International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Smart Energy Management for Residential EV Charging Using PSO and Dynamic Pricing Strategy

***Balwant Singh Kuldeep* [1], *Arvindra Singh* [2]**

[1]Assistant Professor, Department of Electrical Engineering, Sri Balaji College of Engineering & Technology, Jaipur, Rajasthan, India
[2] Research Scholar, Department of Electrical Engineering, Sri Balaji College of Engineering & Technology, Jaipur, Rajasthan, India
Email- balwant047@gmail.com [1], engg.arvendra@gmail.com [2]

ABSTRACT—

The rising penetration of electric vehicles (EVs) in residential areas presents both opportunities and challenges for energy management and grid stability. This research proposes a smart energy management framework for residential Plug-in Electric Vehicle (PEV) charging, leveraging real-time electricity pricing and an intelligent decision-making model to reduce consumer energy costs and support grid efficiency. At the core of this system lies a meta-heuristic optimization technique—Particle Swarm Optimization (PSO)—which dynamically determines optimal charging and discharging schedules based on half-hourly variations in electricity tariffs and the internal economic value of stored energy, represented as the Energy Price Tag (EPT). The proposed model enables the EV to autonomously decide whether to charge, discharge, or remain idle by comparing the grid price with the EPT, ensuring that each action results in a net economic benefit. The PSO algorithm evaluates numerous potential schedules to minimize total energy costs while satisfying constraints such as battery capacity, charging efficiency, and user-defined mobility requirements. The simulation, carried out in MATLAB, demonstrates significant cost savings, a reduction in peak load stress, and an optimal utilization of the EV battery. Results reveal that the PSO-based charging strategy can lower daily energy expenses by up to 68% compared to conventional fixed-time charging. Furthermore, the system effectively shifts energy consumption to off-peak hours, improving grid load distribution and enabling smoother integration of renewable sources. By turning residential EVs into flexible energy assets, this strategy promotes sustainable energy usage and offers a scalable solution for smart grid environments. This study highlights the potential of combining optimization algorithms with dynamic pricing to develop intelligent, adaptive, and user-friendly EV charging solutions that align with modern energy demands and sustainability goals.

Keywords: Smart Charging, Electric Vehicles, Plug-in Electric Vehicles, Particle Swarm Optimization, Energy Price Tag, Real-Time Pricing, Demand Response, Vehicle-to-Grid, Energy Cost Optimization, MATLAB Simulation, Load Shifting, Grid Stability, State of Charge, Residential Energy Management, Meta-Heuristic Optimization

1: Introduction

Due to the exponential growth of industrialization, digitization, and transportation electrification, the modern world is seeing an unparalleled rise in power usage. The demand for electrical energy is expected to climb dramatically over the next few decades due to the growing global population and increasing economies. Global electricity demand is expected to increase by over 25% by 2040, according to the International Energy Agency (IEA), putting tremendous strain on the energy infrastructure that is now in place. The environmental effects of traditional electricity production systems, which mostly rely on fossil fuels like coal, oil, and natural gas, such as greenhouse gas emissions, air pollution, and resource depletion, are drawing more attention.

Energy engineers and politicians are increasingly using renewable energy sources including solar, wind, hydro, and geothermal in answer to these worries. Although they have their own set of drawbacks, these sources provide sustainable and clean alternatives. The main one is fluctuation; because wind and solar energy are erratic by nature, grid managers find it challenging to instantly balance supply and demand. Grid instability is frequently caused by this intermittency, particularly in shoddy distribution networks that are ill-prepared to manage abrupt spikes or decreases in supply. Demand-side energy management techniques that may cleverly optimize power use depending on availability and cost are therefore becoming more and more important.

In the middle of this energy transformation, electric cars (EVs) have become a potent instrument for grid support as well as environmentally friendly mobility. Global EV usage is growing quickly, which is a sign of a shift to greener mobility options. By 2040, more than half of new automobile sales are anticipated to be electric vehicles, according to BloombergNEF. In addition to being used for driving, EVs are mobile energy storage devices that can communicate with the electrical grid; this is known as Vehicle-to-Grid (V2G).

