

Multi-Objective Optimization of EV Charging for Cost and Loss Minimization Under TOU Tariff

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Abstract

This study proposes an optimal electric vehicle (EV) charging (OEVC) management methods to minimize electricity costs and energy losses in the distribution system, which arise from the growing demand for EV charging. a multi-objective particle swarm optimization (MOPSO) algorithm is used to solve the OEVC multi-objective optimization (MOO). Additionally, the time-of-use (TOU) tariff is used to coordinate between the distribution system operator and EV users, which can help increase the efficiency of the charging schedule. Monte Carlo Simulation (MCS) is used to model virtual EV user behavior and create EV charging load profiles. The proposed MOPSO-based OEVC approach is verified on the modified IEEE 33-bus distribution test system, using MATLAB software, under both uncontrolled and controlled charging case studies. The simulation results demonstrate that the proposed method optimizes EV charging efficiently, achieving reductions of approximately 7.60% in electricity costs and 28.73% in energy losses compared to the uncontrolled charging case.

Keywords: optimal EV charging (OEVC), multi-objective optimization (MOO), electricity cost minimization, energy loss minimization, time-of-use (TOU) tariff

1. Introduction

Global warming poses a critical threat to ecosystems and human well-being. Many countries aim to achieve net zero emissions (NZE) as the solution under the Paris Agreement, with a key strategy being the transition from internal combustion engines (ICEs) to electric vehicles (EVs). Fuel combustion in ICEs is a major source of CO₂, and studies indicate that widespread EV adoption can reduce emissions by up to 20% [1-2]. Under the most ambitious scenarios, EVs could account for up to 65% of all light car sales globally by 2030, driven by strong policy support, advancements in battery technology, and market expansion in major regions. This projection aligns with the NZE by 2050 Scenario outlined in the Global EV Outlook 2024 [3].

However, the rapid increase in EV adoption also presents significant challenges for electricity grid management. As EV users typically charge their vehicles after returning home, this coincides with peak electricity demand from other daily activities, leading to elevated peak electricity loads. Without proper planning, this can result in significant negative impacts on the grid, such as voltage instability, increased power losses, and transformer overloading. For instance, studies [4] analyzing the impact of uncoordinated EV charging on grid performance, have shown that peak demand can increase by up to 53%. To address these challenges, implementing strategies such as smart charging, time-of-use (TOU) tariffs, and vehicle-to-grid (V2G) technology is crucial for ensuring the sustainable integration of EVs into the energy system [5]. Fig. 1 demonstrates the impact of EV charging on the load profile.

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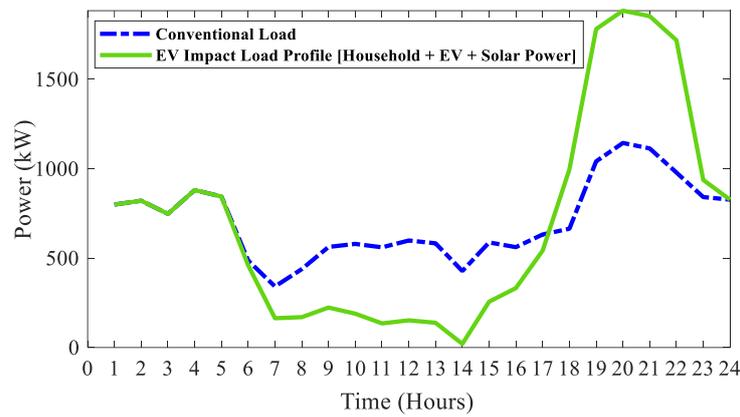


Fig. 1 The impact of EV charging on the load profile

Consequently, many studies are being conducted to find the management approaches to the rapid increase in EV numbers within the electricity system. In [5], an efficient and accurate predictive model for EV charging demand is proposed, specifically designed for use in the management and planning of urban transportation infrastructure. In [6], the authors propose sequential heuristic (SH) and global heuristic (GH) approaches to solve the optimal EV charging (OEV) scheduling problem to minimize charging costs. In [7-8], centralized EV scheduling problems are proposed to minimize grid load imbalance through valley filling. In [9], the optimization of EV charging and discharging primarily aims to decrease energy costs by shifting loads to low-cost periods and regulating power system demand more efficiently.

Various algorithms have been studied and developed to optimize charging scheduling. Heuristic rule-based algorithms have been proposed in [10-11] to handle a variety of scheduling challenges considering variables such as the number of instances, the available limitations, and computational, including the scheduling of EV charging sessions at charging stations while solving an optimal power flow problem. However, heuristic rules are applied to problems with a small number of decision variables and lower computational complexity.

In contrast, metaheuristic algorithms are better suited for handling complicated problems, especially when it comes to scheduling optimization and power system challenges. In [12], the crow search algorithm (CSA) is used to optimize the energy control system and minimize operating costs. In [13], the focus is on minimizing the peak-to-valley difference in grid load and reducing user charging costs, proposing the use of genetic algorithms (GA) for optimal scheduling schemes for electric vehicles. In [14], the particle swarm optimization (PSO) algorithm can be employed to optimize EV charging scheduling to effectively minimize power loss, although it does not account for the uncertainty in user charging behavior. However, in [15], the uncertain behavior of EVs using a Markov decision process, with optimal charging management achieved through the bounded real-time dynamic programming (BRTDP) algorithm. In [16], GA and monte carlo simulation (MCS) are used to minimize distributed generators' investment costs. Adjusting EV users' charging behavior is crucial for optimizing charging schedules for maximum efficiency.

Demand side management (DSM) is an alternative solution for controlling electricity demand, including the demand for EV charging. DSM has been successfully applied in large-scale buildings through various demand response programs, such as real-time demand reduction, load shifting, and energy efficiency enhancement, as demonstrated in real-world case studies proposed in [5]. Dynamic pricing is important for managing conflicting energy demands from EV charging. In [17], it was demonstrated that the dynamic real-time demand electricity pricing mechanism can significantly reduce electricity costs. The TOU considered in [18] was applied for optimal energy scheduling to reduce system costs and minimize CO₂ emissions, utilizing the multi-objective grasshopper optimization algorithm (MOGOA). Meanwhile, [19] introduced a model developed using the learnable partheno-genetic algorithm (LPGA) to determine the optimal EV routes to minimize total distribution costs under the TOU framework.

However, MOGOA is still a relatively new algorithm with limited development and improvements, and LPGA is susceptible to becoming caught in local optima in the absence of a well-thought-out methodology. By contrast, multi-objective particle swarm optimization (MOPSO) is a widely used algorithm with several improved versions, making it highly effective for solving specific problems. MOPSO also has a strong capability to explore solution spaces efficiently and avoid local optima while offering flexibility in various applications. In [20], MOPSO has been used to optimize the power flow. Many studies focus on solving multi-objective scheduling problems, such as [21-22] minimizing grid load imbalance and focusing on reducing EV users' charging prices.

However, many studies primarily target reducing costs for the benefit of EV users. From the perspective of solving scheduling issues to minimize the distribution system operator's (DSO) expenses, this aspect is one of the most challenging issues. In large-scale EV charging, power losses from extensive electricity transmission impose significant challenges that are comparable to other grid impacts. Insufficient electricity to meet rising demand may also force the DSO to procure additional power, often from international sources, which could elevate costs due to fluctuating global energy prices. Moreover, both escalating costs and rising power losses have substantial and interconnected impacts on the grid's sustainability.

Therefore, both issues should be considered simultaneously in any comprehensive optimization strategy. The study in [5] focuses on developing a predictive model to accurately forecast EV charging demand by leveraging advanced deep learning techniques, primarily emphasizing long-term planning and resource allocation for charging station operators. However, it does not address the critical challenges associated with large-scale EV integration into the power grid, such as increased power losses and higher operational costs for DSOs. Meanwhile, this study aims to address this gap by focusing on optimizing EV charging to minimize both electricity costs and energy loss in the distribution system for the benefit of the DSO.

