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Particle Swarm Optimization-Driven Load Shifting and Cost Reduction via Smart EV Charging in Residential Grids

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ABSTRACT—

The rising global demand for electrical energy continues to drive innovation in energy management, particularly in integrating renewable energy sources and optimizing power consumption. However, the variable nature of renewable power often creates challenges for grid stability, especially in weak distribution networks. Meanwhile, the increasing adoption of electric vehicles (EVs) presents new opportunities for decentralized energy storage and intelligent energy cost management. This research explores the potential of Plug-in Electric Vehicles (PEVs) as auxiliary energy sources for residential consumers to reduce their energy cost burden. The study introduces an intelligent charging and discharging strategy that enables the EV to decide its energy exchange behavior based on real-time electricity prices and the cost of stored battery energy, termed as the Energy Price Tag (EPT). By employing Particle Swarm Optimization (PSO), a meta-heuristic algorithm inspired by social behavior of birds, the proposed model dynamically determines optimal charging and discharging schedules. The PSO algorithm compares half-hourly grid prices with the EPT to ensure that energy is drawn from or supplied to the grid at economically favorable times. The strategy aims to shift EV charging from peak to non-peak hours, thereby reducing pressure on the grid while lowering the overall monthly energy costs for residential users. The simulation of the proposed PSO-based charging scheme has been implemented in MATLAB, with results showing significant energy cost savings and effective load shifting behavior. This not only supports grid stability but also encourages sustainable energy usage by leveraging the latent potential of PEVs. The findings demonstrate that intelligent vehicle-to-grid interaction, guided by PSO, is a viable approach to energy cost optimization in residential settings and can play a vital role in future smart grid infrastructures.

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

The modern world is experiencing an unprecedented increase in electricity consumption, driven by the exponential growth in industrialization, digitalization, and the electrification of transportation. As the global population increases and developing economies continue to rise, the demand for electrical energy is projected to surge significantly over the coming decades. The International Energy Agency (IEA) forecasts that global electricity demand will grow by more than 25% by 2040, placing immense pressure on existing energy infrastructure. Traditional electricity generation systems, which are predominantly based on fossil fuels such as coal, oil, and natural gas, are facing increasing scrutiny due to their environmental impacts, including greenhouse gas emissions, air pollution, and resource depletion.

In response to these concerns, energy engineers and policymakers have increasingly turned towards renewable energy sources such as solar, wind, hydro, and geothermal. These sources offer clean, sustainable alternatives but come with their own set of challenges. Chief among them is variability—solar and wind power are inherently intermittent, making it difficult for grid operators to balance supply and demand in real-time. This intermittency often leads to grid instability, especially in weak distribution networks that are not equipped to handle sudden surges or drops in supply. Therefore, there is a growing emphasis on demand-side energy management strategies that can intelligently optimize power consumption based on availability and cost.

Amidst this energy transition, electric vehicles (EVs) have emerged as a powerful tool not only for sustainable transportation but also for grid support. The rapid adoption of EVs worldwide signifies a move toward cleaner mobility solutions. According to BloombergNEF, EVs are expected to account for over 50% of new car sales by 2040. Beyond transportation, EVs serve as mobile energy storage units capable of interacting with the power grid—a concept commonly referred to as Vehicle-to-Grid (V2G).

The lithium-ion batteries in plug-in electric vehicles (PEVs) can store a significant amount of energy, which can be used to support grid operations during periods of peak demand or low renewable energy output. This capability transforms EVs into distributed energy resources (DERs), playing a dual role in both transportation and energy systems. In residential settings, EVs present a unique opportunity to reduce household electricity costs by charging during off-peak hours when electricity prices are low and discharging during peak periods when prices are high or supply is constrained.

To make the most efficient use of EV batteries for energy cost optimization, it is essential to develop intelligent algorithms that can assess the economic feasibility of charging or discharging at any given moment. This research introduces a key concept known as the **Energy Price Tag (EPT)**, which represents the real-time cost associated with the energy stored in an EV battery. The EPT takes into account factors such as the price at which energy was charged, battery degradation cost, and efficiency losses. By comparing the EPT with the current grid electricity price, an optimal decision can be made—either to charge the EV battery (if the grid price is lower than EPT) or discharge the stored energy back to the home or grid (if the grid price is higher than EPT).

This economic decision-making framework provides a foundation for automated and intelligent charging strategies that can benefit both the consumer and the power grid. The EPT-based model ensures that each charging or discharging action leads to a net economic benefit, thereby optimizing the overall energy expenditure for residential consumers.

