

Adaptive dynamic pricing for optimal electric vehicle charging and load balancing in smart distribution networks

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ABSTRACT

The growing use of electric vehicles (EVs) in distribution networks has brought both environmental benefits and operational problems. When people quickly adopt something without proper planning, it can cause grid congestion and voltage instability. This paper introduces an improved dynamic pricing system that evenly distributes the load between residential and commercial distribution networks by changing how EVs charge. The proposed framework uses localized demand profiles and time-of-use (TOU) rates to create dynamic charging incentives that encourage users to charge their devices at the best times. The system changes prices automatically based on how much the grid is being used, which makes load curves smoother and makes better use of assets. Simulation results show that when charging isn't coordinated, load imbalance causes mean absolute percentage errors (MAPE) to reach almost 28%. The proposed scheme, on the other hand, lowers this to less than 6%, showing a big improvement in the performance of the distribution network and voltage stability.

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1. INTRODUCTION

Over the past ten years, the use of electric vehicles (EVs) has grown quickly as countries try to lower carbon emissions and move toward more environmentally friendly transportation systems [1]. The International Energy Agency (IEA) says that by 2030, there will be more than 130 million EVs on the road. This shows how much the global car market is changing [2]. Even with these improvements, there are still a number of problems that make it hard to integrate a lot of EVs, such as high costs of buying them, not enough charging stations (CS), and the fact that existing distribution networks have to handle more power [3]. Many power grids weren't made to handle a lot of EV charging at once, which could cause problems like overloading, power loss, and grid instability [4]. There are two main types of EVs: plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). PHEVs use both battery and internal combustion engine power, while BEVs only use stored electrical energy to move. EVs are cheaper to run and maintain

than internal combustion engine vehicles (ICEVs) because they have fewer mechanical parts and use little or no fossil fuels [4]. Also, using renewable energy to power EVs makes their environmental benefits even better by cutting down on carbon emissions over their whole life [5]. But as more EVs are on the road, managing the grid and processing data becomes harder, especially in smart grids where charging data must be collected and processed all the time [6]. Charging EVs without rules or coordination can put a lot of stress on the grid, especially in older distribution networks that don't have modern load management features. Expanding physical infrastructure could be a solution, but it is still expensive and takes a lot of time. This shows how important intelligent coordination mechanisms are. Several studies have suggested coordinated charging methods that take into account the state of charge (SOC), the distance traveled, or the availability of CSs [7]–[9]. These models help make the grid more efficient and lower load variance, but they often depend on fixed assumptions. Also, most of the research right now is about making charging schedules better in single-area networks, which means that cross-regional load balancing opportunities are being missed. In the real world, residential areas usually have the most demand in the evening, while commercial or industrial areas usually have the most demand during the day. This complementary load behavior makes it possible to dynamically move EV charging demand from one region to another. Most existing EV charging coordination approaches focus on single-region scheduling or fixed time-of-use (TOU) pricing, ignoring cross-regional load balancing opportunities. This study addresses this limitation through a dual-region adaptive pricing mechanism.

This paper proposes a dynamic pricing approach that uses distribution-level data to motivate EV owners to charge during suboptimal network utilization, filling the gap. Summary of this work's main contributions: i) a dual-region EV charging model that uses dynamic pricing to balance load between residential and commercial/industrial distribution networks; ii) a time-of-use (TOU)-based adaptive pricing algorithm that continuously adjusts charging costs based on grid loading; and iii) a full performance evaluation that shows that the proposed approach smooths load profiles, improves grid efficiency, and reduces overload risk. EVs are increasingly being used in power networks, necessitating research on charging coordination, cost reduction, and network stability. In preliminary investigations, Sohail *et al.* [10] examined how uncoordinated EV charging affects residential distribution networks at varying penetration levels. They found that peak-hour charging caused undervoltage and overcurrent issues. Later, Sohail *et al.* [11] used time-of-use TOU pricing and discovered that most EVs charged when electricity rates were lowest, creating a nighttime peak. Kim [12] showed that TOU tariffs boosted night-time charging and created a dual-peak demand pattern—one in the early evening (18:00–20:00) and another close to midnight—using household energy meter data. Gilleran *et al.* [13] applied similar study to business buildings and found that EV charging demand peaked between 12:00 and 18:00, coincident with high conventional commercial loads, increasing neighborhood congestion. Many optimization and incentive-based solutions reduce these impacts. Qureshi *et al.* [14], [15] proposed a menu-based pricing method using mobile charging stations (MCS) to dynamically adjust prices across regions to reduce user costs and charging units. Saha *et al.* [16] proposed a game theory-based paradigm for optimal charging and discharging, encouraging EV users to charge off-peak and discharge back to the grid during peak demand. This decreases energy costs and boosts operator profits.