Based on the discussion above, this study proposes an integrated approach for OEVC that uses the MOPSO algorithm to minimize electricity costs and energy losses, achieving a balanced optimization between both objectives. In the methodology presented in this article, dynamic pricing is incorporated by integrating a TOU tariff as a representative example of price-based demand response actively used in Thailand in conjunction with MOPSO. Moreover, the versatility of MOPSO allows adaptation to other pricing schemes, which provides a flexible framework for diverse market conditions. While accounting for the uncertainty in the user charging behavior, the MCS generates EV load profiles based on actual usage data. The proposed MOPSO-based OEVC algorithm was tested on the IEEE 33-bus distribution system using the central Thailand household load profiles. The simulation results show that the proposed OEVC method effectively minimizes electricity costs and energy losses compared to charging profiles generated by MCS.

This study is structured as follows: Section 2 addresses the OEVC problem formulation, Section 3 presents the MOPSO method for solving the OEVC, Section 4 presents the simulation results and discusses the results of the MOPSO base OEVC, and Section 5 presents the conclusions.

2. Problem Formulation

In this section, objective functions are formulated to minimize electricity costs and energy losses. The MCS is used to model EV user behavior and handle the variability resulting from EV user behavior uncertainty. This part will also cover the TOU tariff, which is a time-based program that encourages response to the OEVC scheduling.

2.1. Time of Use (TOU) Tariff

The TOU rate is an electricity rate that represents the cost of generating power over two periods. Electricity costs are calculated based on the user's electricity usage period. As shown in Fig. 2, electricity costs during peak hours (from 9:00 AM to 10:00 PM) are higher than those during off-peak hours (from 10:00 PM to 9:00 AM). Implementing the TOU tariff encourages EV users to adjust their charging times to take advantage of the lower rates.

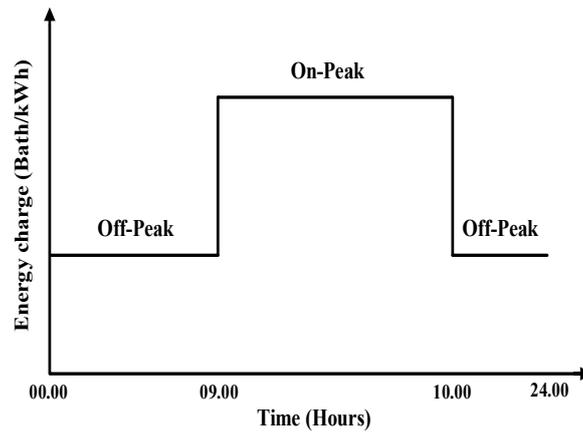


Fig. 2 Typical TOU tariff pattern

2.2. The probabilistic modeling of the EV user's behavior

For the behavior of EV users, MCS is applied to address the uncertainty of EV users' behavior. The random variables considered include the time at which EVs depart from home (T_{edr}), the duration from home to work (T_{htw}), the duration back from work to home (T_{ebh}), and the duration EVs are parked at work without being connected to the grid (T_{eop}). Additionally, the model considers battery capacity and distance. The probability distributions and parameter values used for these variables were derived from empirical studies on real-world EV user behavior in European countries, which investigated travel patterns, parking durations, and charging preferences. These findings provided the basis for determining the means and standard deviations for each parameter, as presented in Table 1 from [23]. The lower and upper bounds of random variables are 0-24 hours. Fig. 3 illustrates the EV user activity model generated using MCS. This model creates an EV charging load profile, which is combined with the household load profile. These inputs and network data are provided to the MOPSO algorithm to solve the OEVC.

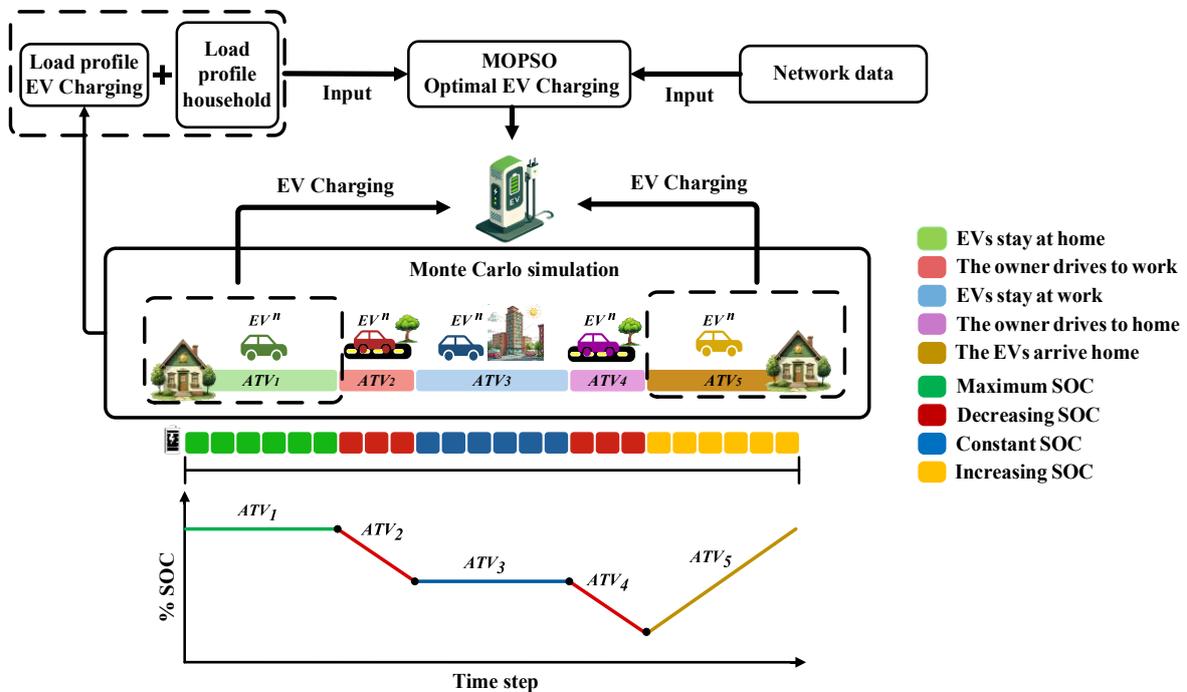


Fig. 3 Framework of MOPSO-based OEVC with probabilistic EV user activity model

Once these random time variables are obtained from the MCS, they serve as inputs to model the EV usage activities of users. The model for EV usage activities is based on the assumption that EVs are primarily used for commuting within urban areas, where they only travel from home to work and do not account for regional variations in user behavior or external factors

such as traffic conditions or weather. Therefore, the activities of EV users include the time of departure from home, the time of return to home, the travel duration, and the duration of parking without charging, as described in Eqs. (1)–(6).

$$ATV_{day}^n = [ATV_1^n + ATV_2^n + ATV_3^n + ATV_4^n + ATV_5^n], \quad (1)$$

$$ATV_1^n = \{1 : T_{edr}^n - 1\}, \quad (2)$$

$$ATV_2^n = \{T_{edr}^n : T_{edr}^n + T_{htw}^n\}, \quad (3)$$

$$ATV_3^n = \{T_{edr}^n + T_{htw}^n + 1 : T_{edr}^n + T_{htw}^n + T_{eop}^n\}, \quad (4)$$

$$ATV_4^n = \{T_{edr}^n + T_{htw}^n + T_{eop}^n + 1 : T_{edr}^n + T_{htw}^n + T_{eop}^n + T_{ebh}^n\}, \quad (5)$$

$$ATV_5^n = \{T_{edr}^n + T_{htw}^n + T_{eop}^n + T_{ebh}^n + 1 : np\}, \quad (6)$$

$$\text{for } n = 1, \dots, NC, t = 1, \dots, np$$

where, ATV_{day}^n represents the daily activities of the n^{th} EV usage. The n^{th} EVs stay at home before leaving for work in activity ATV_1^n . ATV_2^n is the owner who drives the n^{th} EVs to work. The user of the n^{th} EV parks the EVs at work without connecting to the grid by ATV_3^n is the activity in which the user of the n^{th} EV parks the EV at work without connecting to the grid. The owner, ATV_4^n takes the n^{th} EVs home. Lastly, ATV_5^n represents the owner of the n^{th} EVs after they get home from work.