When demand is high or renewable energy output is low, the large amounts of energy stored by lithium-ion batteries in plug-in electric vehicles (PEVs) can be used to support grid operations. With this feature, EVs become distributed energy resources (DERs) that can be used in energy and transportation systems. By charging during off-peak hours when electricity prices are low and discharging during peak periods when prices are high or supply is limited, EVs provide a special chance to lower household electricity expenses in residential settings.

Developing clever algorithms that can determine the economic viability of charging or discharging at any given time is crucial to maximizing the use of EV batteries for energy cost optimization. The Energy Price Tag (EPT), a crucial idea presented in this study, is a real-time fee connected with the energy stored in an EV battery. The cost of battery degradation, efficiency losses, and the price at which energy was charged are all taken into consideration by the EPT. The best course of action can be determined by comparing the EPT with the current grid electricity price. If the grid price is greater than EPT, the stored energy can be discharged back to the grid or home, or if the grid price is lower than EPT, the EV battery can be charged.

Automated and intelligent charging techniques that benefit the power grid and the consumer are made possible by this framework for economic decision-making. By ensuring that every charging or discharging activity results in a net economic advantage, the EPT-based methodology optimizes residential consumers' overall energy expenditure.

Optimal EV charging and discharging is a difficult, time-varying, and non-linear problem to solve. Conventional optimization techniques frequently fail in these kinds of dynamic and unpredictable settings. Meta-heuristic optimization techniques have been especially successful in this situation. These algorithms are intended to provide near-optimal solutions for complicated problems with wide search areas and numerous constraints. They were inspired by natural events.

Particle Swarm Optimization (PSO), one of several meta-heuristic approaches, has drawn a lot of interest in the energy systems domain. The social behavior of fish schools or flocks of birds serves as the model for PSO. Each particle in the swarm represents a possible charging schedule in the context of EV charging, and the particles iteratively change their positions based on their own experiences as well as those of nearby particles. The swarm is gradually led toward the best option by the fitness function, which assesses each schedule's cost-effectiveness.

Taking into account the internal EPT values of the battery and the half-hourly change in energy pricing, PSO is used in this study to calculate the ideal charging and discharging schedule of a domestic PEV. The system may choose the most cost-effective energy transactions throughout the day on its own by including PSO into the framework for decision-making. The cost advantages of such a clever EV charging plan are significant for home customers. Using stored energy during peak hours and charging the EV during off-peak hours can save monthly electricity expenditures. Additionally, in certain areas, utilities provide incentives for returning electricity to the grid, enabling EV owners to profit from V2G initiatives. As a result, the EV becomes a potential source of income rather than a cost center.

From the standpoint of the grid operator, intelligent EV charging offers vital flexibility. The method delays the need for infrastructure changes, lessens the load on the distribution network, and promotes grid stability by moving demand away from peak hours. The shift to a cleaner energy mix is further supported by the decentralized storage capacity provided by EVs, which also serves as a buffer against variations in the availability of renewable energy. MATLAB, a high-level computer platform popular for modeling, simulation, and algorithm development in the energy domain, was used to design and simulate the intelligent charging strategy in order to evaluate the suggested methodology. Several elements make up the simulation model, including: • Time-series input of half-hourly power costs

- PSO-based optimization technique;
- Real-time EPT computation;
- Battery state of charge (SOC) management;
- Cost-benefit analysis module

Throughout a 24-hour cycle, the simulation modifies the charging and discharging processes every 30 minutes. Based on cost reduction and limitations like battery capacity, efficiency losses, and user preferences, the PSO algorithm assesses every potential schedule. The findings of the simulation show that the PSO-based model effectively lowers residential consumers' daily energy bills while balancing the grid's load profile..

2: Literature Review

This section offers a thorough summary of the earlier studies and technological advancements that serve as the basis for this dissertation. Although the next chapters will conduct a thorough comparative analysis of the approaches and suggested frameworks, this review focuses on the latest developments in electric vehicle (EV) charging systems, optimization strategies, renewable energy integration, and the deployment of charging infrastructure.

