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CONGESTION BASED DYNAMIC PRICING FOR CHARGING OF EVS

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Abstract

The rapid increase in electric vehicles (EVs) adoption presents new challenges for distribution system operators (DSOs), particularly in managing local network congestion and capacity limit violations. Concentrated EV charging during peak times can momentarily overload the electricity distribution network and compromise electricity supply reliability and quality. This research addresses the challenge of mitigating grid congestion by exploring a new pricing strategy for EV charging stations. The core research question investigates how dynamic pricing, based on real-time network congestion levels, can be used to balance load distribution and prevent overloading in specific network sections. This article proposes a dynamic pricing model that adjusts charging costs in response to network utilization rates, incentivizing EV users to charge during less congested hours or in less congested areas. The proposed model employs machine learning techniques to predict congestion levels, balancing user satisfaction, grid reliability, and station profitability. The findings demonstrate that dynamic pricing significantly reduces congestion during peak hours, improves load distribution, and enhances grid stability without compromising user accessibility. This research offers valuable insights for DSOs and policymakers aiming to develop sustainable and resilient EV charging infrastructure.

1 Introduction

In recent years, the adoption of EVs has significantly increased, driven by both consumer preference and government support, due to lower fuel costs and the shift towards greener solutions [1]. Electric car sales continue to grow and are projected to reach approximately 17 million units in 2024, representing over 20% of global car sales [2]. In the future, these numbers are expected to rise further as advancements in battery technology, expanded charging infrastructure, and continued government incentives make EVs more accessible and practical for consumers [3]. Additionally, growing awareness of climate change and stringent emission regulations will likely reinforce the global transition toward electric mobility, positioning EVs as a cornerstone of sustainable transportation systems.

On the other hand, the European Union (EU) has set the targets to achieve net-zero greenhouse gas emissions by 2050, driving a transition to Renewable Energy Sources (RES) and sustainable practices across all sectors. However, the integration of RES, such as wind and solar, presents significant challenges to the stability and flexibility of the electricity grid. These challenges are exacerbated by the growing adoption of EVs, which contribute to higher demand variability as uncoordinated charging services can inevitably result in line congestion and transformer overloading, for instance [4] and require innovative solutions to balance supply and demand effectively.

Despite the rapid deployment of demand response technologies such as smart meters, the implementation of dynamic pricing has not kept pace. Dynamic pricing refers to electricity contracts that “reflect the price variation in the spot markets, including in the day-ahead and intraday markets” defined by European Directive 2019/944 [5]. However, in Finland, current legislation mandates uniform distribution fees for all customers within the same DSO network, posing a limitation to implementing dynamic tariffs [6].

This study focuses on dynamic pricing as a feasible and scalable approach, offering a practical alternative to local flexibility marketplaces. Dynamic pricing can be implemented with minimal regulatory changes and leverages existing technologies, such as smart meters, to provide real-time price signals. In contrast, local flexibility marketplaces, while offering DSOs a mechanism to procure flexibility, require significant infrastructural development and market readiness. Dynamic pricing thus provides a straightforward pathway to enhance demand-side flexibility and support grid sustainability goals.

Given the rising adoption of EVs and the variability in their charging demands, innovative pricing mechanisms are essential to mitigate their impact on grid stability. Building on this, the focus of this research is to develop and analyse a dynamic pricing strategy specifically tailored for EV charging stations. The proposed approach leverages real-time congestion data and artificial intelligence algorithms to dynamically adjust charging costs based on network

utilization. This strategy aims to incentivize EV owners to shift the charging demand to off-peak hours or less congested locations, thereby alleviating grid stress and preventing capacity violations.
Through the analysis of EV charging data, this study evaluates the efficiency and impact of the proposed pricing model in reducing peak-hour congestion, optimizing load distribution, and ensuring fair access to charging infrastructure. The results demonstrate how dynamic pricing can serve as a practical tool for DSOs and policymakers to enhance grid reliability, improve user satisfaction, and promote sustainable energy practices.

