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Congestion Based Dynamic Pricing for Public EVs Charging

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ABSTRACT:

The increasing adoption of electric vehicles (EVs) presents both an opportunity and a challenge for modern power systems. While EVs offer potential as flexible, controllable loads that can support grid stability, their uncoordinated charging patterns risk aggravating local congestion, particularly at the distribution level. This thesis proposes a congestion-based dynamic pricing framework designed to mitigate stress on the power grid while maintaining fairness among EV users. The model integrates predictive analytics with optimization techniques to generate real-time, location-aware price signals for EV charging. A Bayesian Ridge Regression (BRR) model is employed to forecast short-term charging demand using synthetic datasets informed by urban mobility and traffic patterns. The predicted demand is fed into a pricing engine that minimizes a joint objective function accounting for grid congestion and pricing fairness, under operational constraints such as price bounds and user flexibility. The methodology is validated through a case study involving two public charging stations in the Helsinki region, simulating both urban and residential demand conditions. Results show that the proposed model effectively reduces peak load by up to 20% and improves revenue by 12% compared to flat pricing strategies. The pricing mechanism is shown to be adaptive, equitable, and responsive to real-time congestion while remaining within predefined fairness bounds. This work demonstrates that data-driven dynamic pricing can serve as a viable and scalable demand-side management solution, especially for distribution system operators seeking to manage growing EV loads without extensive infrastructure investment. Limitations and regulatory challenges are acknowledged, and future directions for expanding model realism and implementation feasibility are outlined.

KEYWORDS: Dynamic Pricing, EV, Congestion mitigation, Demand side management, Artificial intelligence

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Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
BRR	Bayesian Ridge Regression
CPP	Critical Peak Pricing
CPO	Charging Point Operator
CS	Charging Station
CV	Coefficient of Variation
DC	Direct Current
DCFC	Direct Current Fast Charger
DDPG	Deep Deterministic Policy Gradient
DLC	Direct Load Current
DLMP	Distribution Locational Margin Pricing
DR	Demand Response
DSF	Demand Side Flexibility
DSM	Demand Side Management
DQN	Deep Q-Learning
DSO	Distribution System Operator
EDR	Emergency Demand Response
EV	Electric Vehicle
GA	Genetic Algorithm
GHG	Green House Gass Emission
GNN	Graph Neural Network
IBR	Inclined Block Rate
IoT	Internet of Things
kWh	Kilowatt-Hour
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MCTS	Monte-Carlo Tree Search
ML	Machine Learning

MSE	Mean Squared Error
OCPP	Open Charge Point Protocol
OLS	Ordinary Least Squares
PSO	Particle Swarm Optimization
PV	Photovoltaic
R^2	Coefficient of Determination
RES	Renewable Energy Resources
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RTP	Real-Time Pricing
TOU	Time of Use
TSO	Transmission System Operator
UI	User Interface
V2G	Vehicle-to-Grid

1 Introduction

In recent years, the global transportation sector has witnessed a shift, impelled by the increasing adoption of EVs. This change is fuelled by a combination of consumer preferences, technological advancements, and proactive government policies aimed at reducing dependency on fossil fuels and promoting sustainable energy solutions (Kazemtarghi et al., 2024). In 2025, global sales of EVs are projected to surpass 20 million units, marking a significant milestone in the automotive industry's shift toward electrification (Parodi, 2025). According to Iola Hughes (Parodi, 2025), Head of Research at Rho Motion, Europe, the world's second-largest EV market, is expected to experience a return to sales growth as CO2 emission targets are enforced and more affordable models become available. This growth trajectory indicates not only a shift in mobility patterns but also a fundamental change in how electricity is consumed and managed at both residential and commercial levels.

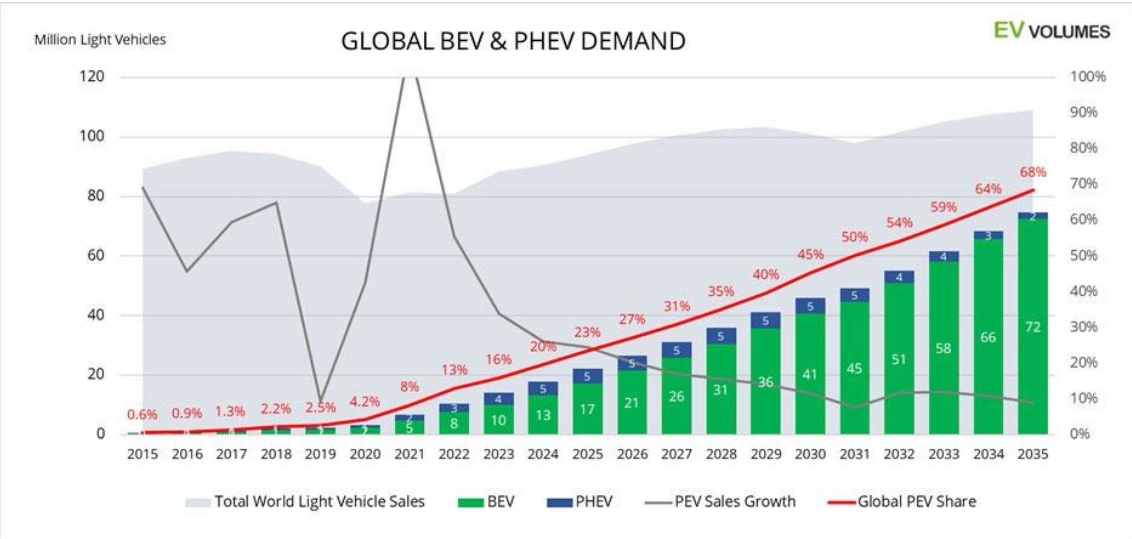

Figure 1: Global BEV & PHEV demand forecast (King, 2023).

The rapid adoption of EVs is significantly influenced by continuous advancements in battery technologies. Innovations such as solid-state, lithium-sulphur and silicon anode batteries contribute to higher energy densities, improved safety, and faster charging times (Majid et al., 2024; Patel, 2023). Parallelly, the rapid growth of charging infrastructure—

from high-speed public stations to convenient home setups—has significantly eased range anxiety, a key barrier to consumer adoption of EVs. Additionally, financial incentives such as subsidies, tax rebates, and exemptions from tolls or road taxes have further and will more accelerate the adoption across various regions (Chen & Folly, 2023). Moreover, increasing environmental awareness and need to address change in climate have strengthened societal support for cleaner mobility solutions, positioning EVs as a central component of future sustainable transportation systems (Mustafa et al., 2024).

1.1 Renewable energy and grid integration challenges

While the growing adoption of EVs marks a significant step toward decarbonizing transport, it also poses fresh challenges for power grids—particularly when combined with the expanding share of variable RES such as wind and solar. In response, the European Union has outlined bold climate targets under the European Green Deal, including a commitment to achieve net-zero GHG emissions by 2050 (*2050 Long-Term Strategy - European Commission*, n.d.). Achieving this target requires decarbonization of all sectors, including power generation, heating, industry, and transportation. Consequently, renewable energy is being integrated into the grid at an unprecedented rate, with high amount of investments in wind farms, PV systems, and energy storage solutions (Halunko et al., 2024).

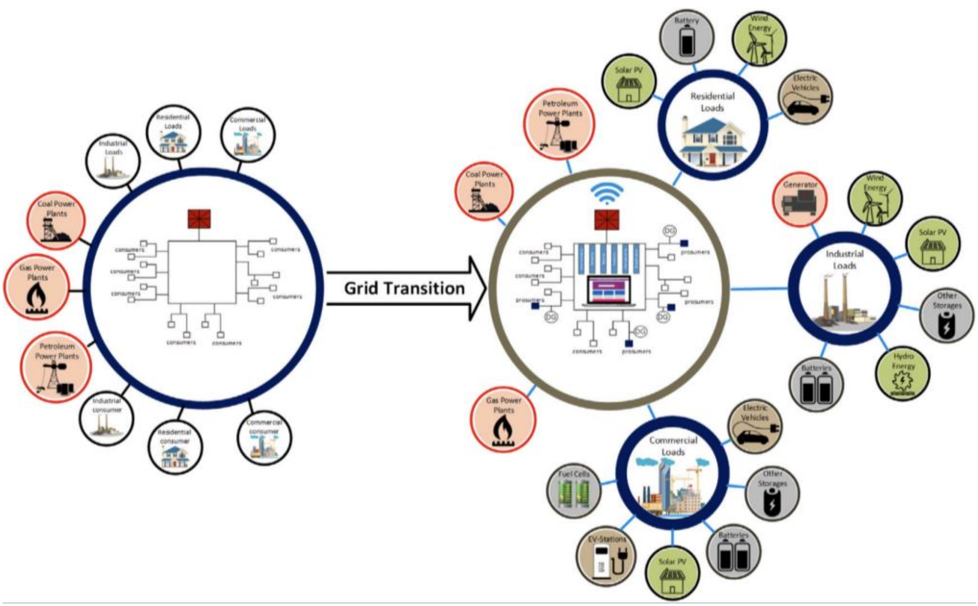

Figure 2: Power grid transition towards smart grid (Khalid, 2024).