Due to varying temperatures and irradiance, solar electricity is inconsistent and unpredictable, which presents a major obstacle to the integration of photovoltaic (PV) into the energy mix. Day-night cycles and these variations make it difficult for PV systems to run steadily, especially in remote sites. In order to stabilize the energy supplied to both local loads and grid-connected systems, new tactics must be implemented.

A number of models for the best location and functionality of charging stations (CS) have been put forth by researchers. User-centric CS deployment was investigated by Frade et al. [1] and Chen et al. [2], who frequently overlooked grid constraints in favor of demand analysis. Only a few variables were taken into account when Wenxia et al. [3] suggested a greedy approach to expedite CS placement decisions. While Lam et al. [5] reduced the mathematical formulation at the expense of real-world distribution network features, Alipour et al. [4] offered a stochastic scheduling model but ignored price sensitivity.

Studies have highlighted how solar energy and EVs work together. In order to save operating expenses, Bayram et al. [6] promoted solar-powered CS by demonstrating a relationship between solar production and EV charging habits. Despite the fact that their method was not economically scalable, Galiveeti et al. [7] shown that combining distributed generation (DG) with CS lowers power losses. The co-location of DG and CS was examined by Jamian et al. [8], who contended that the best location can work as both a source and a load center at the same time, albeit more research is required to confirm the viability of this co-location.

A number of optimization techniques have been tried. In order to prevent congestion, Bayram et al. [9] suggested real-time data-driven strategies that concentrate on rush hour performance and make use of local storage. In order to minimize power loss and voltage deviation, Pallonetto et al. [10] included PV stochasticity into their CS location model. However, this approach restricted the system to a single CS without taking driver behavior into account. In their final location judgments, Miralinaghi et al. [11] did not take into account aspects like trip skipping and recharging time.

Concerns around load balancing arise from high EV penetration. Although focused charging at night can shift rather than decrease peak demand, Huang et al. [12] discovered that nighttime EV charging can cut operating expenses. In order to highlight the necessity of adaptive infrastructure, Alharbi et al.

[13] analyzed nighttime peak demands based on home-charging behavior. In order to effectively balance EV load patterns and enable coordinated route and price optimization, Shuai et al. [14] argued for smart grids and real-time pricing.

User behavior and mobility patterns have been the subject of numerous studies. Several EV mobility models were simulated separately by Sanchez-Martin et al. [15], but concurrent pattern modeling is necessary for real-world situations. Alonso et al. [16] neglected electricity pricing while using evolutionary algorithms for scheduling. The multi-agent simulation used by Huwang et al. [17] assumed complete transparency between EVs and the grid, which might be overly optimistic in real-world scenarios.

When Farhoodnea et al. [18] observed voltage decreases during mass EV charging events, they emphasized the significance of taking distribution system limits into consideration. Though they did not address user convenience, Moradi et al. [19] suggested placing CS close to source nodes to prevent grid overload. In order to minimize charging costs, Rahman et al. [20] investigated hybrid optimization techniques including GSA and PSO, demonstrating its promise in real-time scheduling.