In order to estimate the electricity consumption from EV charging and create the load profile for uncontrolled charging of EVs, it is necessary to calculate the state of charge (SOC). Based on the assumption that EV usage begins in the morning after overnight charging, it is initially considered that the battery is fully charged, as indicated in Eq. (7) [24]. Considering only the charging state, it is assumed that the SOC^t is limited to a minimum depth of discharge (DOD), determined by the fraction P_{dod} and the maximum SOC when fully charged, denoted as SOC_{max} , as shown in Eq. (8).

$$SOC_0^n = SOC_{max}^n \quad (7)$$

$$P_{dod} SOC_{min}^n \leq SOC_t^n \leq SOC_{max}^n \quad (8)$$

The level of SOC changes according to EV usage activities. It increases when the EV is charged at home and decreases when the user drives the EV. For the time step of the SOC at time increases from its initial state according to the charging power when the EV is charged. It decreases according to the energy consumption when the EV is driven, as calculated in Eq. (9).

$$SOC_{t+1}^n = \begin{cases} SOC_t^n + P_c \Delta t, & \text{for charging mode} \\ SOC_t^n - C^t \Delta t, & \text{for driving mode} \\ SOC_t^n, & \text{else} \end{cases} \quad (9)$$

$$\text{for } n = 1, \dots, NC, t = 1, \dots, np$$

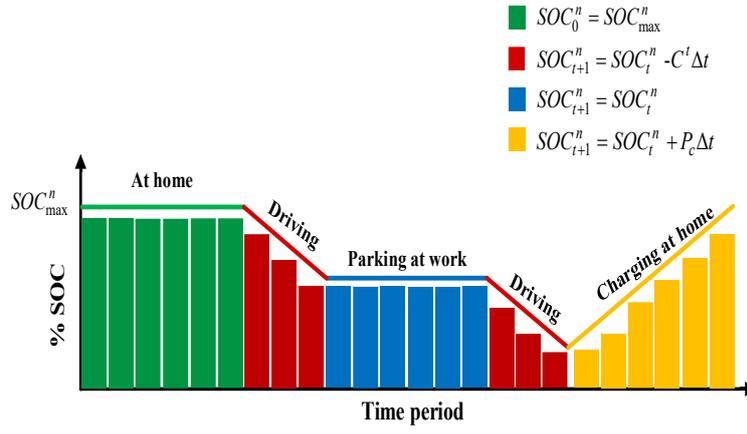


Fig. 4 The SOC varies over time under different EV charging strategies

Fig. 4 illustrates the SOC profiles of an EV under different charging strategies across key activity periods, including staying at home, driving to work, parking at work without charging, EV driving back home, and charging at home. Each segment reflects the change in SOC based on the corresponding activities, where SOC decreases during driving, remains constant while parked at work, and increases when charging at home, following Eqs. (7)-(9).

The EV charging load profile $P_{ev,i,t}^n$ will be equal to or dependent on P_c following the vehicle usage activities at that time initially, as shown in Eq. (10). The total EV charging load profile is determined by summing the charging loads of all EVs, as described in Eq. (11).

$$P_{ev,i,t}^n = \begin{cases} P_c & , \text{for charging mode} \\ 0 & , \text{else} \end{cases} \quad (10)$$

$$P_{ev,i,t}^{total} = \sum_{n=1}^{NC} P_{ev,i,t}^n \quad (11)$$

$$\text{for } n = 1, \dots, NC, t = 1, \dots, np$$

The power EV charging $P_{ev,i,t}^n$ must be taken into account hourly in the data analysis to ensure that the information is in line with the objective function, understandable, and adheres to standard procedure. The outcome of changing the time step from one minute to one hour is displayed in Eq. (12).

$$P_{ev,i,h}^{total} = \sum_{n=1}^{NC} P_{ev,i,h}^n \quad (12)$$

$$\text{for } n = 1, \dots, NC, h = 1, \dots, 24$$

2.3. Objective functions

This research focuses on managing the increasing electricity demand resulting from EV charging by searching for the OEVC time with two objectives. The first objective is to reduce electricity costs, and the second is to minimize energy losses in the system. The objective functions of the electricity cost minimization problem are presented in Eq. (13) and the energy loss minimization problem is presented in Eq. (14).

$$\text{Minimize } C_{ep}^{total} = \sum_{h=1}^{24} C_{ep}^h \quad (13)$$

$$\text{Minimize } E_{\text{loss}}^{\text{total}} = \sum_{h=1}^{24} P_{\text{loss}}^h \quad (14)$$

where the hourly electricity cost can be calculated by:

$$C_{ep}^h = \sum_{i=1}^{NB} C_{en,i}^h + C_{Ft,i}^h + C_{vat,i}^h \quad (15)$$

$$C_{en,i}^h = (P_{hh,i}^h + P_{ev,i}^h) \times r_{\text{tou}}^h \quad (16)$$

$$C_{Ft,i}^h = (P_{hh,i}^h + P_{ev,i}^h) \times Ft_i^h \quad (17)$$

$$C_{vat,i}^h = (C_{en,i}^h + C_{Ft,i}^h) \times VAT \quad (18)$$

$$\text{for } i = 1, \dots, NB, h = 1, \dots, 24$$

The hourly loss can be calculated using Eqs. (19)-(20), the equations are referred from the load flow equations in [25].

$$P_{\text{loss}}^h = \sum_{i=1}^{NB} P_{G,i}^h - (P_{hh,i}^h + P_{ev,i}^h) \quad (19)$$

$$P_{\text{loss}}^h = V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \quad (20)$$

$$\text{for } i = 1, \dots, NB, h = 1, \dots, 24$$

2.4. Constraints

According to the MCS of EV user behavior, EVs are not charged from the moment they leave home until they return. Thus, $P_{ev,i}^{h,on}$ represents the charging power at the time h at bus i when the EV is charging, with its value ranging between a maximum, the total power charge of all EVs at bus i , and the minimum is a percentage of the total number of cars (pnc). While $P_{ev,i}^{h,off}$ indicates the total power charge at the time h at bus i when the EV is not charging, which equals 0. According to Eqs. (21)-(22).

$$(pnc \times \sum_{n=1}^{NC} P_{c,i,n}^h) \leq P_{ev,i}^{h,on} \leq (\sum_{n=1}^{NC} P_{c,i,n}^h), \quad (21)$$

$$P_{ev,i}^{h,off} = 0, \quad (22)$$

$$\text{for } i = 1, \dots, NB, n = 1, \dots, NC, h = 1, \dots, 24$$

The equality constraints, which represent the load flow equations, are as follows in Eqs. (23)-(24)[25].

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad (23)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad (24)$$

for $i = 1, \dots, NB, h = 1, \dots, 24$

The inequality constraints establish the system's operational bound, as follows. Generator constraints, including voltage, active power, and reactive power at the i^{th} bus, are restricted between their upper and lower bounds, as shown in

$$\begin{aligned} |V_{Gi}|^{\min} &\leq |V_{Gi}| \leq |V_{Gi}|^{\max} \\ |P_{Gi}|^{\min} &\leq |P_{Gi}| \leq |P_{Gi}|^{\max}, \\ |Q_{Gi}|^{\min} &\leq |Q_{Gi}| \leq |Q_{Gi}|^{\max} \end{aligned} \quad (25)$$

Transformer tap settings are confined within specified limits, as detailed in

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad (26)$$

Shunt compensations are subject to their respective limits, as outlined in

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max}, \quad (27)$$

and line flow constraints in

$$f_l \leq f_l^{\max} \quad (28)$$

3. Multi-Objective Particle Swarm Optimization (MOPSO)

In this section, the MOPSO algorithm designed for the problem considered in this article is discussed. Furthermore, the concept of Pareto dominance, which is important for the operation of MOPSO for handling multi-objective optimization (MOO) problems, is explained.