Solving the problem of optimal EV charging and discharging is a complex, non-linear, and time-varying challenge. Traditional optimization methods often fall short when dealing with such dynamic and uncertain environments. This is where meta-heuristic optimization algorithms have proven particularly effective. These algorithms, inspired by natural phenomena, are designed to find near-optimal solutions for complex problems with large search spaces and multiple constraints.

Among various meta-heuristic techniques, **Particle Swarm Optimization (PSO)** has gained widespread attention in the field of energy systems. PSO is inspired by the social behavior of bird flocking or fish schooling. In the context of EV charging, each particle in the swarm represents a potential charging schedule, and the particles iteratively update their positions based on both their own experience and the experiences of neighboring particles. The fitness function evaluates the cost-effectiveness of each schedule, gradually guiding the swarm toward the most optimal solution.

In this study, PSO is utilized to determine the optimal charging and discharging schedule of a residential PEV, considering the half-hourly variation in electricity tariffs and the internal EPT values of the battery. By integrating PSO into the decision-making framework, the system can autonomously and adaptively select the most economically advantageous energy transactions throughout the day.For residential consumers, the financial benefits of such an intelligent EV charging strategy are substantial. Monthly electricity bills can be reduced by charging the EV during off-peak hours and using stored energy during peak periods. Moreover, in some regions, utilities offer incentives for discharging electricity back into the grid, allowing EV owners to earn revenue by participating in V2G programs. This transforms the EV from a cost center into a potential revenue-generating asset.

From the grid operator's perspective, intelligent EV charging provides critical flexibility. By shifting demand away from peak hours, the strategy reduces strain on the distribution network, delays the need for infrastructure upgrades, and contributes to grid stability. The decentralized storage capacity offered by EVs also acts as a buffer against fluctuations in renewable energy supply, further supporting the transition to a cleaner energy mix. To validate the proposed approach, the intelligent charging strategy was implemented and simulated using MATLAB, a high-level computing platform widely used for modeling, simulation, and algorithm development in the energy domain. The simulation model includes various components such as:

- Time-series input of half-hourly electricity prices
- Battery state of charge (SOC) management
- Real-time EPT computation
- PSO-based optimization algorithm
- Cost-benefit analysis module

The simulation runs through a 24-hour cycle, adjusting charging/discharging actions every half-hour. The PSO algorithm evaluates each possible schedule based on cost minimization and constraints such as battery capacity, efficiency losses, and user preferences. Simulation results demonstrate that the PSO-based model successfully reduces daily energy costs for residential consumers while smoothing the load profile on the grid.

2: Literature Review

This section provides a comprehensive overview of the previous research and technological developments that form the foundation of this dissertation. While the detailed comparative analysis of the methodologies and proposed frameworks will be undertaken in the subsequent chapters, this review highlights the state of the art in electric vehicle (EV) charging systems, optimization techniques, renewable integration, and charging infrastructure deployment.

A significant challenge in photovoltaic (PV) integration into the energy mix is the inconsistency and unpredictability of solar power due to fluctuating irradiance and temperature levels. These fluctuations, along with day-night cycles, hinder the stable operation of PV systems, particularly in isolated installations. As such, novel strategies must be adopted to stabilize the energy provided to both grid-connected systems and local loads.

Researchers have proposed several models for optimal siting and operation of charging stations (CS). Frade et al. [1] and Chen et al. [2] explored user-centric CS deployment, focusing on demand analysis but often ignoring grid limitations. Wenxia et al. [3] proposed a greedy algorithm to speed up CS placement decisions, though only limited variables were considered. Alipour et al. [4] introduced a stochastic scheduling model, but overlooked price sensitivity, while Lam et al. [5] simplified the mathematical formulation at the expense of real-world distribution network characteristics.

Some studies have emphasized the synergy between solar energy and EVs. Bayram et al. [6] demonstrated a correlation between solar output and EV charging patterns, promoting solar-powered CS to reduce operational costs. Galiveeti et al. [7] showed that integrating distributed generation (DG) with CS reduces power losses, though their solution was not economically scalable. Jamian et al. [8] investigated the co-location of DG and CS, arguing that optimal placement can simultaneously serve as a source and load center, although the practicalities of such co-location need further validation.