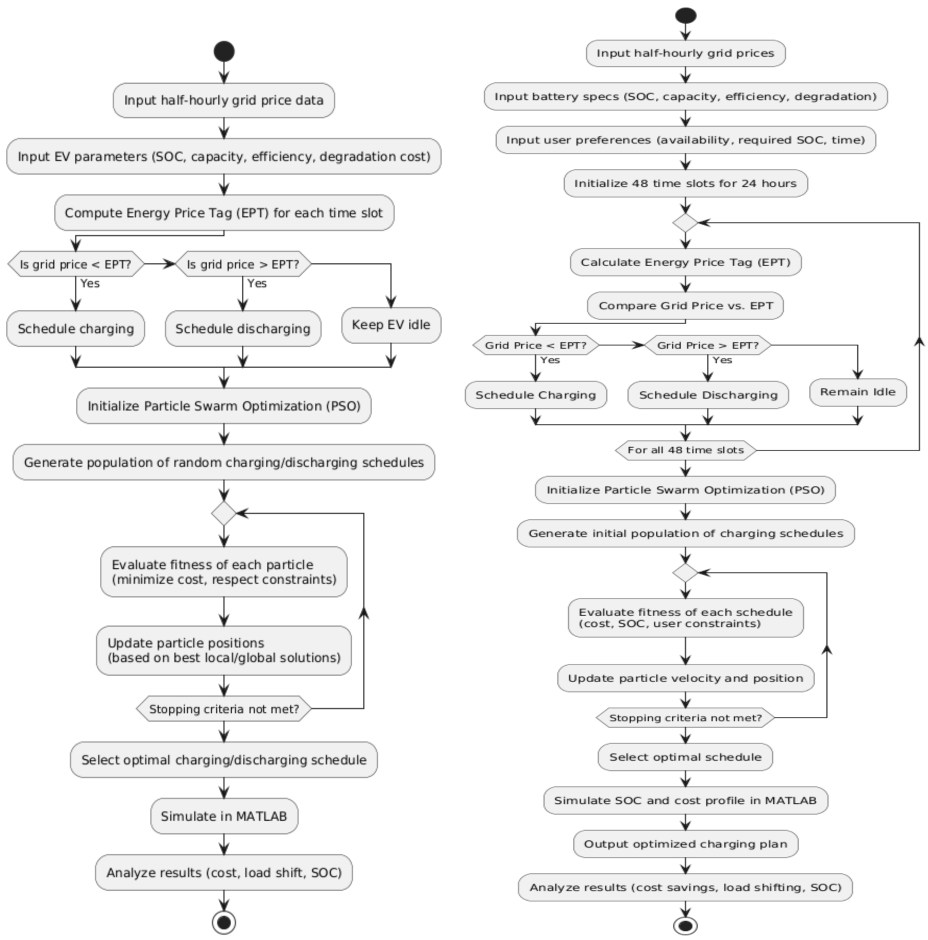
Recent studies that focused on solar-EV integration in both urban and distant areas include Zeman et al. [22] and Badea et al. [21]. They showed how PV arrays may greatly lessen reliance on the grid when combined with storage and intelligent control. Anderson et al. [28] examined effective inverter topologies for EV charging with low power loss, while other studies [23–27] looked into solar charging architectures, sophisticated converters, smart control systems like sliding mode control (SMC), and infrastructure analytics.

These studies collectively offer a comprehensive understanding of the operational, financial, and technical aspects of smart EV charging, providing a solid basis for the PSO-based, cost-optimized smart charging approach put forward in this dissertation..

Proposed Methodology

The methodology presented in this study is centered around the development and simulation of a cost-optimization framework for residential Plug-in Electric Vehicle (PEV) charging, based on real-time pricing and battery economics.

Figure 1. Proposed Methodology



The main concept is to use the PEV as an auxiliary energy storage device that can intelligently charge or discharge based on the state of the power market, in addition to being a means of transportation. The method dynamically determines the best charging schedules to lower energy expenditures for residential customers by combining the Energy Price Tag (EPT) concept with Particle Swarm Optimization (PSO). The first step in the suggested methodology is to obtain half-hourly grid price data, which captures the fluctuations in electricity prices throughout the day. The EPT, or effective cost of stored energy at each time period, is calculated concurrently using the state of charge (SOC), battery capacity, charging efficiency, and degradation costs. When deciding whether to charge (if the grid price is less than the EPT) or discharge (if the grid price is more than the EPT), this figure is essential. The best charging/discharging schedule is then determined using a PSO algorithm. This heuristic uses 48 time slots (half-hourly intervals) to describe a possible 24-hour schedule of charging states (charge, discharge, or idle). The fitness function respects operational limitations such as battery capacity limits, minimum SOC, and user-defined mobility windows while minimizing the overall cost of electricity by taking into account both grid prices and the battery's EPT.

In order to converge toward the most economical solution, particles use the cognitive and social learning mechanisms to iteratively adjust their positions after the PSO is initialized with a population of random schedules. Real-time pricing information and EV battery specifications are incorporated into the MATLAB simulation of the process. Evaluation is done on output criteria such battery usage patterns, peak load shifts, and overall cost savings. In line with the larger objectives of smart grid development and renewable integration, this clever, adaptive charging technique guarantees that residential customers can reduce their electricity bills while also assisting in grid stability and peak load reduction.