3.1. Basic Concept of Pareto Dominance

Problem-solving with multiple objectives, as presented in this article, targets reducing electricity costs and minimizing energy losses. Therefore, it requires carefully balancing conflicting goals. The Pareto dominance concept is applied to analyze and solve the MOO problem. The Pareto dominance helps identify solutions in which an improvement in one objective cannot be achieved without causing a deterioration in another. In other words, if a solution x_1 is better than a solution x_2 , then the solution x_1 is said to be the dominating one. Thus, the set of non-dominated solutions, which is known as the Pareto frontier, naturally represents a balanced trade-off between the two objectives.

Coello and Salazar Lechuga were among the first to extend the PSO algorithm to handle multi-objective problems by incorporating the principle of Pareto dominance. The key advancements include using an external repository to store and update non-dominated solutions and employing a leader selection mechanism based on Pareto criteria. These modifications guide the swarm toward less crowded regions of the objective space, promoting diversity and ensuring that the final set of solutions maintains a balanced trade-off between minimizing electricity costs and reducing energy losses. This method is known as MOPSO [26].

3.2. MOPSO algorithm

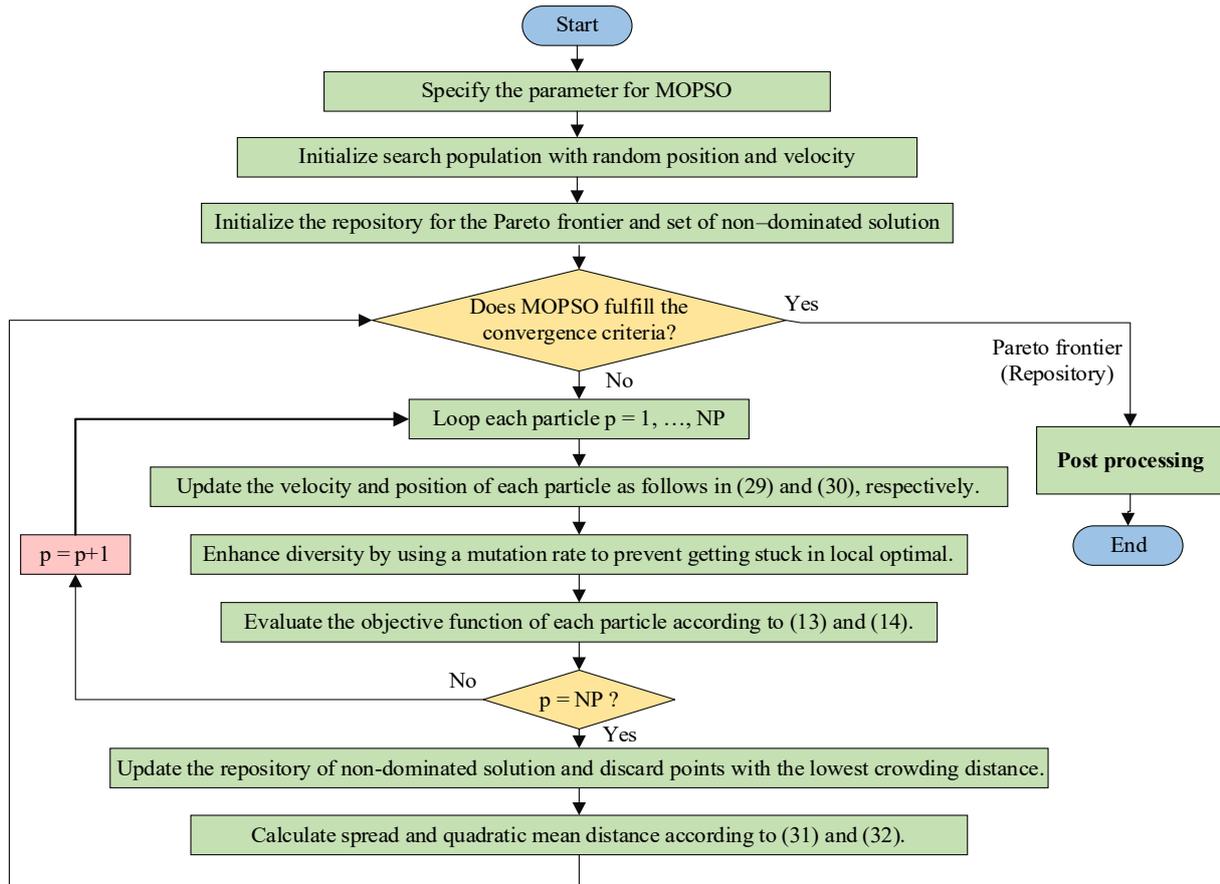


Fig. 5 The proposed MOPSO-based OEVC computational procedure

MOPSO is an extension of the PSO concept, maintaining the fundamental principles of PSO while incorporating the core concept of Pareto dominance to manage MOO [27-28]. Therefore, in each iteration, the equations for velocity and position updates remain as defined in Eqs. (29)-(30), respectively. $V_{i,t}$ is the velocity at iteration t and $V_{i,t+1}$ is the updated velocity at iteration $t+1$ of particle i . $x_{i,t}$ is position at iteration t , and $x_{i,t+1}$ is the updated position at iteration $t+1$ of particle i . w is the inertia weight. Parameters c_1 and c_2 are the cognitive constant and the social constant respectively. r_1 and r_2 are the random numbers uniformly distributed between 0 and 1. $x_{i,t}^{Pbest}$ is the best position of particle i at an iteration. This is the best solution that the particle has found till the current iteration. $x_{i,t}^{Gbest}$ is the global best position across all particles up to the current. This is the non-dominated solution or best solution found by the swarm.

$$V_{i,t+1} = wV_{i,t} + c_1r_1(x_{i,t}^{Pbest} - x_{i,t}) + c_2r_2(x_{i,t}^{Gbest} - x_{i,t}) \quad (29)$$

$$x_{i,t+1} = x_{i,t} + V_{i,t+1} \quad (30)$$

The MOPSO algorithm has been developed and detailed in [29] and is called the multiple design option (MDO)-MOPSO. In this research, the MDO-MOPSO algorithm has adapted to suit the specific characteristics of the problem in this article while still considering the spread and the mean of the crowding distances (quand mean) as convergence criteria according to Eqs. (31)-(32). Fig. 5 illustrates the methodology of the MDO-MOPSO algorithm.

$$spread = \frac{\mu + \sigma}{\mu + Qd} \quad (31)$$

$$quand\ mean = \sqrt{\frac{1}{Q} \sum_k d_k^2} \quad (32)$$

where μ is the parameter that quantifies whether the extreme values of the Pareto frontier have changed between two consecutive iterations. σ and \bar{d} are the standard deviation and the arithmetical average of the crowding distances of point k , and Q is the number of points on the Pareto frontier. This modified version of the MOPSO algorithm integrates performance metrics and includes a post-processing step to identify MDO. The iterative process stops when one of the following three conditions. The first is when the maximum number of iterations is reached. The second is that the change in the spread measure falls below a specified relative and absolute tolerance of, or the final, the change in the quadratic mean of crowding distances falls below a specified absolute and relative tolerance.

In the post-processing section, a process is conducted to identify the optimal solutions according to predefined criteria. The steps are as follows:

- (1) Identify the search area for selecting extreme values and conducting trade-off analysis based on the Pareto frontier.
- (2) Remove any outliers to ensure only relevant and feasible solutions are considered.
- (3) Select extreme designs that maximize energy shares, focusing on solutions that provide the best balance between objectives.
- (4) Calculate key performance indicators (KPIs). KPIs are computed to evaluate and compare the diversity characteristics among the original Pareto frontier, the enhanced Pareto frontier, and the selected MDO points. The calculation of KPIs is based on the Manhattan measure. Details of this calculation are presented in [29].
- (5) Plot the trade-offs and results to visually assess and compare the final solutions.