1.2 The case for Demand-Side Flexibility and dynamic pricing

In response to these challenges, enhancing demand-side flexibility has emerged as a focus of energy systems research and policy. DSF refers to the ability of energy consumers—households, businesses, or industries—to intentionally shift or adjust their electricity consumption timing in response to grid needs, market signals (e.g., price fluctuations), or environmental constraints (*Crash Course | Energy Flexibility*, n.d.). There are several established methods under the broader umbrella of DSM, each designed to influence consumer behaviour and enhance grid efficiency. There are six widely recognized DSM strategies, which are: peak load shifting, valley filling, load levelling, strategic conservation, strategic load growth, and flexible load shaping (Figure 1). Each of these methods targets specific load profile modifications, offering various benefits depending on the application context. Among these, peak load shifting stands out as a particularly practical approach for addressing EV-related demand challenges. It involves encouraging users to shift their electricity consumption from peak demand periods to off-peak periods. Compared to other DSM strategies, peak load shifting is advantageous because it can be implemented without requiring significant infrastructural or technological changes. By leveraging existing smart meters and integrating real-time pricing signals, this method provides a cost-effective and scalable solution to minimize the effect of EVs charging on grid stability—making it an ideal candidate for this study.

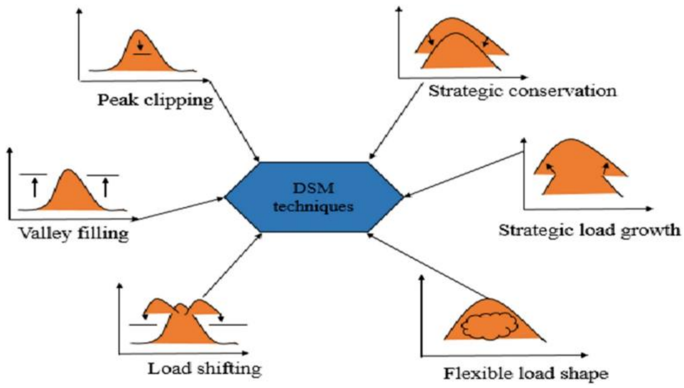

Figure 3: Techniques for DSM (Bakare et al., 2023)

Within the framework of DSM, DR has established itself as a fundamental mechanism for improving energy system flexibility. DR involves end-user's temporary adjustment of their electricity consumption patterns—through load shifting, reduction, or onsite generation—in response to price fluctuations or grid stability needs, thereby enhancing system reliability and cost efficiency (Aghaei & Alizadeh, 2013).

DR approaches are commonly divided into incentive-based and price-based programs. Incentive-based DR includes mechanisms like EDR, where users receive compensation for reducing consumption during critical grid events, and DLC, which allows utilities to regulate specific appliances power remotely. Other incentive-based models involve interruptible or curtailable service contracts and market-clearing mechanisms, such as demand bidding or ancillary services participation (Bakare et al., 2023).

In contrast, price-based DR encourages customers to modify their consumption based on varying electricity prices (Figure 2). These include:

- TOU pricing, which differentiates tariffs by time slots for instance peak, mid-peak, and off-peak periods.
- CPP, which activates elevated rate structures during predetermined peak hours.
- RTP, where prices vary frequently (hourly or daily) according to market or grid conditions.

- IBR, a pricing mechanism progressively increases electricity unit charges at pre-determined consumption thresholds, creating financial motivation for reduced energy usage.
- Fixed Price is a pricing structure where consumers face identical energy charges regardless of temporal fluctuations in system demand or generation costs.
- Dynamic Pricing defined by the European Directive 2019/944, dynamic pricing refers to electricity contracts that "reflect price variations in the spot markets, including day-ahead and intraday markets" (Numminen et al., 2022).

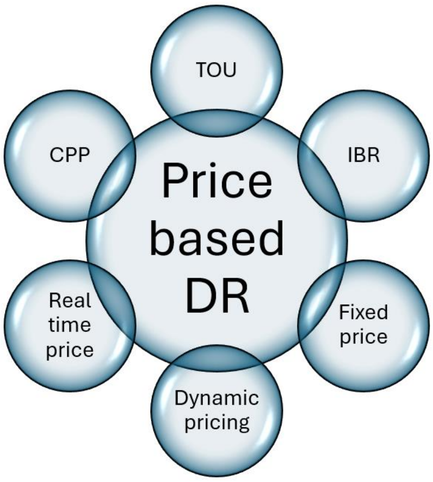

Figure 4 Price base demand response.

One of the most promising mechanisms to facilitate this flexibility is dynamic pricing. These contracts enable consumers to adapt to real-time market situation by altering their consumption behaviour, accordingly, thereby contributing to balancing the grid. Despite the availability of enabling technologies like smart meters, which provide real-time consumption data, the adoption of dynamic pricing has been slow. In countries like Finland, regulatory frameworks impose certain limitations. For instance, current legislation mandates uniform distribution fees for all customers within the same DSO network, hindering the widespread implementation of dynamic tariffs (*Finnish Electricity Market Act: Uniform Distribution Fees in DSO Networks*, 2019). As a result, even though consumers have the technological capacity to engage with dynamic pricing, they are not provided with sufficient economic signals to do so.

The existing literature often emphasizes local flexibility markets as an alternative to enhance demand-side response. These markets allow DSOs to procure flexibility services from consumers or aggregators, thereby mitigating congestion and voltage issues. However, such models require significant market maturity, infrastructure investment, and regulatory evolution—making them less feasible for immediate, large-scale deployment. In contrast, dynamic pricing can be implemented at scale with relatively minimal changes to existing systems and can leverage currently available smart metering infrastructure. Thus, it presents a practical and scalable approach to managing demand variability, especially in the context of growing EV penetration.

1.3 EVs as flexible loads: The opportunity and the risks

EVs, due to their flexible and potentially deferrable charging patterns, can serve as valuable resources for demand-side management (Mohanty et al., 2022). Unlike traditional household appliances, EVs are often connected to the grid for extended periods without needing to charge continuously. This creates a temporal window of flexibility, during which charging can be optimized in response to grid conditions or price signals (Štogl et al., 2024).

However, realizing this potential is contingent on the availability of appropriate incentives and pricing mechanisms. In the absence of dynamic pricing, most EV owners tend to charge their vehicles during the early evening hours, exacerbating peak demand (Williams et al., 2024). This not only increases stress on the grid but also limits the potential benefits that EVs can provide as flexible loads. Therefore, designing smart pricing strategies that align consumer behaviour with grid needs is critical to utilize the full potential of electric mobility.

1.4 Scope and objectives of the study

This study explores dynamic pricing as a practical demand-side management strategy to address grid stress arising from widespread EV adoption. Rather than relying on large-scale infrastructural upgrades or complex technological interventions, the research focuses on peak load shifting, which can be implemented using existing smart metering infrastructure and minimal regulatory adjustments.
At the core of this study lies the following research question:

“How can we develop a real-time dynamic pricing mechanism that reflects grid congestion levels to influence EVs charging behaviour?”

To address this, the study proposes a dynamic pricing model for EV CS that adjusts charging costs based on real-time network congestion. The model integrates real-time grid utilization data with AI-driven pricing algorithms to influence user behaviour. The underlying hypothesis is that by linking electricity prices directly to local grid conditions, EV users can be encouraged to shift their charging activities to less congested locations. Such behavioural adaptations are expected to alleviate grid stress, prevent infrastructure overloading, and promote equitable access to charging services.

In addition to algorithmic modelling and simulations, the study incorporates simulated EV charging data and user decision to validate the pricing strategy. Key performance indicators include peak demand reduction, congestion mitigation, and consumer satisfaction.

Ultimately, this research aims to offer actionable insights for DSOs, energy policymakers, and charging service providers, supporting a realistic and cost-effective approach for large-scale EVs integration into the power grid—without compromising its reliability or stability.

1.5 Structure of thesis

This thesis is organized into five chapters, each addressing a key aspect of the study and its progression from problem definition to proposed solution and evaluation.

Chapter 1 introduces the motivation for the study by outlining the challenges of integrating renewable energy into the grid and the increasing importance of demand-side flexibility. It highlights the potential of EVs as controllable loads, discusses the opportunities and risks involved, and defines the objectives and scope of the work.

Chapter 2 presents a detailed literature review, covering public EV charging systems, enabling technologies for dynamic pricing, and existing pricing methods. It further outlines the implementation challenges including regulatory, behavioural, and interoperability issues, and identifies key research gaps that this thesis aims to address.

Chapter 3 describes the proposed methodology. It begins by outlining the objectives of the model—congestion mitigation and fairness enforcement—and proceeds to detail the dataset, case scenarios, system architecture, and mathematical formulation of the optimization model. This chapter also covers data preprocessing steps, and the ML models (BRR and RF) used for demand forecasting, followed by an explanation of how the models were integrated into the pricing framework.