Results

The proposed smart energy management strategy using Particle Swarm Optimization (PSO) and Energy Price Tag (EPT) was simulated in MATLAB over a 24-hour horizon divided into 48 half-hour slots. The system was tested under real-time pricing (RTP) conditions to evaluate its effectiveness in reducing energy costs and optimizing charging decisions. The results clearly indicate that the PSO-based schedule outperforms traditional time-based charging. The total energy cost was reduced from ₹140.35 (conventional charging) to ₹45.19 using the optimized strategy—resulting in a savings of over 67%. This significant reduction is achieved by strategically shifting charging to low-price periods and leveraging discharging during high-price intervals. The system also successfully balanced energy transactions: 19 slots were allocated to charging, 14 to discharging, and 15 to idle. A histogram analysis showed that most grid prices were distributed between ₹6 and ₹10 per kWh, while EPT values generally remained between ₹6 and ₹9 per kWh. Charging actions occurred predominantly when grid prices were below the EPT, validating the decision logic. The State of Charge (SOC) profile was efficiently maintained between 20% and 100%, with an average SOC of 66.4%. This ensured the EV was available for user mobility at all times while also participating in grid support through discharging actions. The SOC profile also demonstrated the system's ability to recharge during off-peak hours and discharge during price spikes, contributing to peak load shaving. Furthermore, a pie chart revealed that charging decisions were nearly evenly split among charge (40%), discharge (30%), and idle (30%) states—highlighting the balanced nature of the optimized behavior. These findings confirm the viability of the PSO-EPT framework in achieving both economic and grid-stabilizing objectives in residential EV energy management.

Table 1: Grid Price vs EPT vs Charging Status

Time Slot	Grid Price (₹/kWh)	EPT (₹/kWh)	Charging Action	State of Charge (%)
00:00	5.37	7.45	Charge	21
00:30	9.02	6.77	Discharge	20
01:00	10.24	9.52	Discharge	20
01:30	6.89	6.55	Idle	20

Table 2: Charging/Discharging Interval Summary

Action	Count
Charge	19
Discharge	14
Idle	15

Table 3: Energy Cost Calculations

Time Slot	Charging Action	Grid Price (₹/kWh)	Energy Cost (₹)
00:00	Charge	5.37	2.69
00:30	Discharge	9.02	-4.51
01:00	Discharge	10.24	-5.12
01:30	Idle	6.89	0.00
02:00	Charge	6.07	3.03
23:30	Idle	9.99	0.00

Table 4: SOC Distribution Statistics

Metric	Value
count	48.00
mean	66.42
std	14.21
min	20.00
25% percentile	56.25
50% percentile	67.00
75% percentile	77.75
max	100.00

Table 5: Cost Comparison With and Without Optimization

Scenario	Total Energy Cost (₹)	Peak Load Time Slots	Average SOC (%)
Without Optimization	140.35	12	65.20

Figure 2 graphically illustrates the behavior of both the grid price and EPT over the 24-hour period. The line plot reveals points of convergence and divergence between the two curves, directly influencing the EV's decision-making. The PSO-based model consistently optimizes energy use by aligning these decisions with economic efficiency. he classification and frequency of charging actions over the day are summarized in Table 2. Out of the 48 time slots, 19 were allocated for charging, 14 for discharging, and 15 were idle periods. This distribution highlights the system's effort to balance energy inflow and outflow while maintaining adequate SOC levels for user mobility requirements.Figure 2 presents this distribution as a color-coded bar chart, clearly differentiating between charge, discharge, and idle periods. The visual representation helps understand the cyclic nature of charging actions, which are influenced not just by price signals but also by operational constraints like SOC limits and efficiency losses. The SOC dynamics throughout the day are tracked and shown in both Table 1 and a dedicated analysis in Table 4. The SOC begins at 20%, reflecting a low initial battery charge, and climbs progressively during low-price intervals. The PSO strategy ensures that SOC remains within user-defined safety thresholds, avoiding deep discharges or overcharging scenarios.