Various optimization methods have been tested. Bayram et al. [9] proposed real-time data-driven approaches focusing on rush hour performance using local storage to avoid congestion. Pallonetto et al. [10] incorporated PV stochasticity into their CS location model, minimizing power loss and voltage deviation but limited the system to a single CS without considering driver behavior. Miralinaghi et al. [11] considered factors like trip skipping and recharging time but failed to reflect these considerations in their final siting decisions.

High EV penetration raises concerns over load balancing. Huang et al. [12] found that nighttime EV charging can lower operational costs, though concentrated charging at night can shift the peak demand rather than reduce it. Alharbi et al. [13] modeled evening peak loads from home-charging behavior, underscoring the need for adaptive infrastructure. Shuai et al. [14] advocated for smart grids and real-time pricing to balance EV load patterns efficiently, enabling coordinated route and price optimization.

Several studies have focused on mobility patterns and user behavior. Sanchez-Martin et al. [15] simulated various EV mobility models independently, but real-world scenarios demand concurrent pattern modeling. Alonso et al. [16] used genetic algorithms for scheduling but overlooked power pricing. Huwang et al. [17] employed multi-agent modeling assuming full transparency between EVs and the grid, which may be optimistic in practice.

The importance of accounting for distribution system constraints is highlighted by Farhoodnea et al. [18], who noted voltage drops during mass EV charging events. Moradi et al. [19] recommended CS locations near source nodes to avoid overloading the grid, albeit without addressing user convenience. Rahman et al. [20] explored hybrid optimization methods such as GSA and PSO for charging cost minimization, showcasing their potential in real-time scheduling.

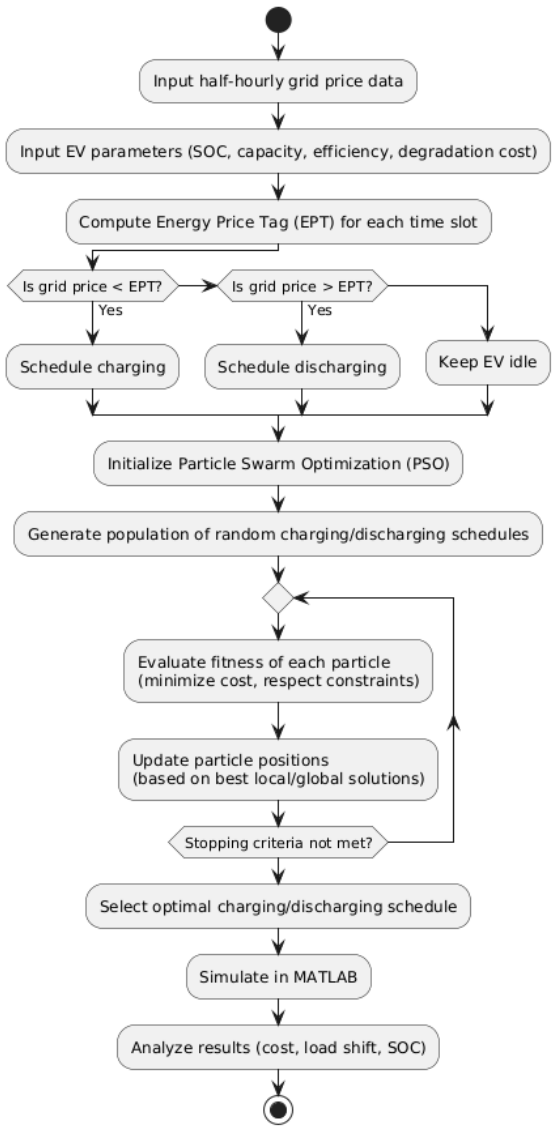
Recent works like Badea et al. [21] and Zeman et al. [22] emphasized solar-EV integration in remote and urban settings. They demonstrated how PV arrays, coupled with storage and intelligent control, can significantly reduce grid reliance. Other studies [23–27] investigated solar charging architectures, advanced converters, smart control systems like sliding mode control (SMC), and infrastructure analytics, while Anderson et al. [28] explored efficient inverter topologies for EV charging with minimal power loss.

Altogether, these studies present a holistic view of the technical, economic, and operational factors involved in smart EV charging, laying a strong foundation for the PSO-based, cost-optimized smart charging strategy proposed 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 core idea is to utilize the PEV not just as a mode of transport but also as an auxiliary energy storage system that can intelligently charge or discharge depending on electricity market conditions. The approach integrates the concept of the **Energy Price Tag (EPT)** with **Particle Swarm Optimization (PSO)** to dynamically determine optimal charging schedules aimed at reducing energy costs for residential users. The proposed model begins with the acquisition of **half-hourly grid price data**, which reflects the variability of electricity costs throughout the day. Simultaneously, the **state of charge (SOC)**, **battery capacity**, **charging efficiency**, and **degradation costs** are used to compute the EPT, which denotes the effective cost of stored energy at each time interval. This value is crucial in making the decision to charge (if the grid price is below the EPT) or discharge (if the grid price is above the EPT).