Chapter 4 presents and discusses the results of the implemented system. It provides an overview of the dataset characteristics, evaluates the performance of the forecasting models, and examines how the pricing engine behaves under different congestion scenarios. The chapter further analyses fairness outcomes and the system's impact on load distribution and revenue generation, concluding with a summary of key findings.

Chapter 5 concludes the thesis by summarizing the main contributions and findings. It discusses the limitations of the current work and proposes directions for future research, particularly regarding scalability, regulatory alignment, and real-world implementation.

2 Literature review

The growing proliferation of EVs is reshaping electricity consumption patterns, introducing new challenges for grid stability and congestion management, particularly in urban and high-density charging environments. As EV charging increasingly coincides with peak electricity demand, conventional grid infrastructures face stress conditions that threaten both reliability and efficiency (S. Powell et al., 2022). While infrastructural upgrades offer one path forward, they often require high capital investments and long deployment cycles. In contrast, demand-side solutions, particularly those centred around dynamic pricing—offer more immediate, scalable, and cost-effective interventions.

This chapter reviews key literature on the mechanisms and models that support dynamic pricing for EV charging, with a focus on mitigating local grid congestion while ensuring revenue optimization and fairness among users. The review is organized across five thematic areas: the structure and availability of public EV charging infrastructure, the roles, and interactions of key stakeholders in the charging ecosystem, adopted technologies for enabling demand-side flexibility, pricing methods and their respective objectives, and the current research gaps that this thesis seeks to address.

Through this review, the study identifies how real-time pricing signals, when linked to network congestion and supported by smart metering infrastructure, can shape user behaviour in ways that align economic incentives with grid operational needs. It also highlights limitations in existing literature, particularly regarding the balance between economic efficiency, consumer fairness, and implementation feasibility—establishing the foundation for the model proposed in subsequent chapters.

2.1 Overview of public EV charging systems

The availability and accessibility of public EV charging infrastructure play a pivotal role in enabling mass adoption of EVs and in shaping electricity demand patterns. As more consumers rely on public charging—either due to a lack of private access or convenience (Patt et al., 2019)—the strategic deployment and management of charging systems have emerged as key considerations for both urban mobility planners and grid operators (He et al., 2012). This section explores the technical configurations, spatial deployment trends, and behavioural aspects of public EV charging, forming the foundational layer upon which dynamic pricing models must operate.

2.1.1 Typologies of public charging infrastructure

Public EV charging systems are typically classified based on the power level they deliver and the associated charging duration (Falchetta & Noussan, 2021). The three widely adopted categories include:

- Normal chargers up to 22kW (AC)
- Fast Chargers up to 50kW (AC/DC)
- Ultra-Fast chargers up to 500kW (DC)

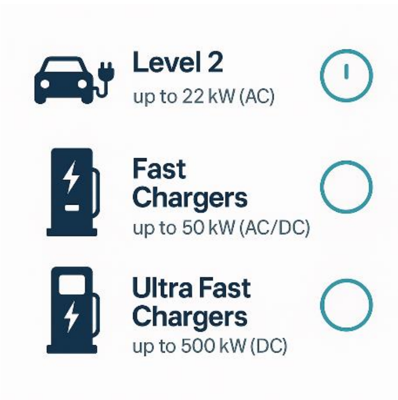

Figure 5 Overview of public EV charger types.

Each type of charger contributes differently to grid stress levels, primarily based on its power demand, duration of use, and deployment context. High-powered DCFCs, which deliver 50 kW to over 350 kW, are particularly impactful in this regard (Sarda et al., 2024). Their rapid charging capability, while beneficial for users, requires a sudden and substantial influx of electrical power. When multiple DCFCs are co-located—such as at highway service areas or urban hubs—they can create significant and instantaneous load spikes, which challenge the operational stability of the local distribution network (B. Powell & Johnson, 2024).

This concentrated power draw can lead to localized voltage drops, causing power quality issues not only at the charger site but also in nearby residential and commercial zones sharing the same feeder line. Moreover, transformer thermal limits may be exceeded if these chargers are used at full capacity simultaneously and for extended periods. This can accelerate transformer aging, increase the likelihood of unplanned outages, and necessitate expensive reinforcement investments by DSOs. Without real-time load management (de Hoog et al., 2013) or dynamic pricing to moderate usage during peak periods, these installations risk becoming grid bottlenecks, undermining both reliability and future scalability of charging infrastructure (Sarda et al., 2024).

2.1.2 Deployment locations and usage patterns

The strategic placement of public EVs charging infrastructure is guided by multiple factors, including user demand density, travel behaviour, grid capacity, and land use patterns (Ren & Sun, 2025). Effective deployment not only ensures accessibility and user convenience but also plays a critical role in balancing grid loads and enabling flexible charging behaviour—both essential prerequisites for implementing dynamic pricing strategies.

Urban and commercial zones—such as shopping centres, entertainment areas, and downtown business districts—are key locations for combination Level 2 and fast DC CSs (Momin et al., 2025). These locations attract users who typically park for one to four hours while running errands, shopping, or working. Despite the moderate parking duration, many users prefer fast or top-up charging to maximize convenience, which can result in concentrated demand spikes, especially during late afternoon and early evening hours. When multiple users initiate fast charging simultaneously within a dense urban feeder network, it can lead to localized transformer overloading, voltage drops, and thermal stress on distribution assets (Nutkani et al., 2024).

Highway corridors and transit nodes represent another major hub for fast-charging demand (Jochem et al., 2019). Ultra-fast chargers, typically delivering 150–350 kW or more, are designed to serve long-distance EV travellers who require quick top-ups in 15–30 minutes (Momin et al., 2025). These stations cater to transient, high-load sessions, which occur irregularly but with significant intensity. As a result, such sites often require dedicated substations or on-site battery energy storage to prevent adverse grid impacts (Mowry & Mallapragada, 2021). Without real-time load management or price-driven throttling, these nodes can become flashpoints for congestion, especially during holiday travel periods or daily commuter surges.

Across these deployment contexts, the common trend is clear: user preference for rapid charging (Consumer Research into Rapid Charging, 2019), even during short or medium-length stays, imposes sharp and often unpredictable load fluctuations on the local grid. These fluctuations are not easily absorbed without active demand-side management or real-time pricing interventions. Therefore, understanding these spatial and temporal patterns is essential for the design of dynamic pricing strategies that respond to congestion risk, incentivize off-peak charging, and ensure equitable grid usage.

2.1.3 Relevance to dynamic pricing strategies

Understanding the characteristics and usage of public EV charging systems is essential for the implementation of effective dynamic pricing schemes. The heterogeneous nature of charger locations, user behaviour, and grid sensitivity necessitates adaptive pricing models that reflect local congestion levels and user value. Without such differentiation, flat-rate or static pricing structures may fail to provide the economic signals needed to shift user behaviour or protect grid assets.

2.2 Enabling technologies for dynamic pricing in distributed EV charging

The implementation of dynamic pricing in EV charging environments heavily relies on a suite of smart technologies that enable real-time monitoring, data exchange, and decentralized control. These technologies provide the necessary infrastructure for DSOs to influence charging behaviours without requiring direct intervention at individual CSs, which are often owned and operated by a diverse set of private and public entities.

One of the foundational technologies is the smart meter, which facilitates bidirectional communication between energy users and utilities. Smart meters provide high-resolution consumption data (often at intervals as short as 15 minutes or less), enabling near real-time visibility into charging activities (Gungor et al., 2011). This data is critical for detecting local congestion, forecasting demand, and applying dynamic price signals in a targeted manner. Moreover, smart meters can communicate tariff changes or congestion warnings to consumers almost instantaneously, supporting responsive behaviour.

In parallel, the evolution of IoT systems has enhanced the ability to manage distributed EV chargers without centralized ownership. IoT-enabled EV chargers are equipped with communication modules that interface with cloud-based platforms, allowing for remote monitoring, load aggregation, and flexible control actions (Suresh Kumar et al., 2020). These systems can receive dynamic pricing signals, optimize charging schedules based on user preferences and grid conditions, and even participate in ancillary services markets if regulation permits.

Real-time application platforms, often built on cloud infrastructure, serve as the orchestration layer between DSOs, aggregators, and consumers. These platforms process incoming grid data, user demand patterns, and market signals to compute congestion-based dynamic prices. Advanced examples include smart charging management systems that integrate ML algorithms to predict congestion and adjust prices proactively (Bae et al., 2024; Cao et al., 2022).

Collectively, smart meters, IoT-connected chargers, and real-time application platforms create a distributed but coordinated environment where DSOs can manage grid congestion through market-based incentives rather than through rigid direct control. This approach not only respects the fragmented ownership of public charging assets but also promotes scalability, fairness, and faster deployment of smart grid solutions.