Additionally, advanced meta-heuristic approaches have showed potential. Zhang *et al.* [17] improved photovoltaic-storage hybrid station charging service fees and peak-to-valley load discrepancies using the non-dominated sorting genetic algorithm II (NSGA-II). Adetunji *et al.* [18] used a whale optimization algorithm (WOA) to control EV charging in a smart grid, minimizing power loss and improving IEEE 33-bus voltage profiles. WOA and the gravitational search algorithm (GSA) connected renewable energy and EVs while reducing emissions and power loss [19]. Adetunji *et al.* [20] used genetic algorithms (GA) and WOA to optimize distributed generation (DG), battery energy storage systems (BESS), and EV-CSs, improving network performance in IEEE 33- and 118-bus test systems. Other studies examined user-centered cost reduction. Wang and Khan [21] proposed a user-driven charging/discharging control technique that cuts expenses when prices fluctuate using particle swarm optimization (PSO). Shang *et al.* [22] improved EV charging and discharging schedules using a blockchain-based dual-objective gray wolf algorithm while protecting user privacy and balancing grid load. Habib *et al.* [23] used battle royale optimization (BRO) on the Conseil International des Grands Réseaux Électriques (CIGRE) 14-bus test system to analyze distributed generator and EV coordination, outperforming GA and PSO. We also examined centralized power-flow-based scheduling. Aygun and Kamalasadan [24] developed a centralized MATPOWER algorithm to optimize IEEE 123-bus EV charging distribution. Mazhar *et al.* [25] used decision trees, random forests (RF), support vector machines (SVM), K-nearest neighbors (KNN), deep neural networks (DNN), and long short-term memory (LSTM) networks to recommend efficient and cost-effective CSs. They found that RF and LSTM models were most accurate. Privacy-preserving techniques are suggested for EV charging communications. A blockchain-enabled privacy-preserving scheme by Knirsch *et al.* [26] allows CSs to compete for EV charging requests while protecting customer data. Xia *et al.* [27] developed a two-layer hybrid optimization

model with LSTM-based departure-time prediction in the upper layer and GA–PSO in the lower layer to improve residential charging user satisfaction. This work introduces a distribution-level dynamic pricing system that balances temporal and spatial demand. By altering EV charging prices based on regional load patterns, the proposed system promotes grid efficiency, minimizes congestion, and distributes load fairly across network zones. Unlike conventional TOU pricing methods, the proposed framework dynamically adjusts charging tariffs across residential and commercial feeders by exploiting complementary demand cycles, thereby reducing congestion without centralized scheduling.

2. METHOD

To achieve balanced utilization of the distribution network between residential and commercial or industrial regions, this study proposes a dynamic pricing-based coordination framework that regulates EV charging in both spatial and temporal domains. The framework combines charging-station aggregation, real-time data exchange, and an adaptive tariff-generation algorithm that modifies prices according to the current and forecasted loading conditions of each region. Through coordinated communication among CSs, aggregators, and a central control unit, the system ensures that EV users are encouraged to charge when and where network stress is minimal, thereby smoothing the overall grid demand profile [28]. The proposed model operates within a smart-grid environment in which CSs are grouped into two categories: i) residential-area stations, characterized by low daytime utilization and high evening peaks and ii) commercial/industrial-area stations, which exhibit heavy loading during business hours and lower demand at night.

A centralized aggregator collects operational data from CSs within each region—such as the station identifier, geographic location, number of charging slots, instantaneous power usage, and slot availability. This information is transmitted to a cloud-based control platform accessible to both grid operators and EV users. Figure 1 illustrates the high-level architecture of the proposed EV-charging load-balancing framework.

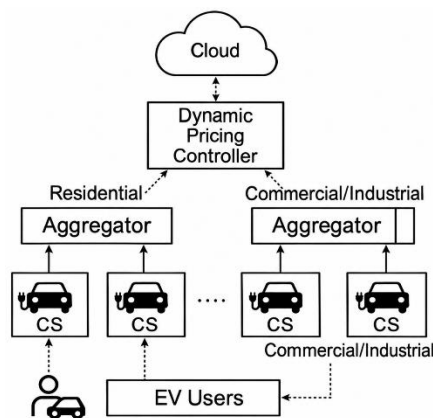


Figure 1. High-level schematic of the EV-charging load-balancing framework

The schematic shows a two-tier data-exchange structure. At the lower level, multiple CS in each region send load and availability data to the regional aggregator. At the upper level, the aggregators forward aggregated information to a cloud server that runs the dynamic pricing controller. EV users query this server to identify nearby stations, compare real-time charging prices, and select the most cost-effective option. This closed feedback loop enables demand-responsive coordination between users and the grid. The core objective of this framework is to redistribute EV load so that residential and commercial feeders operate near their optimal utilization levels. In essence, the system maximizes EV charging activity in areas and periods of low conventional demand while discouraging charging when a region approaches its thermal or voltage limits. By coupling real-time monitoring with adaptive tariff adjustment, the framework effectively transforms EVs into controllable, price-responsive loads that contribute to peak shaving and valley filling.