1.1 Related Work

Dynamic pricing has been extensively studied as a solution to address EV charging station congestion and grid stability. Yang et al. [7] investigated consumer acceptance of peak and off-peak pricing, identifying economic benefits as a key driver, though their work focused on residential electricity. The findings indicate that approximately two-thirds of residential electricity consumers are open to adopting peak and off-peak pricing [7]. Kong et al. [8] introduced a bi-level optimization model for EV load management, but their approach lacked real-time adaptability. Wong and Alizadeh [9] introduced a framework for plug-in electric vehicle (PEV) charging stations using a queuing model. Their proposed pricing strategy, based on socially optimal congestion, aimed to minimize both the total latency experienced by PEV users and the total electricity costs incurred by charging stations. However, their queuing model did not account for specific charging rates, nor did it address load management of PEVs during peak hours.

Building on these, Limmer and Rodemann [10] applied multi-objective optimization to balance profit and user satisfaction, while Mrkos and Basmadjian [11] leveraged an MDP with MCTS for revenue-maximizing dynamic pricing, prioritizing station profitability. Kim et al. [12] focused on optimizing charging prices, vehicle scheduling, and battery swapping station (BSS) charging and discharging to enhance station profitability, but they did not consider load shifting for plug-in PEVs. Most of these studies primarily focus on user-centric objectives, such as optimizing prices or minimizing queuing times [13], leaving a gap in integrating real-time grid-level congestion mitigation strategies with dynamic pricing models.

2 Methodology

In this section, we will describe our model and formulization. The methodology comprises of key components: data analysis, model development and evaluation.

2.1. Dataset

Charging station data for the Helsinki region was synthetically generated to simulate realistic EV charging patterns. Traffic-related information was obtained from the TomTom Traffic Index [14], a platform that compiles mobility data from over 500 cities across six continents. This resource provides insights into global urban mobility trends, highlighting the movement of people, goods, and ideas [14]. Two 4-charger (AC 22kW) stations were modelled: one in the city centre and another in a less frequented suburban area. Temporal variations, including peak and off-peak demand, were derived from traffic indices and user behaviour patterns (e.g., travel times and rush hours). Randomization was applied to simulate variances in user behaviour, including charging durations, arrival times, and energy consumption patterns, ensuring robustness and generalizability. Figure 1 illustrates the distribution of charging session start times for the city centre station (CS 1) and the suburban station (CS 2). The data used for this plot represent the average distribution of charging sessions over a full year, calculated by analysing the charging patterns from two datasets.

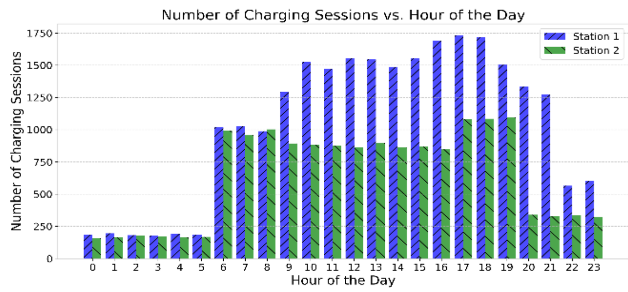


Fig. 1 Histograms show the start of charging sessions, blue (forward slash) for CS 1 and green (back slash) for CS 2

The high-level overview of the proposed dynamic pricing framework for EV charging stations is depicted in Figure 2. The EV users interact with charging stations, whose pricing is dynamically adjusted based on real-time demand and grid conditions. When users initiate charging requests, their actions contribute to the overall station load, which is continuously monitored.

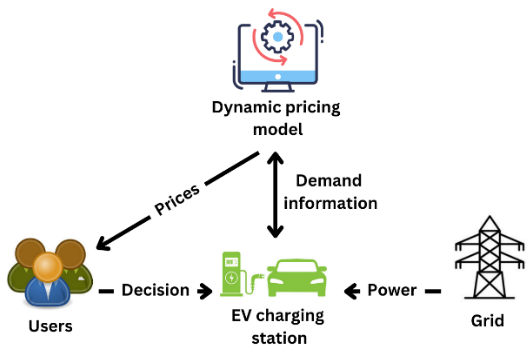


Fig. 2 System overview of the dynamic pricing model architecture.