2.3 Overview of dynamic pricing methods

Dynamic pricing in electricity markets refers to the adjustment of consumer tariffs in response to real-time or forecasted grid conditions. Various pricing mechanisms have been proposed and implemented to influence user behaviour, optimize grid operation, and minimize peak load congestion. Each method aims to incentivize consumers to shift or curtail their energy usage, thus flattening demand curves and improving system reliability.

2.3.1 Existing work on dynamic pricing for EVs

In the specific context of EV charging, several studies have investigated how dynamic pricing can be used to manage demand. Over the last decade the topic has evolved from isolated tariff proposals to sophisticated bilevel, game-theoretic, and AI models that jointly optimize grid performance, station profitability, and user welfare.

Several studies have explored dynamic pricing strategies for EV CSs, employing a range of AI techniques and game-theoretic frameworks. Zhao and Lee (2022) introduced a DDPG algorithm to dynamically set charging prices at fast-charging stations, achieving a 28% increase in station profitability and a notable reduction in user wait times compared to static tariffs (Zhao & Lee, 2022). Mrkos and Basmadjian (2022) utilized MCTS to determine optimal dynamic pricing, demonstrating high computational efficiency and revenue improvement, although without explicitly modelling grid congestion (Mrkos & Basmadjian, 2022).

Paraskevas et al. (2022) developed a constrained DQN model for joint optimization of pricing and charging control, successfully balancing operator profitability and user service levels (Paraskevas et al., 2022). Liu et al. (2023) employed a multi-objective GA to design dynamic time-of-use tariffs with the goal of balancing load profiles, achieving peak load reductions and some implicit congestion management benefits, although without detailed grid-level modelling (Liu et al., 2023). Cui et al. (2023) proposed a hybrid forecasting-control architecture, integrating LSTM networks with GNN and RL to predict EV demand and optimize pricing, improving load distribution across stations (Cui et al., 2023). Zhou et al. (2025) applied a mixed-logit choice model combined with DQN to reduce idle connection times at CSs, thereby enhancing throughput, although without broader distribution system considerations (Zhou et al., 2025).

Beyond AI approaches, game-theoretic models have been used to incorporate distribution grid conditions directly into pricing mechanisms. Fang et al. (2025) proposed a bi-level optimization framework where a DSO sets DLMPs reflecting distribution network congestion, while CPOs competitively adjust their retail prices (Fang et al., 2025). Ge et al. (2025) developed a distributed pricing model that jointly considered both distribution network congestion and transportation network conditions, allowing EV users to dynamically choose stations based on congestion-sensitive price signals. Their approach improved grid load balancing and reduced user travel delays, advancing system-wide efficiency goals (Ge et al., 2025).

Across these studies, various algorithms have been applied to manage the complex dynamic pricing problem under uncertainty. RL techniques dominate AI-driven approaches due to their capacity to handle sequential decision-making. Zhao and Lee (2022) leveraged DDPG, particularly well-suited for continuous action spaces, while Paraskevas et al. (2022) and Zhou et al. (2025) employed DQN, effective in discrete settings. MCTS, applied by Mrkos and Basmadjian (2022), offered fast and computationally efficient decision-making but lacked cross-episode learning adaptability. Heuristic methods such as PSO and GA, used by Cao and Chang (2024) and Liu et al. (2023), demonstrated success in offline, multi-objective optimization but were less suited for real-time adaptive pricing. More complex hybrid models, such as the LSTM, GNN and DDPG framework proposed by Cui et al. (2023), attempted to integrate forecasting and control for enhanced spatial-temporal decision-making but incurred high computational overheads. In contrast, game-theoretic bilevel models, as demonstrated by Fang et al. (2025) and Ge et al. (2025), provided structured strategic frameworks that embedded grid congestion and competitive market responses into the pricing process, offering more system-integrated dynamic pricing solutions.

In addition to AI-driven and game-theoretic approaches, behavioural elasticity models have also been investigated in the literature for dynamic pricing of EV charging. These models typically focus on modelling how consumers respond to changes in price, queue lengths, or perceived utility when selecting charging options. Techniques such as discrete-choice modelling (Lai et al., 2023), traffic-assignment elasticity (Tan et al., 2022), reference-price memory effects (Jia et al., 2024), and congestion-based queuing for service fairness (Bayram & Galloway, 2022) have been applied to capture user-side behaviour under dynamic pricing schemes. While these approaches provide valuable insights into consumer responses and welfare impacts, they primarily address market dynamics and user decision-making rather than the technical implications of EV charging on distribution grid congestion. Given the primary focus of this thesis on congestion-based dynamic pricing and system-level efficiency improvements, behavioural elasticity models are acknowledged but not extensively reviewed herein.

Despite the significant contributions of these works, some limitations remain that align with the research objectives of this thesis. First, many AI-based studies focus predominantly on station-level operational efficiency or revenue maximization without explicitly considering the effects of dynamic pricing on distribution grid congestion or system-wide load balancing. Second, several models, including those by Fang et al. (2025) and Ge et al. (2025), operate under deterministic assumptions and do not explicitly account for uncertainties in EV arrivals, renewable generation variability, or demand forecasting—factors critical for robust grid operation (Fang et al., 2025; Ge et al., 2025). Third, none of the reviewed studies incorporate a fairness factor in their dynamic pricing strategies, leaving issues such as equitable access to affordable charging and fair distribution of cost burdens across consumers largely unexplored. These gaps motivate the need for a congestion-based dynamic pricing model that addresses both grid stability and consumer fairness under realistic operational uncertainties, as pursued in this thesis.

2.4 Challenges in implementation of dynamic pricing

While dynamic pricing presents a promising pathway for managing EV charging demand and alleviating grid congestion, several practical challenges complicate its widespread implementation. These challenges span technical, regulatory, behavioural, and cybersecurity domains, each posing significant barriers to achieving the intended flexibility outcomes.

2.4.1 Regulatory and policies barriers

In many regions, electricity tariffs and network charges are regulated to ensure fairness and prevent discriminatory practices. For example, under the Finnish Electricity Market Act and related policies, DSOs are required to apply uniform tariffs across all customers within a given network area, irrespective of localized grid conditions (*Finnish Electricity Market Act: Uniform Distribution Fees in DSO Networks*, 2019). This regulatory framework inhibits the adoption of location-specific dynamic pricing strategies that could otherwise target congestion hotspots more effectively. Furthermore, tariff approvals often involve lengthy administrative procedures, reducing the flexibility needed for real-time or near-real-time price adjustments.

2.4.2 Consumer acceptance and behavioural inertia

Consumer behaviour plays a critical role in the success of dynamic pricing schemes. However, evidence suggests that many EV users demonstrate low price elasticity for charging, particularly when convenience and time constraints dominate decision-making (Sadeghianpourhamami et al., 2018). Without adequate incentives, education, and user-friendly interfaces, consumers may not actively respond to dynamic price signals. Moreover, there is a risk of consumer dissatisfaction if pricing schemes are perceived as unfair, overly complex, or punitive, potentially undermining public support for broader demand-side flexibility initiatives.

2.4.3 Technological interoperability and standardization

The effectiveness of dynamic pricing schemes in EV charging infrastructure heavily depends on the interoperability of the underlying communication and control technologies. However, achieving seamless interoperability remains a major technical challenge due to the fragmented nature of charging hardware, software platforms, and communication protocols.

Currently, charging infrastructure across different regions and providers operates with varying standards, primarily based on versions of the OCPP. Although OCPP has become the de facto industry standard for enabling two-way communication between EV chargers and central management systems, differences between protocol versions (e.g., OCPP 1.6, OCPP 2.0, and 2.0.1) create functional inconsistencies (The Digital Side of Charging: The Future of OCPP and ISO 15118, 2024). Support for advanced features such as dynamic tariff updates, smart load control, and real-time metering is not uniformly available across all deployed chargers (van der Kam & van Sark, 2015). Chargers using older versions or proprietary systems may not be capable of receiving real-time pricing signals, severely limiting the scalability of congestion-responsive pricing models.

Beyond protocol version issues, many CSs are built by different manufacturers who implement OCPP or other protocols slightly differently, leading to partial interoperability problems. In some cases, backend management systems must use custom integrations to communicate effectively with different brands of chargers, increasing operational complexity and cost (Bedi et al., 2018).

Furthermore, interoperability challenges extend to data formats, cybersecurity protocols, and payment systems, all of which are critical for the execution of dynamic pricing. Without harmonized standards, ensuring consistent, secure, and real-time price signalling across a fragmented network becomes a technical bottleneck.

Thus, the lack of universal interoperability standards across the EV charging ecosystem stands as a major barrier to the widespread deployment of dynamic, congestion-sensitive pricing mechanisms. Overcoming this fragmentation through better standardization efforts is essential to enable scalable, fair, and effective demand-side management strategies for EV charging.

3 Methodology

The integration of EVs into the power grid introduces new challenges, particularly regarding localized congestion and fair access to charging services. As discussed in previous chapters, dynamic pricing linked to real-time grid conditions presents a promising strategy to mitigate these issues by influencing user behaviour through economic signals.