4. Simulation Results and Discussion

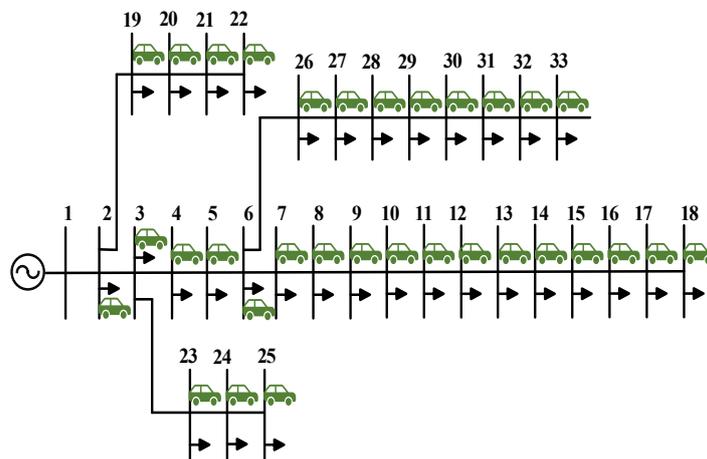


Fig. 6 The modification IEEE 33-bus distribution test system with EV charging devices

This section discusses the simulation of a system modified from the IEEE 33-bus distribution test system by adding EV connections at each bus, as shown in Fig. 6. According to this research study, the OEVC scheduling controls the increasing demand for electricity to minimize electricity costs and energy losses in the system. The MOPSO algorithm is used for OEVC scheduling, and the simulation is performed with MATLAB software.

4.1. IEEE 33-bus distribution system without EV charging device

The IEEE 33-bus distribution system is used as the base system for this study, as shown in Fig. 6. In the base case, the simulation is performed without connecting any EV charging devices to the system, while other cases include EV charging

devices. The load profile used as the system's base load for households is the central Thailand load profile for July, as shown in Fig. 7. This case study contrasts the outcomes of the OEVC scheduling for objective functions of different purposes.

4.2. IEEE 33-Bus distribution system with EV charging device

The IEEE 33-bus distribution system with the integration of EV charging devices, as shown in Fig. 6. This system is used for the simulation under uncontrolled and controlled charging conditions. For the controlled scenario, three case studies are presented to assess and compare the performance of the proposed algorithm in solving the OEVC problem.

4.2.1. Uncontrolled EV charging devices

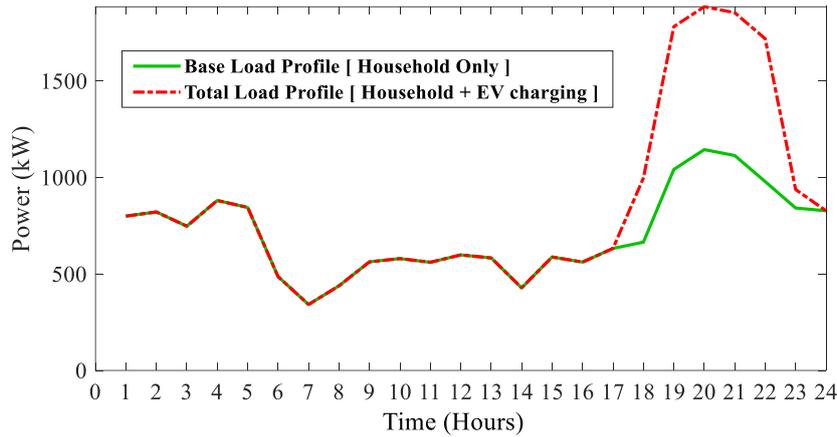


Fig. 7 The Load Profiles of the System without and with EV Charging

IEEE 33-bus distribution system with EV charging device, as shown in Fig. 6. EV charging input parameters are as in [24] and the BYD Atto 3 model, as shown in Table 2. The load profile for EV charging follows user behavior as suggested by the MCS, which is shown in Fig. 7. The uncontrolled EV charging load profile, location status based on user activities and SOC by considering the time period $np = 1440$ minutes, is shown in Fig. 8. Simulation results indicate that without controlling EV charging, the daily electricity cost for the entire system is 105.6815 kTHB/kWh, and the daily energy loss is 6.16 MWh.

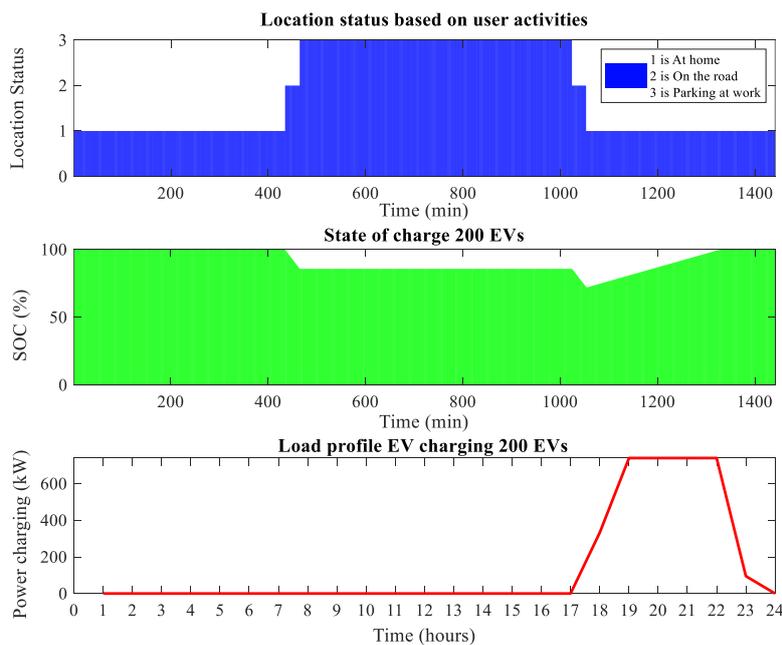


Fig. 8 Uncontrolled EV charging simulation

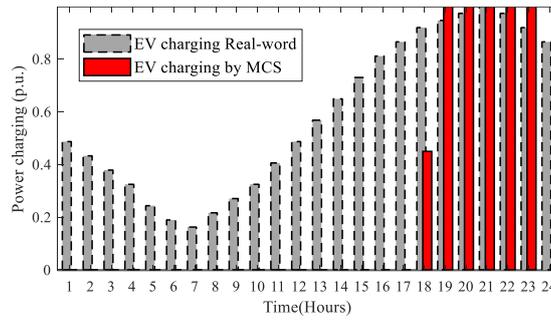


Fig. 9 Comparison of real-world EV charging and MCS results

Fig. 9 presents the comparison of the EV charging load profile from the MCS and the real-world EV charging data from the Denmark study [30]. The outcomes indicate that the load profile generated by the MCS agrees with the real-world data. In particular, the peak electricity demand is close to real-world values and occurs between 8:00 PM and 9:00 PM.

Table 1 Mean and variance of EV usage patterns

Random variable	Mean (μ)	Variance (σ^2)
T_{edr}	7:15 AM	30 min
T_{htw}	30 min	15 min
T_{eop}	9 h and 20 min	50 min
T_{ebh}	30 min	15 min

Table 2 Input parameters of EV charging

Parameter values	
SOC_{max}	60.48 kWh
P_c	3.7 kWh
P_{dod}	0.6
C_s^t of un-Aug	1.1
v_m	60 km/h
c_m	0.257 kWh/km
Δt	1/60 h
pnc	0.1

4.2.2. Controlled EV charging devices

In this article, household consumption at a voltage level lower than 12 kV is used, using the TOU pricing of Thailand as indicated in Table 3. In this study, the OEVC scheduling is proposed in three case studies to assess the effectiveness of optimal charging planning, including using the algorithms differently to solve the problem. The three case studies are as follows:

Table 3 Time of Use rate (TOU rate) for type 1 residential households

Voltage level	Energy charge (Bath/kWh)	
	Peak (09:00 a.m.-10:00 p.m.)	Off-Peak (10:00 p.m.-09:00 a.m.)
At voltage level 12 – 24 kV	5.1135	2.6037
At voltage level lower than 12 kV	5.7982	2.6369

(1) Case I: Single objective for minimizing Electricity cost

In this case, the PSO and GA determine the OEVC scheduling, considering the single objective function of minimizing the electricity cost of the system. The result of the PSO achieved a minimum daily electricity cost of 96.92823 kTHB, leading to a daily energy loss of 5.4966 MWh. In comparison, the result of the GA produced a minimum daily electricity cost of 98.1728 kTHB, leading to a daily energy loss of 5.5542 MWh. Across 30 trials in this case, the resulting averages of PSO and GA were 97.1056 kTHB and 98.4532 kTHB.