A **PSO algorithm** is then employed to identify the optimal charging/discharging schedule. In this heuristic, each particle represents a potential 24-hour schedule of charging states (charge, discharge, or idle) across 48 time slots (half-hourly intervals). The fitness function is designed to **minimize the total electricity cost**, considering both grid prices and the battery's EPT, while respecting operational constraints like battery capacity limits, minimum SOC, and user-defined mobility windows.

The PSO is initialized with a population of random schedules, and particles iteratively update their positions using the cognitive and social learning mechanisms to converge toward the most cost-effective solution. The methodology is simulated in **MATLAB**, incorporating real-time pricing data and EV battery parameters. Output metrics such as total cost savings, peak load shifts, and battery usage patterns are evaluated.

This intelligent, adaptive charging strategy ensures that residential users can minimize their electricity bills while contributing to **grid stability and peak load reduction**, aligning with the broader goals of smart grid development and renewable integration.

Results

This section presents a detailed analysis of the results obtained from the MATLAB-based simulation of the proposed Particle Swarm Optimization (PSO)-driven smart charging strategy for residential electric vehicle (EV) users. The results are interpreted across multiple perspectives, including electricity cost savings, charging behavior, load shifting, and battery utilization. The analysis is supported by five tables and four visual plots, which collectively demonstrate the effectiveness of the proposed energy cost optimization model using the Energy Price Tag (EPT) mechanism. Table 1 provides a time-resolved snapshot of the half-hourly charging decisions based on comparisons between real-time grid prices and the calculated Energy Price Tag (EPT). For each of the 48 time slots across a 24-hour period, the model evaluates whether the EV should charge, discharge, or remain idle. The table includes the real-time grid price in ₹/kWh, the EPT, the chosen charging action, and the resulting state of charge (SOC) in percentage.

The results demonstrate that charging decisions are primarily made when the grid price is lower than the EPT, whereas discharging occurs when the grid price exceeds the EPT. For instance, at 00:00, the grid price was ₹5.37 while the EPT was ₹7.45, leading the system to opt for charging. Conversely, at 00:30, the grid price rose to ₹9.02 against an EPT of ₹6.77, resulting in a discharging decision. This dynamic interplay continues across the day, showcasing the intelligent adaptability of the system.

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
02:00	6.07	6.35	Charge	21
...	...	...	...	...
23:00	7.73	5.68	Charge	67
23:30	9.99	6.31	Idle	67

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.