2.1. Charging-station aggregator load model

Each CS is assumed to contain n charging slots whose occupancy status over a 24-hour horizon can be represented by a binary matrix:

$$CS = \begin{bmatrix} S_{1,0} & S_{1,1} & \dots & S_{1,23} \\ S_{2,0} & S_{2,1} & \dots & S_{2,23} \\ \vdots & \vdots & \dots & \vdots \\ S_{n,0} & S_{n,1} & \dots & S_{n,23} \end{bmatrix}, \quad (1)$$

Where $S_{i,t} = \begin{cases} 1, & \text{if slot } i \text{ is occupied at hour } t \\ 0, & \text{if slot } i \text{ is unoccupied at hour } t \end{cases}$

The instantaneous load of the station is therefore

$$l_{CS,t} = \sum_{i=1}^n S_{i,t} l_{S_{i,t}} \quad (2)$$

where $l_{S_{i,t}}$ is the power drawn by slot i at time t . For a region containing m stations, the total EV charging load at time t is (3):

$$x_t + y_t \leq \kappa \quad (3)$$

This relationship constrains the optimization algorithm, ensuring that aggregated charging demand never exceeds the safe operational limits of the feeder.

2.2. Distribution-network load representation

To represent the stochastic variations in demand, the conventional load profile of each area is modeled using a gaussian mixture model (GMM). The model approximates daily demand as a weighted sum of multiple normal distributions, capturing both morning and evening peaks in residential zones and midday peaks in commercial zones. The general GMM formulation is given by (4):

$$p(r) = \sum_{i=1}^j w_i \lambda(r|\mu_i, \Sigma_i) \quad (4)$$

where r is the load vector, w_i are component weights, and $\lambda(r|\mu_i, \Sigma_i)$ are multivariate Gaussian densities with means μ_i and covariances Σ_i .

The model parameters are calibrated using historical load data and vehicle-mobility patterns derived from the U.S. National Household Travel Survey (NHTS) [29]. Commuting statistics indicate that most vehicles depart residential zones for commercial areas around 07:00 and return around 17:00, yielding complementary demand cycles. Without coordination, this behavioral pattern results in nighttime overloads in residential feeders and daytime overloads in commercial feeders. Hence, an adaptive mechanism that synchronizes regional prices with complementary demand levels is essential. The mobility patterns used in this study are derived from the NHTS, which contains large-scale travel behavior records used to model EV charging probability and daily mobility distribution.

2.3. Dynamic pricing strategy

The dynamic pricing module forms the intelligence core of the framework. It computes time-varying EV charging prices that reflect the instantaneous utilization of each region's network. The controller updates price every hour for the subsequent 12-hour horizon, using both the current demand pattern and predicted consumption. Figure 2 illustrates the complete operational flow of the proposed pricing process.

The flowchart begins with the input of historical and real-time load data from both regions. After normalization, the algorithm determines the network's utilization level relative to its capacity. It then applies an optimization routine to generate a desired EV-charging-load vector that achieves valley filling and peak shaving. Corresponding charging prices are mapped inversely to the desired load values—lower prices for low-load periods and higher prices for high-load periods. The final prices are uploaded to the cloud server and made visible to all EV users via mobile or web applications. Mathematically, the normalization of the conventional load (x) is expressed as (5):

$$x' = 2 \left(\frac{x}{\zeta} \right) - 1 \quad (5)$$

where ζ is the maximum allowable optimal load, typically set to 80% of the feeder capacity ($\zeta \approx 0.8\kappa$). This scaling confines all values of (x') within $[-1, 1]$. To ensure that the total load does not exceed network limits, two correction factors are introduced:

$$\delta_1 = 1 - \max(x'), \quad \delta_2 = -1 - \min(x') \quad (6)$$

The optimization problem is then formulated as (7):

$$\min \|y' + x' + \delta_1 + \delta_2\| \quad (7)$$

Subject to $-1 \leq y' \leq 1$, where y' represents the normalized EV-charging-load vector to be determined. The optimization is convex and solved using an exponential-cone solver to obtain y' . The result is subsequently demormalized as:

$$y = \zeta \left(\frac{y' + 1}{2} \right)$$

yielding the actual charging load required to balance the distribution network. Once y is computed, its range is discretized into intervals corresponding to the TOU price levels $P_{\tau_1}, P_{\tau_2}, n, P_{\tau_q}$. The algorithm then assigns the lowest charging price to the highest desired EV load and vice versa, producing an inverse mapping that drives users to shift their charging behavior toward off-peak periods. This adaptive price-load correlation ensures that the total network demand remains stable while maximizing the utilization of under-loaded regions.