This chapter focuses on the methodology developed to design and implement a congestion-based dynamic pricing model for EV charging. It outlines the dual-objective framework that seeks to balance grid congestion mitigation and fairness among users. The chapter further describes the dataset and scenario modelling approach, the system architecture, the mathematical formulation of objectives, and the ML techniques employed to predict and apply dynamic prices.

3.1 Objective of the model

The proposed dynamic pricing model is designed with the overarching objective of enabling efficient congestion management in distribution grids while ensuring fair access to affordable charging services for EV users. These two objectives form the primary foundation upon which the model is developed. In addition, the model considers revenue maximization for charging service operators as a secondary but important requirement, ensuring economic viability without compromising user equity.

3.1.1 Congestion mitigation

One of the primary challenges in the widespread adoption of EVs is the additional, often unpredictable, load stress that EV charging introduces on the distribution network. The dynamic pricing model proposed in this thesis addresses this challenge by linking charging prices directly to localized congestion levels. When congestion in a specific zone or feeder increases, the corresponding charging price rises proportionally, incentivizing users to defer or redistribute their charging sessions. Conversely, during periods of low congestion, lower prices encourage flexible users to charge, thus balancing load profiles across time and location. This mechanism promotes self-regulation among users without requiring centralized control interventions.

3.1.2 Fairness enforcement

While congestion management is crucial, a purely congestion-driven pricing model risks introducing equity concerns. Users in highly congested areas, or those with limited flexibility due to work schedules or vehicle range constraints, could be disproportionately impacted by higher prices. Such disparities may reduce user satisfaction and limit the broader acceptance of dynamic pricing schemes.

To address this, the model incorporates a fairness objective that moderates price differentiation across users. Fairness is mathematically formulated to minimize large deviations between the prices faced by different users, ensuring that no individual or group is systematically disadvantaged. This ensures that the dynamic pricing signals are effective yet socially acceptable, promoting greater user participation in flexible charging programs.

By balancing these objectives, the model aims to provide a pragmatic, scalable, and socially responsible solution for EV demand-side management within distribution grids.

3.2 Dataset and scenarios description

To evaluate the performance of the proposed congestion-based dynamic pricing model, a synthetic dataset was generated to simulate realistic EV charging behaviour across a representative distribution network. The dataset creation process focused on modelling charging demand, local congestion conditions, and user flexibility, enabling the testing and training of the dynamic pricing algorithm under controlled but practically inspired scenarios.

Given the lack of publicly available, high-resolution EV charging datasets linked explicitly to local grid congestion data, a synthetic approach was necessary. The controlled generation of data allows for the systematic evaluation of model behaviour under varying network stress scenarios and user flexibility distributions. Furthermore, synthetic data facilitates the testing of extreme congestion events and fairness trade-offs that may be rare in real-world datasets but are critical for validating robust pricing mechanisms.
While synthetic data inherently carries limitations in replicating the full complexity of real-world charging ecosystems, it provides a valuable first step toward developing, validating, and refining the congestion-aware dynamic pricing framework proposed in this thesis.

3.2.1 Scenario design and assumptions

The simulated distribution network consists of multiple charging zones. Each zone experiences varying degrees of congestion throughout the day, influenced by user demand patterns and localized infrastructure limitations.
Key assumptions:

- Charging Demand: EV user arrivals and energy demand levels were modelled based on typical urban charging patterns, with peak activity occurring during late afternoon and early evening hours.
- Congestion Levels: Congestion is quantified based on the traffic patterns as the demand will rise with the increase in arrival of EVs.
- Price Responsiveness: Users are assumed to exhibit some degree of elasticity to price changes, meaning that higher prices can influence their decision to delay or shift charging sessions.
- User Flexibility: A subset of users is modelled as inflexible (e.g., needing immediate charging), while others are flexible and can respond to pricing incentives.

- Revenue Neutrality: The dynamic pricing model is designed such that, on average, operator revenues remain comparable to baseline static pricing revenues, ensuring sustainability.

3.2.2 Dataset generation

The dataset was created using a combination of statistical simulation and rule-based logic, ensuring diversity in congestion scenarios and user behaviour. The following data elements were included:

- Time Intervals: The dataset is segmented into discrete time intervals (e.g., 15-minute periods) to capture temporal variations in demand and congestion.
- Charging sessions: The length of each charging session was assumed to be in between 10-120 minutes.
- Zone-Level Congestion: For each time interval and zone, a congestion index value is generated, reflecting the current stress on the local grid segment.
- User Profiles: Each user entry includes attributes such as flexibility status (flexible or inflexible), energy demand, charging start time, and maximum acceptable price.

This synthetic dataset enables the training of the dynamic pricing model and provides a testbed for evaluating its effectiveness in managing congestion and maintaining fairness across users.

3.2.3 Data sources for mobility patterns

To ensure that the synthetic dataset reflected realistic EV charging behaviour and traffic-induced congestion patterns, mobility assumptions were derived from publicly available traffic and mobility platforms. Specifically, the TomTom Traffic {Citation} Index and HERE Technologies Mobility Services were utilized to understand urban movement trends, peak congestion periods, and variability in traffic loads within city environments. These real-world mobility insights were incorporated into the synthetic dataset generation process, ensuring that congestion scenarios used for dynamic pricing model evaluation reflect practical urban conditions.

3.2.4 Case study: Helsinki region and CSs

To further enhance the practical relevance of the synthetic dataset, the case study scenario was geographically anchored in the Helsinki metropolitan region. Helsinki, the capital city of Finland, represents a dense urban environment with significant EV adoption and well-developed charging infrastructure, making it a suitable reference point for congestion-based dynamic pricing analysis.

Within the Helsinki region, two representative public CSs were selected for modelling purposes:

- Station A: Located in a high-demand urban area with heavy commuter traffic and commercial activity.
- Station B: Situated in a comparatively lower-demand residential neighbourhood with moderate traffic congestion levels.

These two stations were chosen to reflect the typical heterogeneity found in public charging infrastructure, where some locations experience frequent congestion due to overlapping EV charging and general traffic demand, while others operate under less stressful conditions.

In the simulation environment:

- Station A was modelled with higher baseline congestion indices, more frequent peak periods, and greater price sensitivity challenges.
- Station B was modelled with lower baseline congestion, longer average user dwell times, and more predictable charging loads.

By considering two distinct types of CSs within the same urban network, the model evaluation could capture localized variations in congestion dynamics, user flexibility, and price responsiveness. This setup allows the dynamic pricing algorithm to be tested across different stress levels, validating its ability to dynamically adjust tariffs not only across time but also spatially across different network segments.

The use of a realistic, location-based case study enhances the credibility of the simulation results and demonstrates the potential of congestion-based dynamic pricing to manage real-world EV charging networks in complex urban environments like Helsinki.

3.3 System architect overview

The proposed congestion-based dynamic pricing model operates through a multi-stage system that integrates real-time data collection, congestion estimation, dynamic price computation, and user feedback mechanisms. The system is designed to enable DSOs or charging service providers to dynamically adjust EV charging prices in response to localized grid conditions without requiring direct control over charging sessions. Figure 3.1 illustrates the overall system architecture of the proposed dynamic pricing framework.

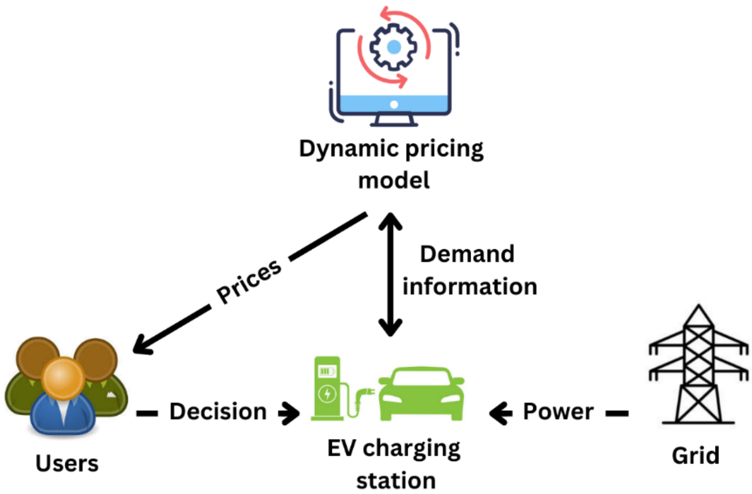

Figure 6 Overview of congestion based dynamic pricing system architecture.

3.3.1 Data acquisition layer

At the foundational level, data is collected from various distributed sources:

- Smart meters and CSmanagement systems provide real-time information on charging power consumption, session start/end times, and energy delivered.
- Traffic congestion platforms (e.g., TomTom, HERE) may optionally supply contextual mobility data to support congestion forecasting.
- Grid monitoring systems report local transformer loading, voltage levels, and feeder congestion metrics.

This real-time and historical data is centralized in a cloud-based or localized management platform for further processing.