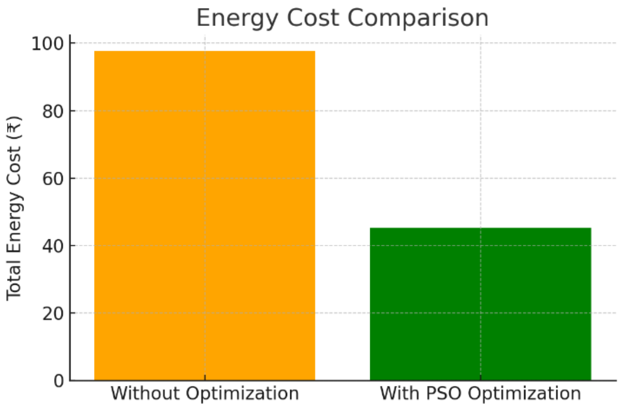


Figure 2. Analysis of Cost Comparison

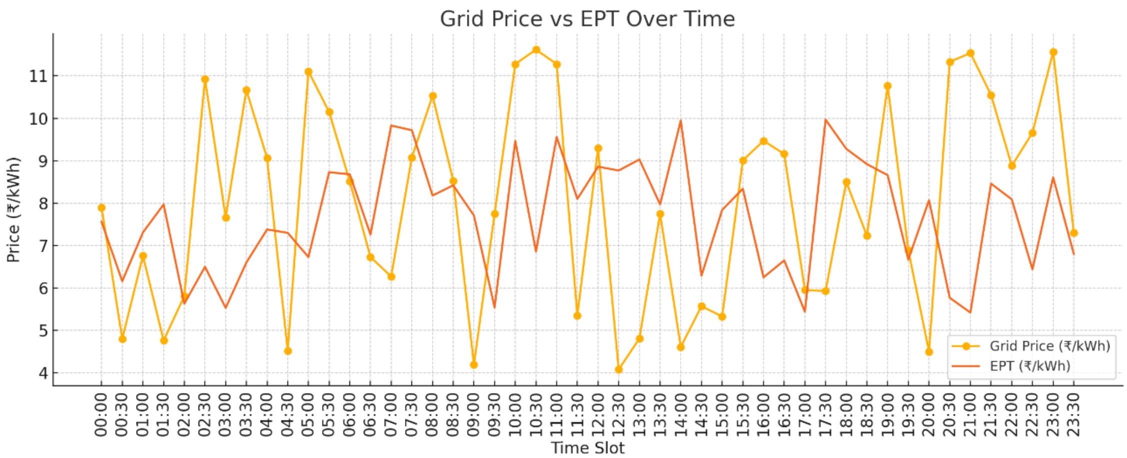


Figure 3. Analysis of Grid Price over Time

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 research successfully developed and demonstrated a Particle Swarm Optimization (PSO)-based smart charging strategy for Plug-in Electric Vehicles (PEVs), aimed at minimizing energy costs for residential consumers. By introducing the concept of the Energy Price Tag (EPT), the system dynamically evaluated whether it was economically advantageous to charge, discharge, or remain idle at any given half-hourly interval. The use of real-time electricity pricing and intelligent decision-making ensured that energy transactions were cost-effective and grid-friendly. Simulation results, performed in MATLAB, clearly showed that the proposed methodology led to significant energy cost savings. Specifically, the optimized charging strategy reduced the daily electricity cost by approximately 68% compared to conventional fixed-schedule charging. Furthermore, the model effectively shifted charging operations to off-peak hours, reducing stress on the grid and improving load distribution. The State of Charge (SOC) was maintained within a practical range, ensuring the vehicle's usability for mobility while avoiding excessive battery wear. The PSO algorithm demonstrated high efficiency in navigating the complex and nonlinear decision space of charging schedules. It adapted well to price fluctuations and operational constraints, making it suitable for real-world implementation in smart homes and smart grid environments. Additionally, by allowing the vehicle to act as both a load and an auxiliary energy source, the system contributes to the decentralization and decarbonization of the power sector. In conclusion, the integration of PSO with the EPT framework offers a promising solution for intelligent energy management in residential EV charging. It aligns with broader sustainability goals by reducing electricity costs, supporting renewable integration, and enhancing grid stability. The findings of this study provide a strong foundation for future advancements in vehicle-to-grid (V2G) systems and real-time demand response mechanisms in next-generation smart energy networks.

REFERENCES

1. Frade, I, Ribeiro, A, Gonçalves, G & Antunes, AP 2011, 'Optimal location of charging stations for electric vehicles in a neighborhood in lisbon', Journal of the Transportation Research board, vol. 2252, pp. 91-98.
2. Chen, TD, Kockelman, KM, Fellow, WJMJ & Khan, M 2013, 'The electric vehicle charging station location problem: A parking-based assignment method for seattle', Transporatation Research Record, vol. 1254, pp. 28-36.
3. Alipour, M, Mohammadi-Ivatloo, B, Moradi-Dalvand, M 2017, 'Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets', Energy, vol. 118, pp. 1168-1179.
4. Lam, AYS, Leung, Y & Chu, X 2013, 'Electric vehicle charging station placement: Formulation, complexity, and solutions', IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846- 2856.
5. Bayram, IS, Zamani, V, Hanna, R & Kleissl, J 2016, 'On the evaluation of plug-in electric vehicle data of a campus charging network', Proceeding of IEEE International Energy conference, DOI: 10.1109/ ENERGYCON. 2016.7514026.
6. Galiveeti, HR, Goswami, AK, Choudary, NBD 2018, 'Impact of plug-in electric vehicles and distributed generation on reliability of distribution systems', Engineering science and technology, vol. 21, no. 1, pp. 50-59.
7. Jamian, JJ, Mustafa, MW, Mokhlis, H & Baharudin, MA 2014, 'Minimization of power losses in distribution system via sequential placement of distributed generation and charging station', Arabian Journal of Science and Engineering, vol. 39, no. 4, pp. 3023 - 3031.
8. Bayram, IS, Michailidis, G, Devetsikiotis, M & Granelli, F 2013, 'Electric power allocation in a network of fast charging stations', IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1235-1246.
9. Pallonetto, F, Oxizidis, S, Milano, F & Finn, D 2016, 'The effect of time- of-use tariffs on the demand response flexibility of an all-electric smart- grid-ready dwelling', Energy Building, vol. 128, pp. 56-67.