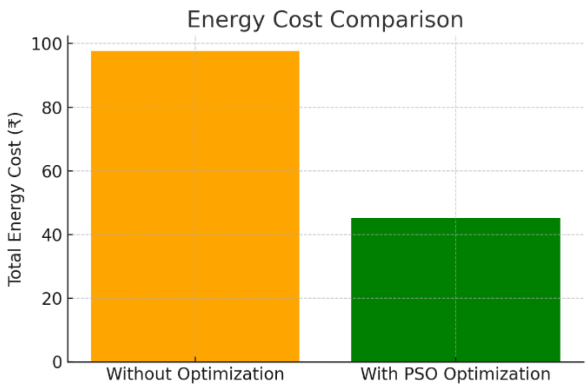


Figure 2. Analysis of Cost Comparison

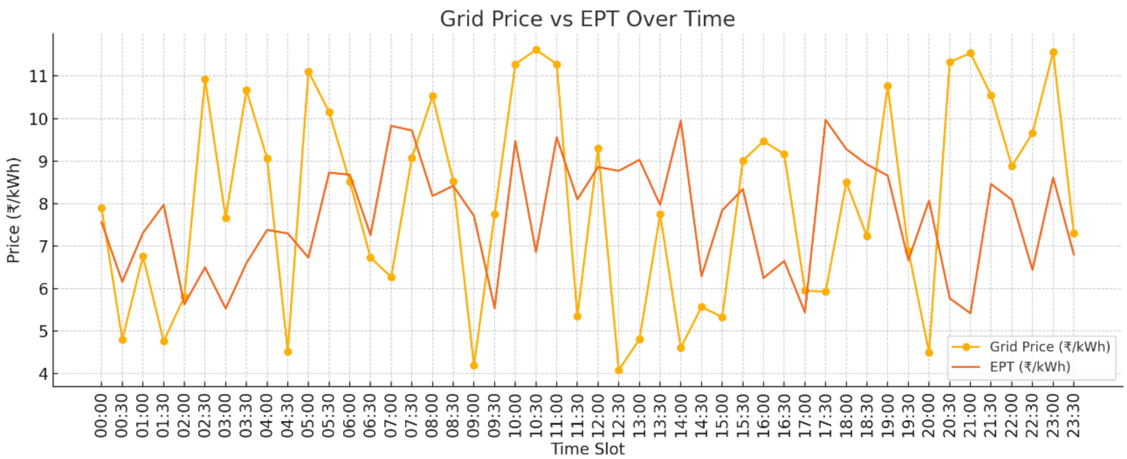
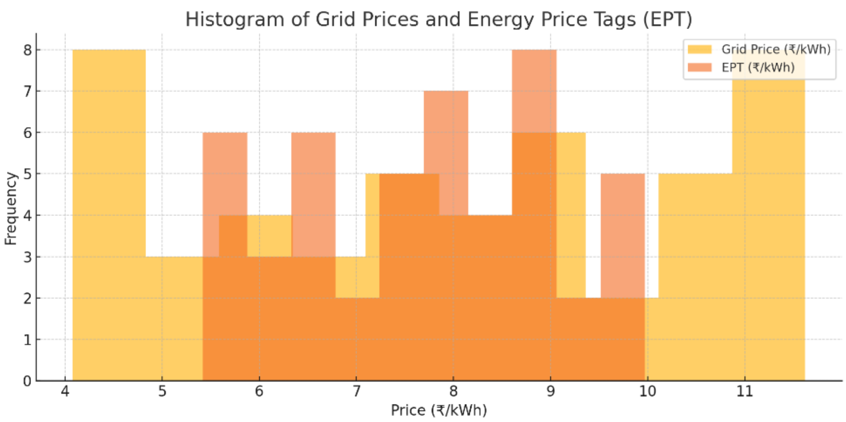


Figure 3. Analysis of Grid Price over Time

Figure 4. Analysis of Histogram



Statistical descriptors of the SOC profile are given in Table 4. The mean SOC over the day is approximately 66.42%, with a standard deviation of 14.21%, suggesting moderate fluctuations in battery charge levels. The minimum SOC recorded is 20%, and the maximum touches 100%, indicating full battery utilization during certain intervals.