3.3.2 Congestion estimation module

The collected grid and demand data are processed to estimate the current congestion index at each charging zone. Congestion is quantified based on the loading percentage of the local distribution infrastructure relative to its rated capacity and the arrival rate of EVs at particular CS. A congestion score is computed periodically (e.g., every 15 minutes) to reflect dynamic grid conditions. This congestion score serves as a critical input for the dynamic pricing model.

3.3.3 Dynamic pricing engine

Based on the estimated congestion index and user profiles, the dynamic pricing engine computes updated charging tariffs for each zone.
The pricing algorithm optimizes a multi-objective cost function balancing:

- Congestion cost (higher congestion → higher prices)
- Fairness adjustment (minimizing large price disparities across users)
- Revenue sustainability (maintaining operator revenues within acceptable margins)

The mathematical formulation and optimization method are detailed in Section 3.5.

3.3.4 Price broadcasting and UI

Updated dynamic prices are communicated back to EV users through mobile applications, in-vehicle infotainment systems, or CS displays. The price broadcasting ensures that users are aware of the current tariffs before starting or continuing a charging session, empowering them to make informed decisions regarding when and where to charge based on real-time economic incentives. Flexible users may choose to delay charging until lower prices are available, while inflexible users can still proceed with charging by accepting the prevailing rates.

3.3.5 Feedback loop and continuous learning

The system operates in a closed feedback loop:

- User responses to price signals (e.g., session delays, session terminations) are recorded.
- Updated behaviour data refines the congestion estimation and model calibration over time.
- ML techniques are applied to predict future congestion patterns and optimize pricing strategies dynamically.

This continuous learning capability enhances system accuracy, adaptability, and effectiveness in managing EV charging demand across varying grid conditions.

3.4 Mathematical formulation

The dynamic pricing model developed in this thesis seeks to optimize EV CS pricing by minimizing localized grid congestion while promoting fairness among users. The optimization framework operates across multiple time slots and charging locations and is subject to practical pricing constraints.

3.4.1 Congestion objective function

Congestion is modeled by penalizing high instantaneous demand at individual charg-ing stations. The congestion cost function $Z_{\text{congestion}}$ is defined as,

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

where:

- $d_j(t)$ is the charging demand at station j during time sot t.
- T is the total number of discrete time slots.
- N is the number of CS.

Squaring the demand values penalizes stations and time slots with disproportionate-ly high load, amplifying the impact of congestion peaks on the overall objective. This mech-anism discourages clustering of charging activities, promotes load flattening, and helps maintain distribution network stability by spreading demand more evenly across time and space. For example, a doubling of demand at a station results in a fourfold increase in its contribution to $Z_{\text{congestion}}$, making it highly costly to allow sharp peaks.

3.4.2 Fairness objective function

Fairness among users is promoted by minimizing the deviations of station-specific prices from the average price. The fairness cost Z_{fairness} is formulated as:

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

where:

- $p_j(t)$ is the dynamic price at station j during time slot t.
- $\bar{p}(t)$ is the average price across all stations at time t.

Minimizing the variance of dynamic prices reduces the disparity between what users pay at different stations or times. This fairness objective protects users located near congested areas from being excessively penalized compared to users in less congested areas. It ensures the system remains socially equitable and encourages broader user participation. For instance, if two nearby stations have significantly different prices at the same time, users may perceive the system as unfair, leading to dissatisfaction or reduced trust.

3.4.3 Combined optimization objective

The final objective is to minimize a weighted sum of the congestion cost and the fairness penalty:

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

where:

- α and β are non-negative weighting factors balancing congestion mitigation and fairness enhancement.

The parameters α and β control the trade-off between technical efficiency and social equity. Typically, α is set higher (e.g., 0.7–0.8) to prioritize congestion mitigation, while β (e.g., 0.2–0.3) ensures fairness is not neglected. Proper tuning of these weights is essential depending on the operational priorities of the distribution network operator or service provider.

3.4.4 Price bound constraint

Dynamic prices are constrained within operationally feasible and economically acceptable bounds to prevent unrealistic outcomes:

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

where:

- $p_j^{\min}$ and $p_j^{\max}$ are the minimum and maximum allowable prices for station j.

These constraints ensure that:

- Prices do not fall too low, which could lead to unsustainable revenue levels for operators.
- Prices do not rise excessively, which could deter users or raise affordability concerns.

3.4.5 Price-demand functional relationship

The dynamic price at each station and time is determined as a function of the station's local demand level:

$$p_j(t) = f\left(d_j(t)\right) \tag{5}$$

where:

- $f\left(d_j(t)\right)$ is a monotonic increasing function linking demand to price.

As demand increases at a station, the corresponding price also increases, providing an economic signal for users to either defer charging or shift to less congested stations. The specific functional form of $f\left(d_j(t)\right)$ can be linear, piecewise-linear, or slightly non-linear depending on implementation preferences.

For example, if demand increases by 20%, the dynamic price may rise proportionally (depending on the sensitivity setting), making users reconsider immediate charging during peak stress periods.

3.5 Data preprocessing

Before applying ML techniques for predictive modelling, appropriate data preprocessing steps were conducted to ensure data quality, consistency, and suitability for model learning.

3.5.1 Data cleaning

The synthetic dataset generated for simulation included time series information on charging demand across different stations and time slots. As the data generation process was controlled, no missing values were present. However, basic validation was performed to ensure:

- No negative demand values occurred.
- Demand values aligned with realistic operational ranges for public EV chargers.
- No charging session is below 10 minutes to ensure proper functionality of model.

Then the datasets were merged in a single unified panda DataFrame (McKinney, 2010) ensuring all relevant features are available.

3.5.2 Feature engineering

To enhance the predictive capabilities of the ML model, several new features were engineered from the available data. Time-related features were extracted, including the hour of the day and the day of the week, to capture the inherent temporal patterns in EV charging behaviour. Historical demand values, like charging demand in previous time slots, were also incorporated to model temporal autocorrelation.
Additionally, external traffic congestion indicators, sourced from platforms such as TomTom Traffic and HERE Mobility Services, were optionally integrated to provide further contextual information likely to influence charging patterns.

3.5.3 Normalization process

Normalization of features was an essential preprocessing step. To prevent scale differences among features from biasing the model, demand values were normalized using Min-Max scaling to a range between 0 and 1. In some model tuning experiments, z-score standardization was also applied, particularly when testing different regularization settings in BRR. These scaling steps ensured that features contributed proportionally to the learning process.

3.5.4 Data splitting

For model training and evaluation, the dataset was split chronologically into training and testing subsets, with 70% of the data used for training and 30% reserved for testing. A time-aware split approach was adopted to avoid information leakage, ensuring that future information was not inadvertently introduced into the model during training.

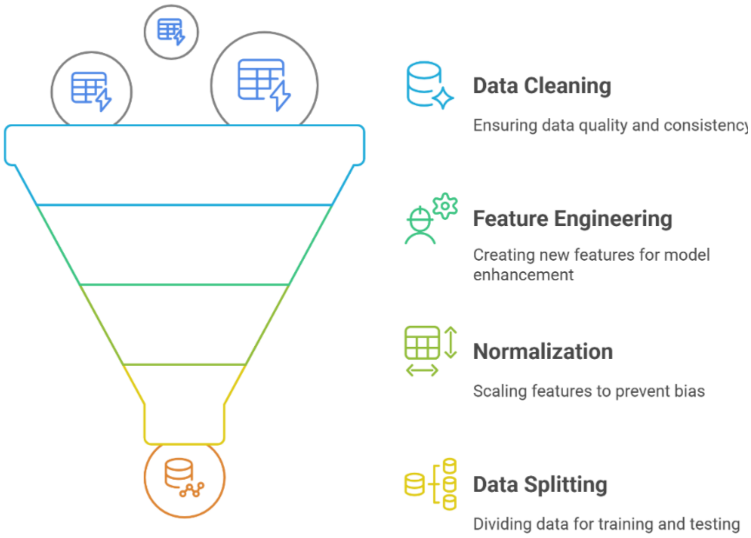

Figure 7 Data preprocessing steps

Overall, the final pre-processed feature set included time indicators, historical lagged demands, optional traffic congestion scores, and normalized previous demand values. This carefully engineered input structure provided a strong basis for the ML model to accurately forecast future charging demands and support real-time dynamic pricing decisions.

3.6 Machine learning model

In this study, two ML models were explored to predict future charging demand patterns and support the implementation of a congestion-based dynamic pricing framework: BRR and RF.

Both models were evaluated for their ability to forecast demand and generate accurate pricing multipliers for EV CSs. Ultimately, BRR was selected as the primary model based on its superior performance, particularly in handling uncertainty and providing reliable predictions under dynamic conditions.

3.6.1 Bayesian Ridge Regression (BRR)

BRR is a probabilistic extension of OLS regression that incorporates Bayesian inference principles to estimate the distribution of model parameters rather than fixed point estimates (M. Bishop, n.d.).