(2) Case II: Single objective for minimizing Energy losses

In this case, the PSO and GA determine the OEVC scheduling, considering the single objective function of minimizing the energy loss of the system. The result of the PSO achieved a minimum daily energy loss of 4.0900 MWh, leading to a daily electricity cost of 97.752 kTHB. In comparison, the result of the GA produced a minimum daily energy loss of 4.208 MWh, leading to a daily electricity cost of 100.442 kTHB. Across 30 trials in this case, the resulting average of PSO and GA was 4.3195 MWh and 4.3560 MWh.

(3) Case III: Multi-objective for minimizing Electricity cost and Energy losses

The MOPSO will be used to determine the OEVC scheduling in this case, considering both the objective function that minimizes electricity cost and minimizes energy loss. The results of the MOPSO indicate that in the system with controlled charging, the daily electricity cost for the entire system is 97.651 kTHB, and the daily energy loss is 4.39 MWh.

Table 4 Objective function values from 30 trials by PSO and GA (Case I and Case II)

Objective function values	Case studies			
	Case I		Case II	
	Electricity cost (kTHB)		Energy loss (MWh)	
Algorithm	PSO	GA	PSO	GA
Max	99.3399	101.8907	4.8523	4.5714
Avg.	97.6148	99.5013	4.3196	4.3560
Min	96.2823	98.1728	4.0900	4.2085

Table 4 and Fig. 10 show the results of the objective function values of the maximum, minimum, and average obtained from 30 PSO and GA trials for case I and case II. The comparison of the performance of PSO and GA for Case I and II, as shown in Fig. 10(a) and Fig. 10(b). Each figure includes the results of 30 trials, showing the average trend line across trials, with the best result marked by a red diamond and the worst result marked by a black circle. The simulation results show that PSO is better than GA in both cases, with the PSO achieving a minimum daily electricity cost of 96.2823 kTHB and a minimum daily energy loss of 4.09 MWh. The EV charging scheduling results by PSO and GA for case I and case II are the minimum electricity cost and energy loss obtained from the simulation results for 30 trials, as indicated in Table 5.

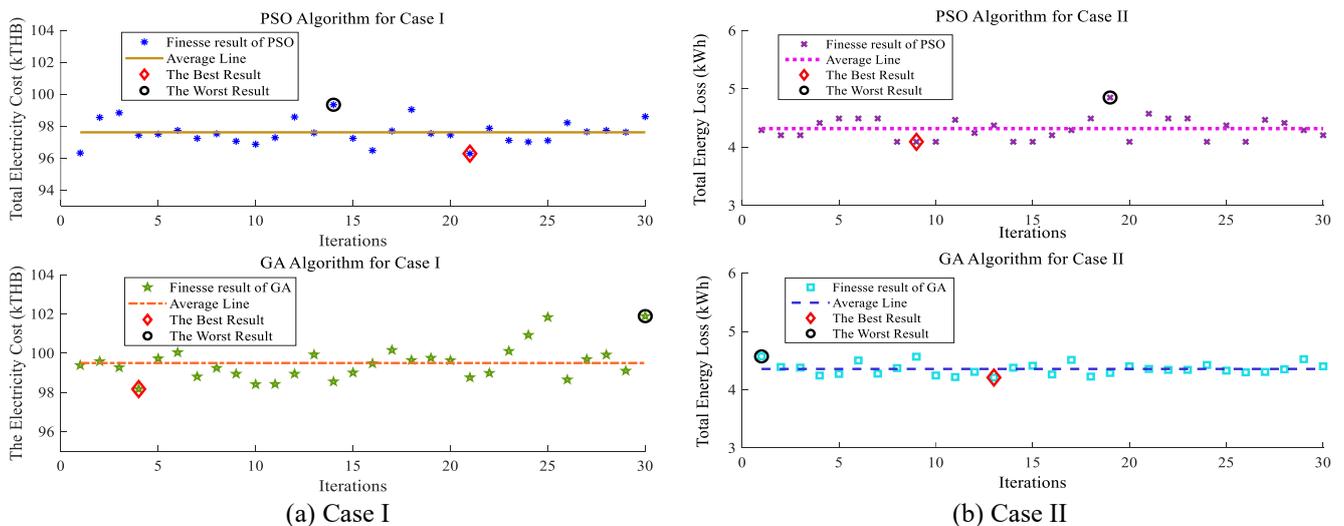


Fig. 10 The results from 30 trials of the PSO and GA algorithm

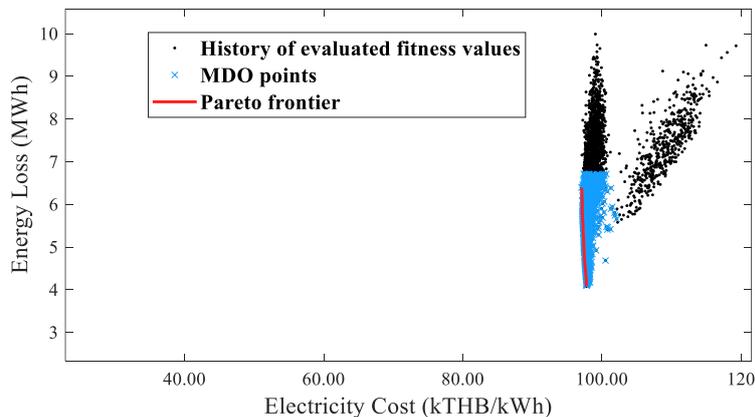


Fig. 11 Pareto Frontier of the proposed MOPSO-based OEVC

Fig. 11 shows the results from MDO-MOPSO for case III. The history of fitness values evaluated during the MOPSO process, including optimal and suboptimal solutions, is represented by black points. The blue points indicate the MDO solution set selected after post-processing analysis. The red line shows the Pareto frontier, representing the optimal trade-offs between electricity cost and energy loss. The most suitable set of solutions is derived from the Pareto frontier after further filtering using a diversity criterion based on crowding distance and a post-processing step that retains only the solutions within a predefined tolerance. This process indicates that the final solutions reflect a balanced trade-off between minimizing electricity costs and reducing energy losses.

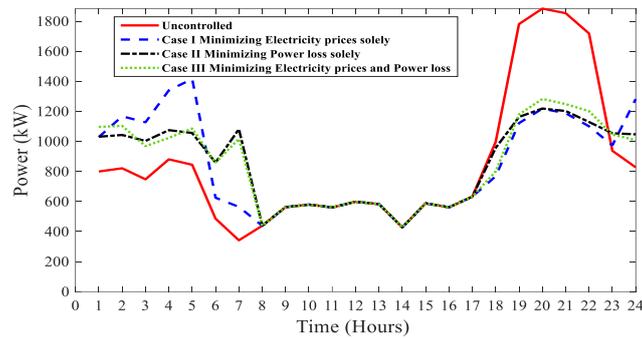
Table 5 EV load profiles and minimum objective function values for the IEEE 33-Bus system

Hours	Power consumption (kWh)					
	Uncontrolled charging	Controlled charging				
		Case I		Case II		Case III
		PSO	GA	PSO	GA	MOPSO
1	0	229.40	331.27	231.58	265.42	296.96
2	0	346.16	173.09	221.73	106.09	282.31
3	0	379.73	468.63	255.62	89.09	221.05
4	0	459.64	225.38	194.35	133.60	143.07
5	0	570.91	224.49	211.49	187.90	241.65
6	0	138.92	105.90	373.12	652.74	372.80
7	0	222.69	249.58	740	408.66	675.08
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0
16	0	0	0	0	0	0
17	0	0	0	0	0	0
18	332.445	103.23	74.66	292.30	382.40	135.02
19	740.000	80.39	74.66	121.54	76.07	138.28
20	740.000	74.01	74.66	74.69	369.62	138.72
21	740.000	74.00	108.62	88.67	175.42	135.02
22	740.000	122.09	339.17	150.63	155.40	222.82
23	96.015	132.41	482.71	212.92	226.21	203.80
24	0	454.92	455.67	219.86	159.88	181.92
C_{ep}^{total} (kTHB)	105.682	96.2823	98.1728	97.752	100.442	97.651
E_{loss}^{total} (MWh)	6.16	5.4966	5.5542	4.0900	4.2085	4.3917