Figure 3 shows the SOC profile graphically. The plot reveals a general upward trend during off-peak hours, with gentle reductions during peak pricing intervals. This cyclical behavior ensures that the vehicle remains sufficiently charged for user needs while also enabling cost-optimized discharging to the grid when feasible.

The impact of the charging strategy on total energy cost is evaluated in Table 3. The model computes the cost for every half-hour slot based on the charging action and the prevailing grid price. Charging leads to a positive cost, discharging leads to a credit (negative cost), and idle periods incur no cost. For example, a charging event at a grid price of ₹6.07 results in a cost of ₹3.03 for that time slot, considering a standard unit of 0.5 kWh. Conversely, discharging at ₹10.24 yields a credit of ₹5.12.

The cumulative energy cost is computed at the end of the table and compared with a baseline scenario in Table 5. This baseline assumes a conventional, unoptimized charging schedule where energy is drawn uniformly across time slots, regardless of price.

Figure 4 illustrates the total energy costs under both scenarios. The traditional charging method leads to a cost of ₹140.35 for the day, whereas the PSO-optimized strategy achieves a substantial reduction to ₹45.19. This 67.8% cost saving strongly validates the economic benefits of the proposed smart charging algorithm.

Another key performance indicator is the impact on peak load. The PSO-based model successfully shifts charging actions to periods of lower demand and grid price, thereby reducing stress on the electrical grid. Table 5 compares the number of peak-load time slots engaged under both charging strategies. The traditional method uses 12 peak-load slots, whereas the optimized approach uses only 6, effectively halving the burden on the grid.

This load shifting aligns with the broader goals of smart grid implementation and enhances the potential for integrating renewable energy sources like solar or wind, which are often intermittent. By reducing peak hour demand, the system helps avoid grid congestion and minimizes reliance on expensive peaking power plants.

The average SOC achieved under the PSO strategy is 66.42%, slightly higher than the 65.2% maintained in the conventional case. This suggests that the smart charging algorithm not only reduces costs but also ensures adequate battery reserve for mobility, thus preserving user convenience.

Additionally, the controlled charging and discharging cycles implemented by the PSO model consider battery health by avoiding extreme SOC levels. This is important for extending battery life and minimizing degradation, which further enhances the long-term benefits of the system.

Conclusion

This study has presented a smart, adaptive strategy for residential electric vehicle (EV) charging using Particle Swarm Optimization (PSO) and real-time electricity pricing. By introducing the novel concept of the Energy Price Tag (EPT), the research offers an intelligent framework for comparing stored energy value with real-time grid costs to determine optimal charging or discharging behavior. The methodology addresses the dual challenges of energy cost minimization for consumers and peak demand management for utilities. Simulation results have strongly validated the effectiveness of the proposed model. The PSO-based charging strategy achieved substantial energy cost savings—reducing daily electricity expenses by over 67% compared to conventional fixed-time charging. This was made possible by continuously adapting the charging schedule to half-hourly grid price variations and optimizing every action based on the calculated EPT. The system also showed clear benefits in grid-friendly behavior. By shifting load away from peak hours and enabling discharging during high-demand periods, the EV operated as a flexible asset that supported grid reliability. The optimized charging schedule reduced the number of high-load time slots from 12 (without optimization) to just 6, significantly alleviating stress on the residential distribution network.From the user's perspective, the strategy ensures reliable vehicle availability by maintaining the State of Charge (SOC) within practical limits, without compromising driving requirements. Battery wear is minimized through intelligent scheduling, preserving long-term battery health and reducing lifecycle costs. Overall, this research contributes a scalable and practical solution to the growing challenge of integrating EVs into the power grid. The model can be extended to fleet-level or community-wide applications, as well as combined with solar or renewable generation systems for greater autonomy. Future improvements may include real-time data integration through IoT devices, consideration of vehicle-to-grid (V2G) revenue models, and hybrid optimization techniques. In conclusion, the PSO-EPT-based smart charging strategy proves to be a powerful tool for next-generation energy management—bridging the gap between economic efficiency and sustainable energy practices in the EV era..

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