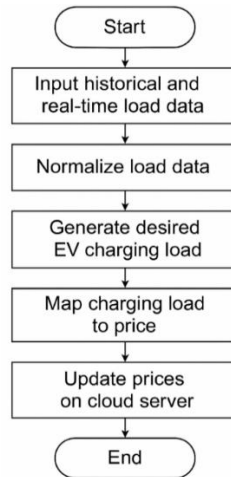


Figure 2. The flowchart of the proposed dynamic pricing strategy

Each CS periodically communicates its status to the regional aggregator. Whenever a new EV connects or disconnects, the aggregator updates the cloud database with real-time slot availability, predicted price, and expected waiting time. EV users can access this information through a mobile application or vehicle dashboard interface. By selecting stations with lower tariffs or shorter queues, users naturally distribute themselves across the network in a manner that aligns individual economic incentives with global grid efficiency. The coordinated exchange of information among EVs, CSs, aggregators, and the central controller forms a cyber-physical feedback loop that enables dynamic control of the charging demand. Over time, this continuous feedback mechanism results in smoother load curves across both residential and commercial feeders, reduced peak-to-valley differences, and improved overall grid reliability.

3. RESULTS AND DISCUSSION

We tested the proposed dynamic pricing strategy by running a lot of simulations in Python. The experiments simulated residential and commercial/industrial distribution feeders over a 24-hour period, integrating realistic load profiles, dynamic charging probabilities, and adaptive tariff modifications. The main goal was to see if the framework could flatten demand curves, reduce peak loading, and balance energy use between regions. At first, a static TOU tariff structure was used for both residential and commercial feeders to set the baseline. The residential feeder had a nominal capacity of 520 kW and a conventional peak of 365

kW. The commercial feeder had a capacity of 830 kW and a peak of 570 kW. The simulation assumed that everyone would use EVs at the same rate, so the total EV load over 24 hours was about the same as the normal demand.

Figure 3 presents the residential and commercial load profiles with and without EV charging under fixed TOU pricing, highlighting the impact of conventional EV charging behavior on load distribution. Figure 3(a) illustrates the baseline residential load without EVs, showing the normal daily demand pattern that remains below the feeder capacity. Figure 3(b) presents the conventional residential load with EV charging under fixed TOU pricing, where most EV users prefer to charge during off-peak hours (22:00–02:00), creating an additional nighttime peak. Consequently, Figure 3(c) shows the total residential load, which approaches 505 kW during night hours, nearly reaching the feeder capacity, while the demand drops below 190 kW between 11:00 and 14:00, indicating poor utilization of network resources. Similarly, Figure 3(d) depicts the baseline commercial load without EVs, where demand mainly occurs during business hours. Figure 3(e) shows the commercial load with EV charging under fixed TOU pricing, where charging is concentrated between 12:00 and 17:00, overlapping with peak business activity. As a result, Figure 3(f) illustrates the total commercial load, which increases to approximately 760 kW, creating significant load clustering. Overall, these results indicate that although TOU pricing shifts some EV charging to off-peak periods, it fails to effectively prevent load clustering, resulting in a MAPE of 28.4% between the ideal and actual load distribution.