The system then processes this data to update pricing through a dynamic pricing model aimed at minimizing congestion and balancing grid load. Updated prices are fed back to the users, influencing their charging decisions. This feedback loop ensures a self-regulating system that promotes efficient energy usage while optimizing user distribution across multiple stations.

2.2. Problem Definition

The dynamic pricing model aims to optimize EV charging station pricing by minimizing congestion at the distribution level to assist DSOs in maintaining grid stability and ensuring fairness for users by providing equitable and cost-effective charging options. Let us consider:

- A set of *N* charging stations (CSs).
- The vector $P(t)\in\mathbb{R}$ represents the price, where $p_j(t)$ represents the dynamic charging price at station *j* during the time slot *t*.
- A single day divided into T discrete time slots (t=1,…,Tt).

The main goal is to determine an optimal P(t) for all time slots that minimizes congestion and ensures fairness.

$$Z_{\text{congestion}} = \sum_{t=1}^{T}\sum_{j=1}^{N}\left(\mathrm{d_j(t)}\right)^2 \quad (1)$$

$$Z_{\text{fairness}} = \sum_{t=1}^{T}\sum_{j=1}^{N}\left(p_j(t) - \bar{p}(t)\right)^2 \quad (2)$$

$$\text{Minimize } Z = \alpha Z_{\text{congestion}} + \beta Z_{\text{fairness}} \quad (3)$$

$$p_j^{\min} \le p_j(t) \le p_j^{\max} \quad \forall j, t \quad (4)$$

$$p_j(t) = f\left(d_j(t)\right) \quad (5)$$

Where Equation (1) represents the congestion minimization objective. The term $(d_j(t))^2$ is the squared demand at station j during time slot t. Squaring the demand amplifies higher congestion levels, disproportionately penalizing time slots or stations with excessive demand. This encourages the optimization model to distribute charging demand more evenly across stations and time slots, thereby reducing the risk of congestion. Equation (2) defines the fairness in pricing objective. Here, $p_j(t)$ represents the dynamic price at station *j* during time *t*, and $\bar{p}(t)$ is the average price across all stations at time *t*. The squared difference ensures that stations with prices deviating significantly from the average are penalized. This enforces fairness by keeping prices at different stations balanced, preventing significant disparities that could disadvantage users at specific locations. These objectives are combined into a single weighted optimization function (Z, Equation (3)), where the weights α and βcontrol the relative importance of congestion reduction and fairness.

Equation (4) introduces price constraints, ensuring that the dynamic price at station j remains within a feasible range $p_j^{\min}$ to $p_j^{\max}$ for all stations and time slots. These constraints ensure that prices are neither too low to cause losses nor too high to deter users. Equation (5) describes the relationship between price and demand. It ensures that pricing responds dynamically to demand levels. For instance, higher demand could result in increased prices, providing an economic incentive for users to charge during off-peak hours or shift to less congested stations.

2.3. Machine Learning Model

Pricing strategy was implemented to address congestion management at EV CS by revising prices based on real-time demand using machine learning. Historical demand patterns were analysed using machine learning models, with Bayesian Ridge Regression (BRR) ultimately selected based on its better performance over Random Forest Regression (RF) in this application. BRR was chosen for its ability to quantify uncertainty in predictions, which is particularly valuable for dynamic pricing in the energy sector. By incorporating prior information, BRR provides probabilistic outputs that offer both accuracy and insight into the confidence of predictions, making it well-suited for scenarios where demand can vary significantly.