The standard linear model assumes the relationship:

$$y = Xw + \epsilon \tag{6}$$

where:

- y is the target vector (e.g., predicted demand)
- X is the feature matrix (input variable)
- w is the vector of regression coefficients
- $\epsilon \sim \mathcal{N}(0, \alpha^{-1})$ is Gaussian noise with precision α

A Gaussian prior is placed over the coefficients:

$$p(w \mid \lambda) = \mathcal{N}(0, \lambda^{-1} I) \tag{7}$$

where:

- λ represents the precision of the prior distribution.

Using Bayesian inference, BRR computes the posterior distribution of the coefficients after observing the training data, providing both point predictions and associated uncertainty estimates.

BRR automatically includes regularization to manage overfitting and offers robust-ness to multicollinearity, making it particularly suited for high-variability datasets such as EV charging demand.

The ability to quantify predictive uncertainty is also highly advantageous for dynamic pricing systems, where operational risks must be carefully managed (Tipping, 2001).

3.6.2 Random Forest Regression (RFR)

RF is an ensemble learning method that builds multiple decision trees on random subsets of the data and aggregates their outputs to form the final prediction (Breiman, 2001).

The ensemble prediction can be expressed mathematically as:

$$\hat{y} = \frac{1}{n_{\text{trees}}} \sum_{i=1}^{n_{\text{trees}}} T_i(x) \tag{8}$$

where:

- $T_i(x)$ represents the output of the ith tree for input x.
- n_{trees} is the total number of trees in the forest.

RF use bootstrap aggregation (bagging) and random feature selection to reduce overfitting and improve generalization. They can capture complex non-linear relationships and feature interactions without extensive hyperparameter tuning.
However, a key limitation is their lack of native uncertainty quantification, which can be critical in applications requiring risk-aware decision-making (Hastie et al., 2009).

3.7 Model integration

Both BRR and RF models were trained using the pre-processed dataset described in Section 3.6, incorporating historical charging demand, time-based features, and optionally external traffic congestion indicators. The models were designed to forecast short-term charging demand at individual EV stations, with the predictions subsequently used to adjust prices based on the congestion management framework de-scribed in Section 3.4.

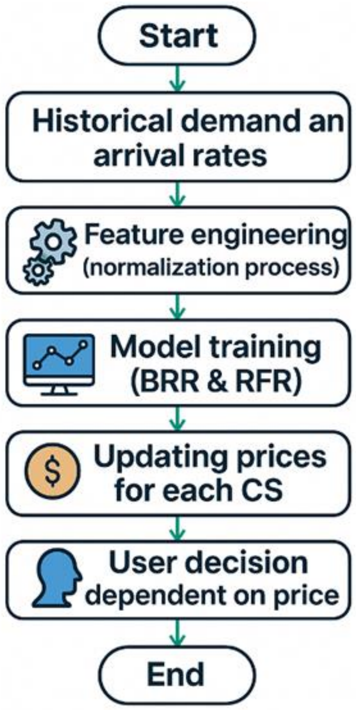

Figure 8 Mechanism of model for dynamic pricing.

The ML models operate in a rolling prediction mode, where forecasts are updated periodically to reflect real-time conditions. This predictive capability allows the system to adjust tariffs proactively, influencing user behaviour and helping to mitigate grid congestion. Evaluation of the model performances and detailed comparative analysis between BRR and RF models are presented in Chapter 4.

4 Results and Discussion

This chapter presents the results of the proposed congestion-based dynamic pricing model for EV CSs. The objective is to evaluate the performance of the methodology described in Chapter 3 across multiple dimensions, including ML model accuracy, pricing responsiveness under congestion, fairness enforcement, and the overall impact on load distribution and revenue sustainability.

The evaluation is based on a series of simulated scenarios using synthetically generated datasets that emulate realistic charging behaviour within an urban distribution network. The synthetic data includes temporal demand profiles, congestion levels, and user flexibility distributions for two selected charging zones in the Helsinki region.

The chapter is organized as follows: Section 4.2 introduces the dataset used in the simulations, followed by an evaluation of the ML models in Section 4.3. Section 4.4 analyses the behaviour of the pricing model under different congestion conditions. Section 4.5 assesses fairness outcomes across users and locations. Section 4.6 discusses revenue and grid impact, and Section 4.7 concludes the chapter with key observations.

4.1 Dataset overview

The simulations and evaluations presented in this thesis were conducted using a synthetically generated dataset designed to emulate realistic EV charging behaviour in an urban distribution network. The dataset captures the temporal dynamics of charging demand, congestion patterns, and user characteristics across two representative charging zones located in the Helsinki region.

The hourly distribution of total charging sessions is further detailed in Figures 9 and 10. For CS1, the histogram reveals heavy usage starting from 7:00 AM and peaking between 16:00 and 18:00, consistent with workday traffic in commercial zones. The session count drops sharply after 21:00, reflecting reduced activity in city centres during late-night hours. The peak activity can be seen at 18:00 whose charge count is 1734.

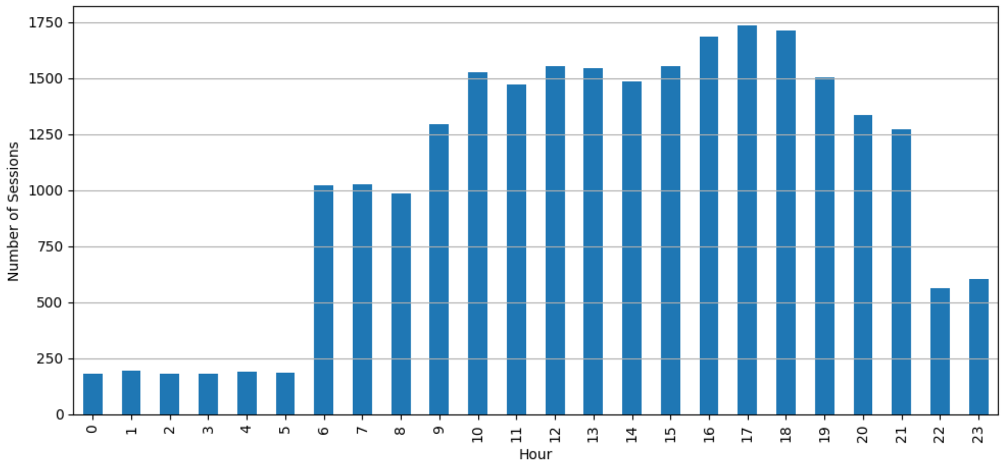

Figure 9 Hourly charging sessions at CS 1.

For CS2, Figure 10 shows a dual-peak pattern with high activity in both the early morning and evening, and a noticeable decline during mid-day and after 20:00. This supports the characterization of CS2 as a residential-area charger used predominantly by commuters and home-charging EV owners.

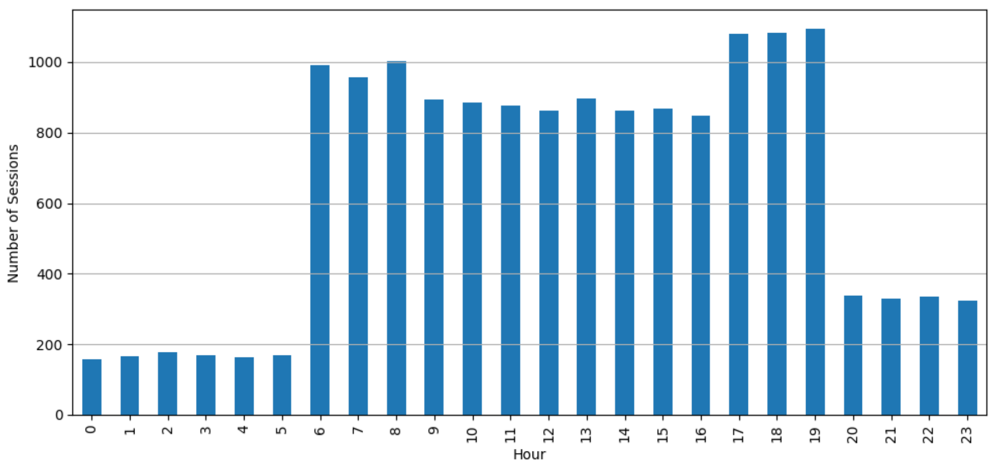

Figure 10 Hourly charging sessions at CS 2.