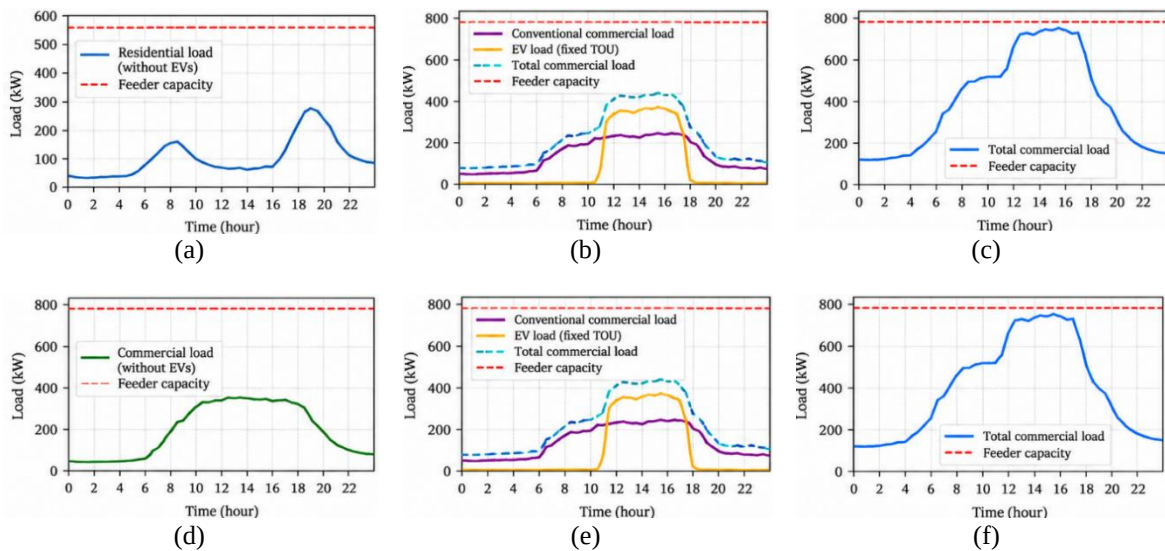


Figure 3. Residential and commercial load profiles with and without EV charging under fixed TOU pricing; (a) residential load without EVs, (b) conventional residential load and EV load under fixed TOU pricing, (c) total residential load under fixed TOU pricing, (d) commercial load without EVs, (e) conventional commercial load and EV load under fixed TOU pricing, and (f) total commercial load under fixed TOU pricing

Figure 4 illustrates the impact of the proposed dynamic pricing algorithm under three EV charging probability scenarios representing low, moderate, and high participation levels. In the residential network, Figure 4(a), the algorithm effectively shifts EV charging demand from peak hours to periods of lower base load, mainly between 04:00 and 13:00, when household demand is relatively low. Similarly, in the commercial network, Figure 4(b), EV charging is moved to late evening and night hours (19:00–01:00), when office operations and equipment loads are minimal. Compared with the fixed-price baseline, this dynamic pricing strategy significantly smooths the load profile and reduces load clustering. As a result, the residential peak-to-valley difference decreases from 412 kW to 61 kW, while the commercial difference reduces from 745 kW to 83 kW. Additionally, overall grid utilization improves by approximately 21%, and the MAPE decreases to 5.7%, indicating a much closer match between the desired and actual load distribution.

Figure 5 presents the peak shaving and valley filling performance under the proposed dynamic pricing mechanism. Figure 5(a) shows the baseline residential load without EVs, where the demand remains below the feeder capacity with a typical daily variation. Figure 5(b) illustrates the residential load with EV charging under dynamic pricing, where the charging price signal shifts EV demand to low-demand periods,

resulting in better load distribution. Consequently, Figure 5(c) shows that the total residential load becomes nearly uniform, maintaining an average demand of around 415 kW throughout the day, indicating effective valley filling as previously underutilized hours are now used for EV charging. Similarly, Figure 5(d) presents the commercial load without EVs, which normally experiences higher demand during daytime business hours. Figure 5(e) shows the commercial load with EV charging under dynamic pricing, where the algorithm redistributes charging activity away from peak hours. As a result, Figure 5(f) displays the total commercial load, where peak shaving is achieved by reducing midday overloads and shifting charging to evening and night hours, producing a smoother and flatter load curve without significant peaks. These results demonstrate that the dynamic pricing strategy effectively balances network demand, automatically adapting to changing load conditions without requiring centralized scheduling or external control signals.

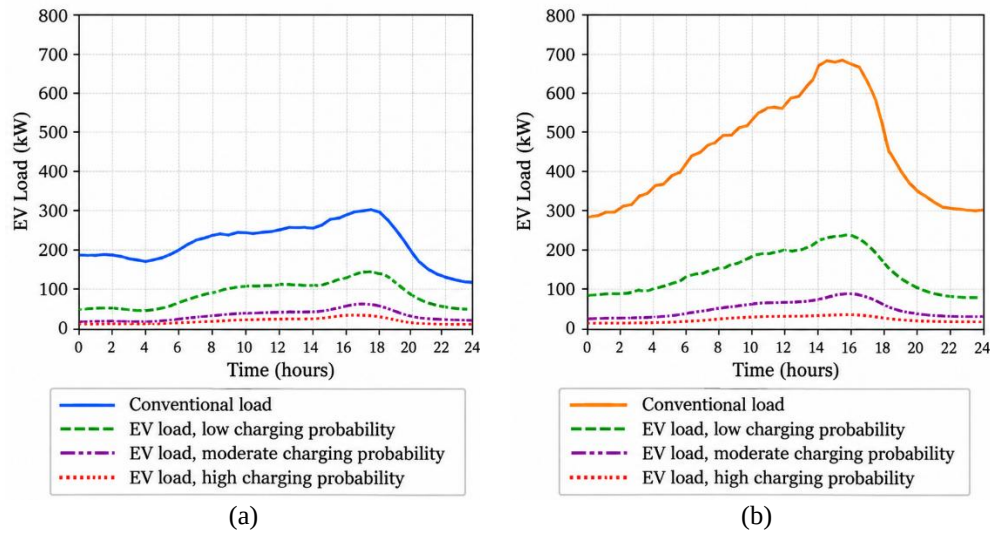


Figure 4. Varying EV load impact in the residential and commercial areas; (a) residential and (b) commercial