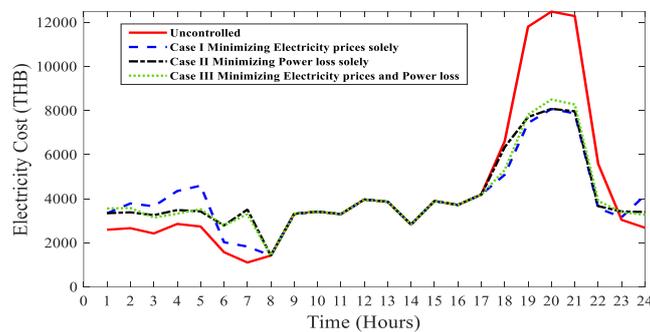
Table 5 presents the results of EV charging scheduling in the three cases compared to uncontrolled EV charging schedules. The results of all three cases show that optimized charging schedules reduce electricity costs and energy loss. In case I, the best result among PSO and GA is a daily electricity cost of 96.922 kTHB, but the energy loss remains relatively high at 5.4966 MWh. In case II, the best result among PSO and GA is a daily energy loss of 4.0900 MWh, but the electricity cost remains relatively high at 97.752 kTHB. The obtained solution in case III is the OEVC. It achieves a daily electricity cost of 97.651 kTHB and an energy loss of 4.3917 MWh. Cases I and II, which consider minimizing a single objective function, using the PSO and GA, achieve the minimum value for that specific objective function. However, the values for the other objective function are higher. Furthermore, the PSO shows slightly superior performance compared to GA.

Conversely, OEVC scheduling with MOPSO considers the balance between the two objective functions in that the results for the obtained objective values are not minimum. But these are the optimal results for both objectives. Therefore, the electricity cost and energy loss values in case III fall between cases I and II. The comparison of the EV load profile, electricity

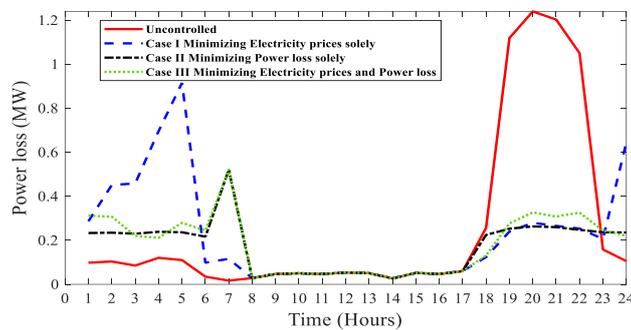
cost, and energy loss for each hour is shown in Fig. 12. The simulation results in Fig. 12(a) compare the system load profiles, showing that the system with charging control under TOU pricing results in lower on-peak energy demand, which helps reduce electricity costs and energy loss, as shown in Fig. 12(b) and Fig. 12(c).



(a) Comparison system load profile



(b) Comparison of electricity cost



(c) Comparison of power loss

Fig. 12 Comparison of results from all cases

5. Conclusions

This study proposed a method for OEVC that uses the MOPSO algorithm to solve the multi-objective optimization problem. The goal is to minimize electricity costs and energy losses in the system caused by the large increase in EVs. MCS is used to model the uncertain behavior of EV usage. Additionally, a TOU tariff was used to promote OEVC. The experiments were conducted using MATLAB software and tested on the IEEE 33-bus distribution system. According to the simulation results, the conclusions are summarized:

- (1) MCS has effectively modeled the uncertain behavior of EV users, which can create realistic EV charging load profiles. This shows that the energy demand during peak periods increases, leading to higher electricity costs and energy losses.
- (2) The MOPSO algorithm is designed to explore a balanced set of solutions using the Pareto frontier. This approach enables it to effectively address the multi-objective challenge of OEVC by reducing both electricity costs and energy losses. However, MOPSO cannot minimize either aim to the lowest possible level because it operates with the Pareto frontier, which focuses on balancing both objectives without allowing one to outperform the other.

In the future, improvements might include adaptive tuning of parameters, combining MOPSO with other techniques, or using real-time data to boost specific performance while still maintaining the overall balance.

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Appendix 1 Abbreviations and Symbols

BEV	Battery Electric Vehicle	P_{Di}	The real power demand at bus i
DOD	Depth of Discharge	P_{Gi}	The real power of the generator at bus i
EV	Electric Vehicle	P_{Gi}^{\min}	The minimum real power of the generator at bus i
MOPSO	Multi-Objective Particle Swarm Optimization	P_{Gi}^{\max}	The maximum real power of the generator at bus i
MDO	Multiple Design Option	Q_{Di}	The reactive power demand at bus i
MOO	Multi-Objective Optimization	Q_{Gi}	The reactive power of the generator at bus i
NB	The total number of buses	Q_{ci}^{\min}	The minimum shunt VAR compensator
NC	The total number of cars	Q_{ci}^{\max}	The maximum shunt VAR compensator
PSO	Particle Swarm Optimization	r_{tou}^h	The electricity pricing at hour h
SOC	State of Charge	SOC_0^n	Initial State of charge of n cars
TOU	Time of Use	SOC_{\max}^n	The maximum state of charge of n cars
B_{ij}	The susceptance on branch ij	SOC_{\min}^n	The minimum state of charge of n cars
C_{ep}^{total}	The total daily electricity prices	T_{edr}^n	The time the n -th EV departs from its residence
C_{ep}^h	The total hourly electricity prices	T_{htw}^n	The duration of time it takes for the n -th EV to travel from home to the workplace
$C_{en,i}^h$	The electricity energy prices at bus i and hour h	T_{eop}^n	The duration of time the n -th EV is parked in the garage at the workplace
$C_{Ft,i}^h$	The electricity fuel adjustment charge prices at bus i and hour h	T_{ebh}^n	The duration of time it takes for the n -th EV to travel from workplace to the home
$C_{vat,i}^h$	The electricity value added tax prices at bus i and hour h	T_i^{\min}	The minimum transformer tap settings
f^l	The MVA flow of line l	T_i^{\max}	The maximum transformer tap settings
f_{max}^l	The maximum limit of line l	V_{ij}	The voltage of bus i and j
F_t	The fuel Adjustment Charge (at the given time)	VAT	The value-added tax
G_{ij}	The conductance on branch ij	δ_{ij}	The phase difference of voltages between bus i and j
E_{loss}^{total}	The total daily energy losses	C_s^t	Season coefficient
$P_{ev,i,h}^{total}$	The total charging power at bus i and hour h	c_m	Electricity consumption in distance (kWh/km)
$P_{ev,i,h}^n$	The charging power of n cars at bus i and hour h	P_c	Charging power (kWh)
P_{loss}^h	The hourly power loss	p_{dod}	Depth of discharge fraction
P_{hh}^h	The hourly power of the household load	p_{car}	Vehicle usage probability
$P_{ev,i,n}^{h,on}$	The charging power of n cars at bus i that is charging	Δt	Time step length (hr)
$P_{ev,i,n}^{h,off}$	The charging power of n cars at bus i that is not charging	v_m	The average velocity for a private vehicle trip

Conflicts of Interest

The authors declare no conflict of interest.