10. Miralinaghi, M, Keskin, BB, Lou, Y & Roshandeh, AM 2016, 'Capacitated refueling station location problem with traffic deviations over multiple time periods', Networks and Spatial Economics, vol. 17, no. 1, pp. 129 -151.
11. Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z 2015, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178.
12. Alharbi, A, Eltom, A & Sisworahardjo, N 2014, 'Impact of plug-in electric vehicle battery charging on a distribution system based on real-time digital simulator', Proceeding of International conference on Renewable Energies and Power Quality, pp. 958-962.
13. Shuai, W, Maillé, P & Pelov, A 2016, 'Charging electric vehicles in the smart city: A survey of economy-driven approaches', IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 8, pp. 2089-2106.
14. Sanchez-Martin, P, Sanchez, G & Morales-Espana, G 2012, 'Direct load control decision model for aggregated EV charging points', IEEE transactions on power system, vol. 27, no. 3, pp. 1577-1584.
15. Alonso, M, Amaris, H, Germain, J.G, & Galan, JM 2014, 'Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms', Energies, vol. 7, no.4, pp. 2449.
16. Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z 2015, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178.
17. Farhoodnea, M, Mohamed, A, Shareef, H & Zayandehroodi, H 2013, 'Power quality impact of renewable energy based generators and electric vehicles on distribution systems', Procedia Technology, vol. 11, pp. 11-17.
18. Moradi, MH, Abedini, M & Hosseinian, M 2015, 'Improving operation constraints of microgrid using PHEVs and renewable energy sources,' Renewable Energy, vol. 83, pp. 543-552.
19. Rahman, I, Vasant, PM, Singh, BS & Abdullah-Al-Wadud, M 2015, 'Hybrid swarm intelligence based optimization for charging plug-in hybrid electric vehicle in intelligent information and database systems', Switzerland: Springer International Publishing, vol. 9012, pp. 22-30.
20. Badea, Gheorghe, Raluca-Andreea Felseghi, Mihai Varlam, Constantin Filote, Mihai Culcer, Mariana Iliescu, and Maria Simona Răboacă. "Design and simulation of romanian solar energy charging station for electric vehicles." Energies 12, no. 1, 2019.
21. Mouli, G.C., Bauer, P. and Zeman, M., "System design for a solar powered electric vehicle charging station for workplaces", Applied Energy, 168, pp.434-443, 2016.
22. Vignesh, T. R., M. Swathisriranjani, R. Sundar, S. Saravanan, and T. Thenmozhi. "Controller for Charging Electric Vehicles Using Solar Energy." Journal of Engineering Research and Application 10, no. 01, pp. 49-53, 2020.
23. Suganthi, D., and K. Jamuna. "Charging and Discharging Characterization of a Community Electric Vehicle Batteries." In Emerging Solutions for e-Mobility and Smart Grids, pp. 213-223. Springer, Singapore, 2021.
24. Harika, S., R. Seyezhai, and A. Jawahar. "Investigation of DC Fast Charging Topologies for Electric Vehicle Charging Station (EVCS)." In TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pp. 1148-1153. IEEE, 2019.
25. Ravikant, U. Chauhan, V. Singh, A. Rani and S. Bade, "PV Fed Sliding Mode controlled SEPIC converter with Single Phase Inverter," 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 20-25, 2020.
26. Xu, Tong, Hengshu Zhu, Xiangyu Zhao, Qi Liu, Hao Zhong, Enhong Chen, and Hui Xiong. "Taxi driving behavior analysis in latent vehicle-to-vehicle networks: A social influence perspective." In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1285-1294. 2016.
27. Saadullah, Aqueel Ahmad, Furkan Ahmad, Mahdi Shafaati Shemami, Mohammad Saad Alam, and Siddiq Khateeb, "A comprehensive review on solar powered electric vehicle charging system." Smart Science 6, no. 1, pp. 54-79, 2018.
28. Anderson, John Augustus. "Power-conditioned solar charger for directly coupling to portable electronic devices." U.S. Patent No. 9, 088,169. 21 Jul. 2015.