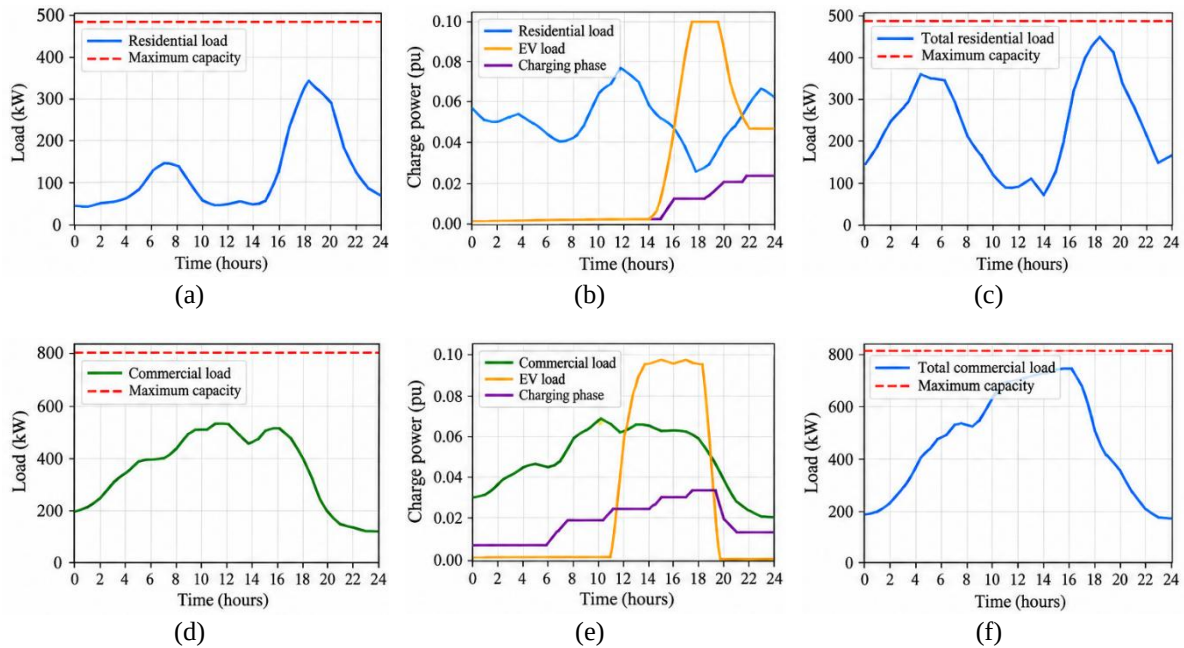


Figure 5. Illustration of peak shaving and valley filling in both areas under dynamic pricing; (a) residential load without EVs, (b) conventional residential load and EV load, (c) total residential load under dynamic pricing, (d) commercial load without EVs, (e) conventional commercial load and EV load, and (f) total commercial load under dynamic pricing

The results show that the suggested framework successfully turns EV-CSs into "demand-responsive assets" that make smart grids work better. The system reduces congestion by dynamically linking tariff levels to feeder use. This delays the costs of network reinforcement and makes sure that all user groups have fair access to energy. From the user's point of view, the strategy offers financial incentives, such as lower charging costs during times of low demand, while keeping the grid reliable. For distribution operators, it improves voltage stability and asset lifespan by reducing over-loading and thermal stress on transformers and conductors. Additionally, since the pricing algorithm only uses aggregated load data and publicly available TOU rates, it can be easily added to existing smart-grid systems with little change. The research shows that price-driven coordination can be a useful alternative to centralized scheduling, especially in areas with a lot of EVs but not a lot of communication infrastructure. Overall, the dynamic pricing method is a cost-effective, scalable way to keep mixed-demand distribution networks running smoothly and sustainably. The proposed pricing strategy can delay costly grid reinforcement, improve feeder voltage stability, and enable fair EV charging access across distribution regions.