References

- [1] Y. Ou, N. Kittner, S. Babae, S. J. Smith, C. G. Nolte, and D. H. Loughlin, "Evaluating Long-Term Emission Impacts of Large-Scale Electric Vehicle Deployment in the US Using a Human-Earth Systems Model," *Applied Energy*, vol. 300, article no. 117364, 2021.
- [2] C. Hofer, G. Jäger, and M. Füllsack, "Large Scale Simulation of CO₂ Emissions Caused by Urban Car Traffic: An Agent-Based Network Approach," *Journal of Cleaner Production*, vol. 183, pp. 1–10, 2018.
- [3] IEA, "Global EV Outlook 2024," <https://www.iea.org/reports/global-ev-outlook-2024>, 2024.
- [4] H. Shareef, M. M. Islam, and A. Mohamed, "A Review of the Stage-of-the-Art Charging Technologies, Placement Methodologies, and Impacts of Electric Vehicles," *Renewable and Sustainable Energy Reviews*, vol. 64, pp. 403–420, 2016.
- [5] R. Gunasekaran, M. B., A. S., P. K. Pareek, S. Gupta, and A. Shukla, "Prediction of Electric Vehicle Charging Demand Using Enhanced Gated Recurrent Units with RKOA Based Graph Convolutional Network," *Discover Applied Sciences*, vol. 6, article no. 605, 2024.
- [6] J. Varga, G. R. Raidl, and S. Limmer, "Computational Methods for Scheduling the Charging and Assignment of an On-Site Shared Electric Vehicle Fleet," *IEEE Access*, vol. 10, pp. 105786–105806, 2022.
- [7] H. Wang, M. Shi, P. Xie, C. S. Lai, K. Li, and Y. Jia, "Electric Vehicle Charging Scheduling Strategy for Supporting Load Flattening under Uncertain Electric Vehicle Departures," *Journal of Modern Power Systems and Clean Energy*, vol. 11, no. 5, pp. 1634–1645, 2023.
- [8] B. Sun, Z. Huang, X. Tan, and D. H. K. Tsang, "Optimal Scheduling for Electric Vehicle Charging with Discrete Charging Levels in Distribution Grid," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 624–634, 2018.
- [9] M. Aurangzeb, A. Xin, S. Iqbal, S. Habib, M. U. Jan, H. U. Rehman, et al., "Decentralized Based Advance Optimized Scheduling Scheme to Charge and Discharge the Electric Vehicles," *Proceedings of 2022 5th International Conference on Energy Conservation and Efficiency*, IEEE Press, pp. 1–7, 2022.
- [10] Y. Wan, D. Gebbran, R. K. Subroto, and T. Dragičević, "Optimal Day-Ahead Scheduling of Fast EV Charging Station with Multi-Stage Battery Degradation Model," *IEEE Transactions on Energy Conversion*, vol. 39, no. 2, pp. 872–883, 2024.
- [11] G. Tsaousoglou, J. S. Giraldo, P. Pinson, and N. G. Paterakis, "Fair and Scalable Electric Vehicle Charging under Electrical Grid Constraints," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 12, pp. 15169–15177, 2023.
- [12] A. Tetuko, Subiyanto, and M. A. Malik, "An Optimal Energy Control System for Campus Microgrid Using Crow Search Algorithm Considering Economic Dispatch," *Advances in Technology Innovation*, vol. 8, no. 4, pp. 303–312, 2023.
- [13] H. Zhang, X. Xu, J. Huang, and G. I. Rashed, "Optimal Scheduling Strategy for Multi-Type Electric Vehicle Charging Based on Improved GA," *Proceedings of 2024 6th International Conference on Energy Systems and Electrical Power*, IEEE Press, pp. 1383–1386, 2024.
- [14] S. Techanok and K. Chayakulkheeree, "Optimal EV Charging Control for Distribution System Loss Minimization," *Proceedings of 2024 12th International Electrical Engineering Congress*, IEEE Press, pp. 1–5, 2024.
- [15] Y. Wu, J. Zhang, A. Ravey, D. Chrenko, and A. Miraoui, "Real-Time Energy Management of Photovoltaic-Assisted Electric Vehicle Charging Station by Markov Decision Process," *Journal of Power Sources*, vol. 476, article no. 228504, 2020.
- [16] Z. Liu, F. Wen, and G. Ledwich, "Optimal Siting and Sizing of Distributed Generators in Distribution Systems Considering Uncertainties," *IEEE Transactions on Power Delivery*, vol. 26, no. 4, pp. 2541–2551, 2011.
- [17] T. M. Aljohani, A. F. Ebrahim, and O. A. Mohammed, "Dynamic Real-Time Pricing Mechanism for Electric Vehicles Charging Considering Optimal Microgrids Energy Management System," *IEEE Transactions on Industry Applications*, vol. 57, no. 5, pp. 5372–5381, 2021.
- [18] M. M. Gamil, H. Masrur, K. M. Muttaqi, Y. Huang, M. E. Lotfy, and T. Senjyu, "Multi-Objective Optimal Power Scheduling of a Residential Microgrid Considering V2G and Demand Response Techniques," *Proceedings of 2022 IEEE Industry Applications Society Annual Meeting*, IEEE press, pp. 1–5, 2022.
- [19] H. Yang, S. Yang, Y. Xu, E. Cao, M. Lai, and Z. Dong, "Electric Vehicle Route Optimization Considering Time-of-Use Electricity Price by Learnable Partheno-Genetic Algorithm," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 657–666, 2015.
- [20] Z. Huang, K. Wang, C. Cao, and Z. Mu, "Multi-Objective Optimal Power Flow Considering Small-Signal Stability Based on MOPSO," *Proceedings of 2022 4th International Conference on Electrical Engineering and Control Technologies*, IEEE Press, pp. 419–423, 2022.

- [21] Maigha and M. L. Crow, "Electric Vehicle Scheduling Considering Co-Optimized Customer and System Objectives," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 1, pp. 410–419, 2018.
- [22] J. Chen, X. Huang, S. Tian, Y. Cao, B. Huang, X. Luo, et al., "Electric Vehicle Charging Schedule Considering User's Charging Selection from Economics," *IET Generation, Transmission & Distribution*, vol. 13, no. 15, pp. 3388–3396, 2019.
- [23] S. Ahmadi, H. P. Arabani, D. A. Haghighi, J. M. Guerrero, Y. Ashgevari, and A. Akbarimajd, "Optimal Use of Vehicle-to-Grid Technology to Modify the Load Profile of the Distribution System," *Journal of Energy Storage*, vol. 31, article no. 101627, 2020.
- [24] P. Grahn, "Electric Vehicle Charging Impact on Load Profile," Ph.D. dissertation, School of Electrical Engineering, Royal Institute of Technology, Stockholm, Sweden, 2013.
- [25] M. Ghasemi, S. Ghavidel, M. Gitizadeh, and E. Akbari, "An Improved Teaching–Learning–Based Optimization Algorithm Using Lévy Mutation Strategy for Non-Smooth Optimal Power Flow," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 375–384, 2015.
- [26] C. A. C. Coello and M. S. Lechuga, "MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization," *Proceedings of the 2002 Congress on Evolutionary Computation*, IEEE Press, vol. 2, pp. 1051–1056, 2002.
- [27] J. Kennedy, "The Particle Swarm: Social Adaptation of Knowledge," *Proceedings of 1997 IEEE International Conference on Evolutionary Computation*, IEEE Press, pp. 303–308, 1997.
- [28] S. Lalwani, S. Singhal, R. Kumar, and N. Gupta, "A Comprehensive Survey: Multi-Objective Particle Swarm Optimization (MOPSO) Algorithm: Variants and Applications," *Transactions on Combinatorics*, vol. 2, no. 1, pp. 39–101, 2013.
- [29] D. Fioriti, G. Lutzemberger, D. Poli, P. Duenas-Martinez, and A. Micangeli, "Coupling Economic Multi-Objective Optimization and Multiple Design Options: A Business-Oriented Approach to Size an Off-Grid Hybrid Microgrid," *International Journal of Electrical Power & Energy Systems*, vol. 127, article no. 106686, 2021.
- [30] F. M. Andersen, H. K. Jacobsen, and P. A. Gunkel, "Hourly Charging Profiles for Electric Vehicles and Their Effect on the Aggregated Consumption Profile in Denmark," *International Journal of Electrical Power & Energy Systems*, vol. 130, article no. 106900, 2021.



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