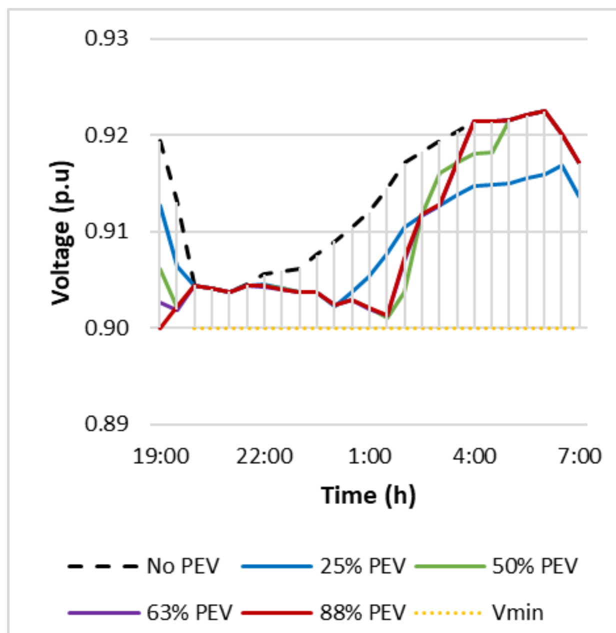


Figure 12 Impact of PEV charging scheduling with HMVO-BMO algorithm on weakest feeder voltage

Table 1 Summary of system power loss for 12 hours (19:00 h until 07.00 h)

PEV Penetration (%)	Total system power loss (kW) for 33-bus network			
	Uncontrolled Charging	Optimal PEV Charging		
		MVO	BMO	HMVO-BMO
25	4781.10	4700.67	4701.61	4699.89
50	4836.24	4684.72	4686.14	4683.76
63	4836.29	4675.30	4677.37	4674.90
88	4853.98	4680.13	4680.95	4679.30

4.0 CONCLUSION

Optimal PEV charging scheduling strategy in a distribution system based on MVO, BMO, and a novel hybrid optimization algorithm termed as HMVO-BMO was proposed in this study. Uncontrolled charging of PEVs causes severe conditions on the grid network. The proposed optimal PEV charging scheduling successfully eliminates the problem. The algorithm schedules PEV charging activities by determining the best combination of network buses with PEV charging which gives the best minimum total power loss in the grid network for each time interval. The total demand consumption, network power losses, and voltage profile of the weakest feeder have been investigated and validated based on four different levels of PEV penetration. The results show that the proposed methods can be used to achieve coordinated PEV charging scheduling as well as the objective function of minimal network power loss even at a high PEV penetration level. The proposed methods also effectively prevent the violation of voltage magnitude and transformer capacity constraints of the test network. A comparison study of the three proposed algorithms shows that the novel HMVO-BMO provided the best results in terms of minimum total network power losses. The algorithms and methods used can be extended to other objective functions, such as improving the voltage profile as well as the operating costs of PEVs and grids.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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