RF was also explored during the evaluation phase. While the model demonstrated strength in capturing non-linear relationships and complex interactions within the data, it was less effective in managing uncertainty compared to BRR. This distinction made BRR the more appropriate choice for predicting pricing multipliers in the context of EV charging, where reliability and adaptability to fluctuating demand patterns are critical.

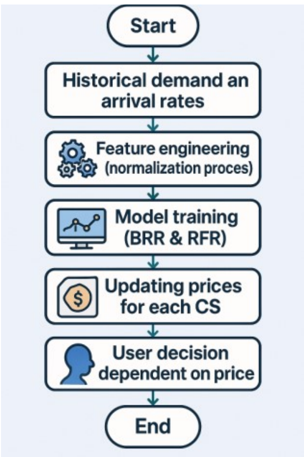


Fig. 3 EV charging station pricing model

Data preprocessing, a vital step in machine learning workflows, ensured that the input data was clean, consistent, and free of outliers, thus enhancing model performance. In this study, preprocessing involved two main steps: data cleaning and normalization. Data cleaning focused on handling missing entries which were imputed using medians, and outliers were capped using interquartile ranges, outliers to provide a robust foundation for analysis. Normalization was applied to scale features to a uniform range of [0,1] ensuring equal contribution of all features, accelerated convergence during optimization, and improved the performance of machine learning models by mitigating the impact of scale differences.

BRR was chosen due to its ability to handle uncertain and noisy data effectively. Unlike traditional regression models, BRR incorporates prior distributions over model parameters, enabling probabilistic predictions. This feature is particularly useful for dynamic pricing, where demand is subject to real-time variability. For instance, BRR's prediction intervals allow DSOs to make informed pricing decisions even when arrival rates deviate significantly from historical patterns.

Table 1 Model performance comparison

Machine learning model	R^2	MSE
BRR	0.9937	0.0014
RF	0.9209	0.0235

3 Results and Discussion

The proposed dynamic pricing model was evaluated for its ability to manage congestion and maximize revenue at EV charging stations. Using machine learning models like RF and BRR, pricing multipliers were predicted for each interval. Simulations across various periods and stations confirmed the model's effectiveness in dynamic pricing optimization.

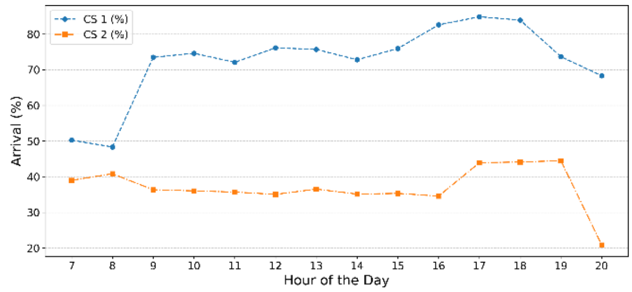
3.1 Evaluation Metrics and Model Performance

The performance of the dynamic pricing model was evaluated using metrics R^2 and Mean Squared Error (MSE). As shown in Table 1, BRR outperformed RF in predicting pricing multipliers, achieving an R^2 of 0.9937 and an MSE of 0.0014, compared to $R^2 = 0.9209$ and MSE = 0.0235 for RF. These results highlight BRR's superior ability to handle the probabilistic nature of the pricing problem and provide highly accurate predictions.

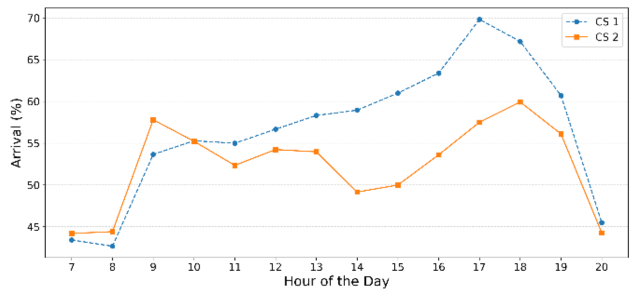
The model effectively managed congestion by redistributing users between the two charging stations. During peak hours (7–20), congestion at CS 1 decreased by 15–20%, while CS 2's utilization increased from 40% to 60%. This redistribution reduced strain on the more congested city-centre station, ensuring fairer access to charging resources (Fig. 4).