4. CONCLUSION

Despite the promising results, this study has several limitations. The proposed framework was validated through simulation using a standard test distribution system, which may not fully capture the complexity of real-world power networks with diverse consumer behavior and infrastructure constraints. In addition, the model assumes reliable communication and accurate load data for real-time pricing adjustments, whereas practical smart-grid environments may experience delays, data uncertainties, or communication failures. The study also does not explicitly consider renewable energy variability, battery degradation effects, or user behavioral uncertainties that may influence EV charging patterns. Therefore, future work should focus on validating the framework in real-world pilot systems, integrating renewable generation uncertainties, and incorporating more detailed consumer behavior models to further enhance the robustness and practical applicability of the proposed dynamic pricing strategy. The framework assumes reliable communication infrastructure and accurate load forecasting. Communication delays, renewable variability, and user behavioral uncertainty may affect real-world deployment.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ding

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this paper.

ETHICAL APPROVAL

This article does not contain any studies involving human participants or animals performed by any of the authors.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

- [1] Z. Ye, Y. Gao, and N. Yu, "Learning to operate an electric vehicle charging station considering vehicle-grid integration," *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3038–3048, Jul. 2022, doi: 10.1109/TSG.2022.3165479.
- [2] International Energy Agency (IEA), *Global EV Outlook 2018: Towards Cross-Modal Electrification*. Paris, France: IEA, 2018.
- [3] S. Aghajan-Eshkevari, S. Azad, M. Nazari-Heris, M. T. Ameli, and S. Asadi, "Charging and discharging of electric vehicles in power systems: An updated and detailed review of methods, control structures, objectives, and optimization methodologies," *Sustainability*, vol. 14, no. 4, 2022, doi: 10.3390/su14042137.
- [4] D. Tariang and G. Das, "A survey on coordinated charging methods for electric vehicles," *ADB Journal of Electrical and Electronics Engineering*, vol. 5, no. 1, pp. 36–48, 2023.
- [5] H. Wang, Y. Jia, M. Shi, P. Xie, C. S. Lai, and K. Li, "A hybrid incentive program for managing electric vehicle charging flexibility," *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 476–488, Jan. 2023, doi: 10.1109/TSG.2022.3197422.
- [6] Z. Wei, B. Li, R. Zhang, and X. Cheng, "Contract-based charging protocol for electric vehicles with vehicular fog computing: An integrated charging and computing perspective," *IEEE Internet of Things Journal*, vol. 10, no. 9, pp. 7667–7680, May 2023, doi: 10.1109/JIOT.2022.3182163.
- [7] C. Guo, D. Liu, W. Geng, C. Zhu, X. Wang, and X. Cao, "Modeling and analysis of electric vehicle charging load in residential area," in *2019 4th International Conference on Power and Renewable Energy (ICPRE)*, 2019, pp. 394–402, doi: 10.1109/ICPRE48497.2019.9034848.
- [8] S. M. S., F. Titus, S. B. Thanikanti, S. S. M., S. Deb, and N. M. Kumar, "Charge scheduling optimization of plug-in electric vehicle in a PV powered grid-connected charging station based on day-ahead solar energy forecasting in Australia," *Sustainability*, vol. 14, no. 6, p. 3498, 2022, doi: 10.3390/su14063498.
- [9] S. Ayyadi, H. Bilil, and M. Maaroufi, "Optimal charging of electric vehicles in residential area," *Sustainable Energy, Grids and Networks*, vol. 19, p. 100240, 2019, doi: 10.1016/j.segan.2019.100240.
- [10] A. Sohail, R. Khan, S. H. Mukhtar, A. Najeeb, and A. Usman, "Effects of uncoordinated electric vehicle charging on a distribution network," in *2022 19th International Bhurban Conference on Applied Sciences and Technology (IBCAST)*, 2022, pp. 591–597, doi: 10.1109/IBCAST54850.2022.9990477.
- [11] M. A. Sohail, R. Khan, S. H. Mukhtar, and A. Usman, "Impact analysis of time-of-use pricing enabled electric vehicle charging to the uncoordinated charging on a distribution network," in *2023 IEEE Power & Energy Society General Meeting (PESGM)*, 2023, pp. 1–5, doi: 10.1109/PESGM52003.2023.10253256.
- [12] J. D. Kim, "Insights into residential EV charging behavior using energy meter data," *Energy Policy*, vol. 129, pp. 610–618, 2019, doi: 10.1016/j.enpol.2019.02.049.
- [13] M. Gilleran *et al.*, "Impact of electric vehicle charging on the power demand of retail buildings," *Advances in Applied Energy*, vol. 4, p. 100062, 2021, doi: 10.1016/j.adapen.2021.100062.
- [14] U. Qureshi, A. Ghosh, and B. K. Panigrahi, "Scheduling and routing of mobile charging stations with stochastic travel times to service heterogeneous spatiotemporal electric vehicle charging requests with time windows," *IEEE Transactions on Industry Applications*, vol. 58, no. 5, pp. 6546–6556, 2022, doi: 10.1109/TIA.2022.3182323.
- [15] U. Qureshi, A. Ghosh, and B. K. Panigrahi, "Dynamic pricing based mobile charging service for electric vehicle charging," in *2023 IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET)*, 2023, pp. 1–4, doi: 10.1109/SeFeT57834.2023.10245310.
- [16] M. Saha, S. S. Thakur, and A. Bhattacharya, "Optimal scheduling of electric vehicles: Leveraging grid-to-vehicle (G2V) and vehicle-to-grid (V2G) prices: A game-theoretic approach," in *2023 IEEE 3rd International Conference on Sustainable Energy and Future Electric Transportation (SEFET)*, 2023, pp. 1–6, doi: 10.1109/SeFeT57834.2023.10245871.
- [17] Z. Zhang, L. Lv, and X. Wang, "Research on dynamic time-sharing tariff orderly charging strategy based on NSGA2 in PV-Storage-Charging stations," *Electric Power Systems Research*, vol. 225, p. 109784, 2023, doi: 10.1016/j.epsr.2023.109784.
- [18] K. Adetunji, I. Hofsajer, and L. Cheng, "A coordinated charging model for electric vehicles in a smart grid using whale optimization algorithm," in *2020 IEEE 23rd International Conference on Information Fusion (FUSION)*, 2020, pp. 1–7, doi: 10.23919/FUSION45008.2020.9190284.
- [19] K. E. Adetunji, I. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng, "Miscellaneous energy profile management scheme for optimal integration of electric vehicles in a distribution network considering renewable energy sources," in *2021 Southern African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA)*, 2021, pp. 1–6, doi: 10.1109/SAUPEC/RobMech/PRASA52254.2021.9377012.
- [20] K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng, "An optimization planning framework for allocating multiple distributed energy resources and electric vehicle charging stations in distribution networks," *Applied Energy*, vol. 322, p. 119513, 2022, doi: 10.1016/j.apenergy.2022.119513.
- [21] Y. Wang and Z. Khan, "Effects of optimization on user-based charging/discharging control strategy," *Recent Advances in Electrical & Electronic Engineering*, vol. 15, no. 2, pp. 158–170, 2022, doi: 10.2174/2215083808666220324144603.
- [22] X. Shang, Y. Li, and R. Huang, "A charging and discharging model for electric vehicles based on consortium blockchain using multi-objective gray wolf algorithm," *Recent Advances in Electrical & Electronic Engineering*, vol. 15, no. 8, pp. 640–652, 2022, doi: 10.2174/2352096515666220513104656.
- [23] H. U. R. Habib *et al.*, "Analysis of optimal integration of EVs and DGs into CIGRE's MV benchmark model," *IEEE Access*, vol. 10, pp. 95949–95969, 2022, doi: 10.1109/ACCESS.2022.3204311.
- [24] A. I. Aygun and S. Kamalasadan, "Centralized charging approach to manage electric vehicle fleets for balanced grid," in *2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE)*, 2022, pp. 1–6, doi: 10.1109/PESGRE52003.2022.9990477.