From a financial perspective, the proposed pricing strategy offered cost benefits for price-sensitive users while ensuring grid optimization. Under the dynamic pricing model, the cost range for the total charging was set at 0.23 €/kWh to 0.39 €/kWh, which was determined using our ML model. In contrast, the flat pricing model charged 0.30 €/kWh during peak hours (7:00–21:00) and 0.30 €/kWh during off-peak hours (21:00–7:00), with an additional fixed cost of 2 € per hour for peak hours.

For users who shifted their charging to off-peak hours or to the less congested station (CS 2), the dynamic pricing model resulted in an average cost savings of 10–15% compared to flat pricing. However, users charging during peak hours or at highly congested locations faced an increase of 5–10% in charging costs. This dynamic behaviour incentivized users to charge during off-peak periods, effectively reducing overall congestion while maintaining accessibility for users with immediate charging needs.



a)



b)

Fig. 4 EV arrival at CS 1(blue) and CS 2 (orange) with (a) flat pricing and (b) proposed pricing

The model accounted for user preferences, including price sensitivity, state of charge (SoC), and time constraints. Price-sensitive users shifted to off-peak hours or the less congested CS 2, while others with low SoC or proximity constraints opted to charge at CS 1 despite higher prices. This dual behaviour underscores the need to balance pricing strategies with user accessibility. Figure 5 illustrates the revenue comparison between flat pricing (left) and the proposed dynamic pricing model (right). The model also increases revenue by optimizing charging costs based on demand, demonstrating its ability to maximize profitability while addressing congestion and improving grid utilization.

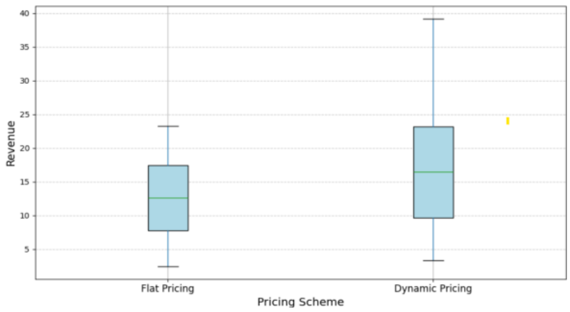


Fig. 5 Revenue with flat pricing (left) and dynamic pricing (right)

The proposed model is scalable to city-wide networks using cloud-based systems for real-time updates. This approach enables DSOs to balance demand across multiple stations, reduce congestion, and ensure equitable access to charging infrastructure. By integrating user behaviour insights, the model aligns with sustainable energy goals, encouraging off-peak charging and optimizing station utilization.

4 Conclusion

The proposed dynamic pricing model effectively reduces congestion and enhances revenue at EV charging stations by leveraging real-time demand data and machine learning techniques. By implementing Bayesian Ridge Regression (BRR) and Random Forest Regression (RF), the study optimized pricing strategies, achieving a 15–20% reduction in congestion at the city-centre station (CS 1) and shifting the demand utilization at the suburban station (CS 2). Additionally, dynamic pricing increased total revenue by 12% compared to flat pricing, while maintaining user accessibility and fairness.

The scalability of the proposed model makes it suitable for city-wide networks, where cloud-based systems can facilitate real-time updates and enable efficient demand balancing across multiple stations. This approach aligns with sustainable energy goals by encouraging off-peak charging, optimizing station utilization, and reducing grid stress. The research offers a practical and scalable solution for DSOs and policymakers aiming to address challenges posed by the growing adoption of EVs. Future work will focus on integrating grid performance metrics and residential load impacts into the pricing model to provide a more holistic approach to grid management. Additionally, field trials using real-world data will be conducted to validate the findings and refine the pricing strategies, ensuring the development of a sustainable and resilient EV charging ecosystem.

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