- 10.1109/PESGRE52268.2022.9715836.
- [25] T. Mazhar *et al.*, "Electric vehicle charging system in the smart grid using different machine learning methods," *Sustainability*, vol. 15, no. 3, p. 2603, 2023, doi: 10.3390/su15032603.
- [26] F. Knirsch, A. Unterweger, and D. Engel, "Privacy-preserving blockchain-based electric vehicle charging with dynamic tariff decisions," *Computer Science—Research and Development*, vol. 33, pp. 71–79, 2018, doi: 10.1007/s00450-017-0348-5.
- [27] M. Xia, T. Liao, and Q. Chen, "Two-layer optimal charging strategy for electric vehicles in old residential areas," *International Transactions on Electrical Energy Systems*, vol. 31, p. e12890, 2021, doi: 10.1002/2050-7038.12890.
- [28] D. A. Reynolds, "Gaussian mixture models," in *Encyclopedia of Biometrics*, S. Z. Li and A. K. Jain, Eds. Boston, MA, USA: Springer, 2015, pp. 827–832, doi: 10.1007/978-1-4899-7488-4_196.
- [29] Federal Highway Administration, U.S. Department of Transportation, "2017 National Household Travel Survey," Washington, DC, USA, 2017. [Online]. Available: <https://nhts.ornl.gov/>. (Accessed: Jul. 15, 2023).

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