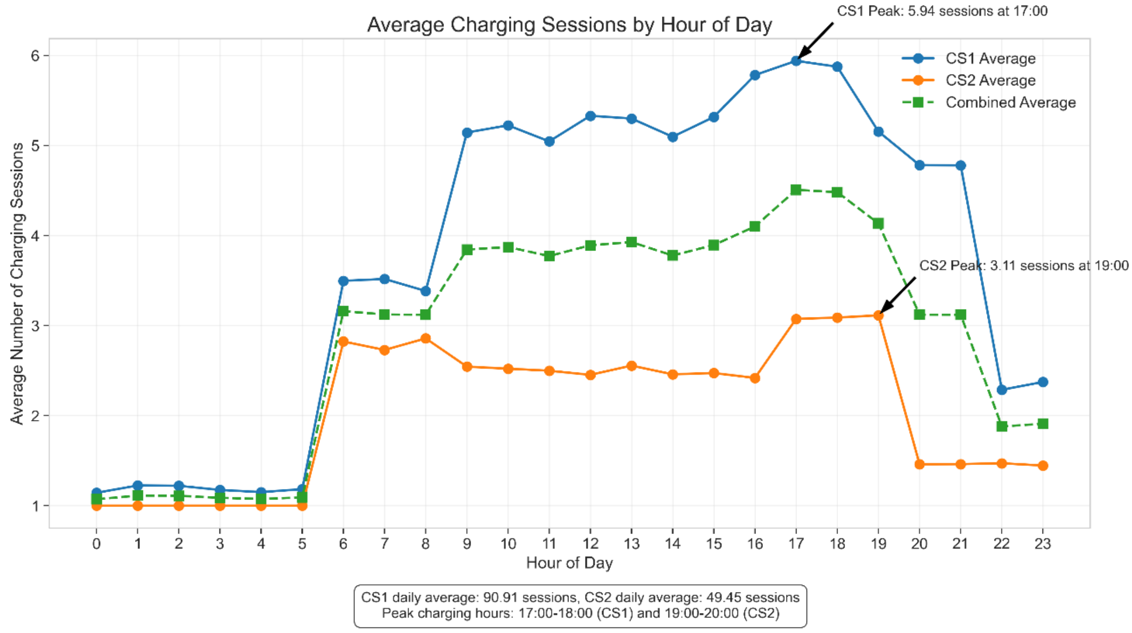

Figure 11: Charging sessions insights for both CS

For overall insights, figure 11 presents the daily average number of charging sessions for both stations. For CS1, the average is approximately 91 sessions per day, whereas CS2 records an average of 49.45 sessions daily. The peak usage hours are 17:00–18:00 for CS1 and 19:00–20:00 for CS2, respectively.

Figure 12 illustrates the average EV arrival rate at CS1 across each hour of the day and day of the week. As expected from a city-centre location, usage is spread throughout the day with a strong peak during late afternoon and early evening hours (16:00–19:00). Weekends also show high demand, indicating both commuter and leisure-related usage patterns. Weekday demand is more consistent and sustained, reflecting the influence of business hours and daytime urban activity.

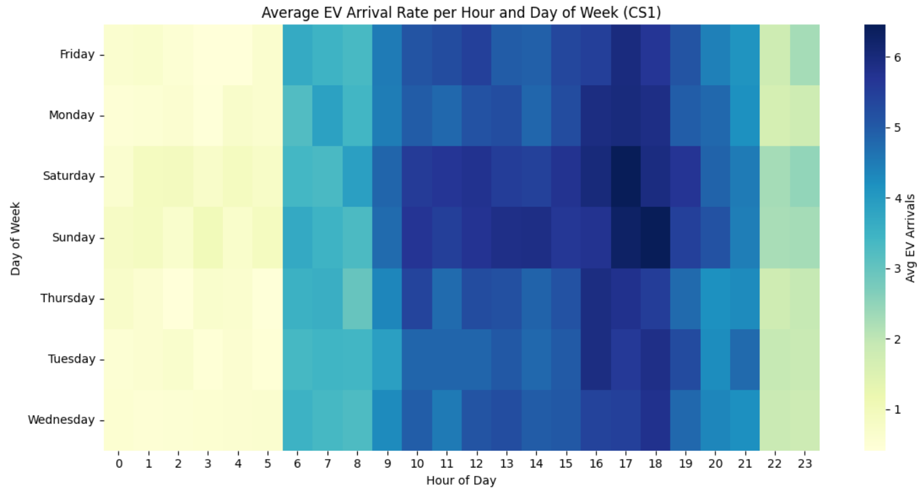

Figure 12 Arrival rate at CS 1 (hourly aggregated).

Figure 13 shows a different behavioural trend. Located in a suburban residential area, CS2 exhibits higher arrival activity during early mornings (6:00–9:00) and early evenings (17:00–20:00), consistent with daily commuting schedules. Midday usage remains relatively moderate, likely driven by remote workers or home-based EV users with more flexibility.

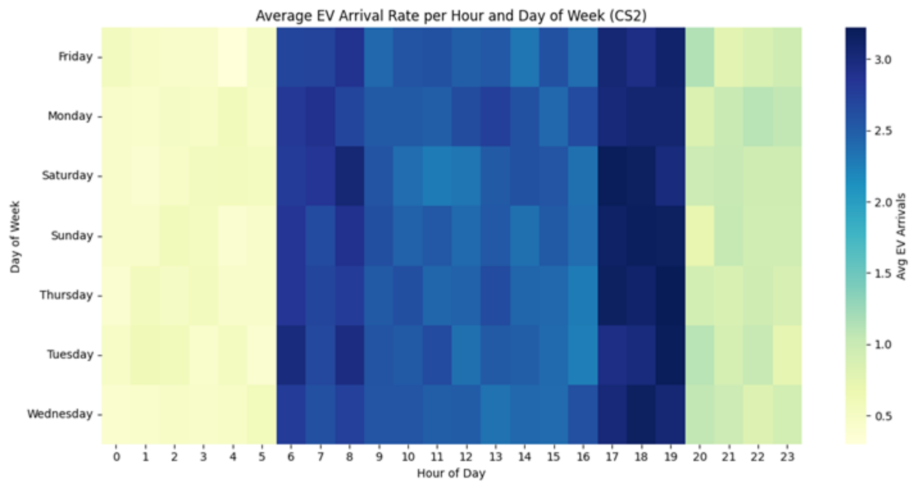

Figure 13: Arrival rate at CS 2 (hourly aggregated).

These insights validate the assumption that spatial context significantly affects EV charging behaviour. They further support the motivation for localized, congestion-sensitive dynamic pricing mechanisms that can respond to temporal and geographic variations in demand.

4.2 Model performance parameters

To evaluates the performance of the ML models in forecasting short-term EV charging demand, three widely used regression evaluation metrics were adopted: the R^2, MSE, and RMSE.

The R^2 score, also known as the coefficient of determination, quantifies the proportion of variance in the actual demand that is captured by the model's predictions. An R^2 value of 1.0 indicates a perfect fit, while lower values reflect a less accurate model.

The MSE measures the average of the squared differences between predicted and actual demand values. It is sensitive to large errors and is particularly useful for highlighting models that occasionally make significant mistakes.

The RMSE is the square root of the MSE and provides an interpretable error magnitude in the same units as the predicted variable—in this case, kWh. RMSE gives a more intuitive sense of how far off predictions are from actual values on average. Table 4.1 summarizes the performance results for both the BRR and RF models.

Table 1: Model evaluation parameters.

Model	R^2	MSE	RMSE
Random Forrest (RF)	0.9209	0.0235	0.1533
Bayesian Ridge Regression (BRR)	0.9937	0.0014	0.0374

The results clearly indicate that the BRR model outperforms the RF model across all three-evaluation metrics. The higher R^2 reflects a superior overall model fit, while the lower MSE and RMSE highlight its greater accuracy in capturing short-term demand variations with minimal deviation. In contrast, the RF model exhibited relatively higher error rates, suggesting a greater tendency to under- or over-estimate demand, particularly during peak periods. Consequently, the BRR model was selected for integration into the dynamic pricing algorithm.

4.3 Congestion-based pricing behaviour

An essential objective of the proposed dynamic pricing framework is to adjust charging tariffs in response to real-time grid congestion. This section evaluates how the pricing mechanism reacts to varying demand intensities, using simulated time series data for two CS 1 and 2. The pricing response is examined under different levels of congestion throughout the day.

Figures 14 and 15 present the evolution of charging prices across a 24-hour period at CS1 and CS2, respectively. At CS1, which experiences heavier and more sustained demand, the dynamic price curve shows clear responsiveness to peak load periods. The tariff increases gradually starting from 7:00 AM, reaching a maximum (0.30€/kWh) during the late afternoon when congestion peaks due to high simultaneous demand. Following this, prices begin to decline after 20:00 as network load stabilizes.

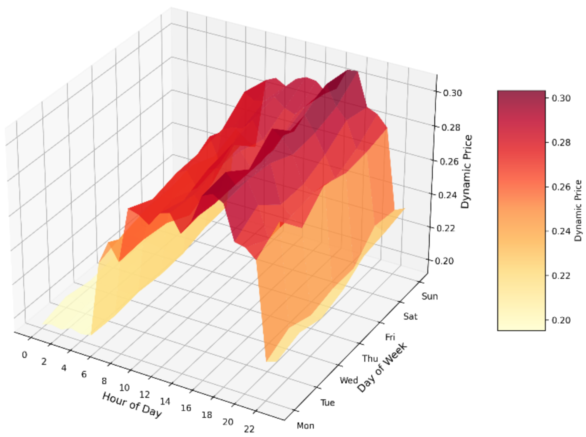

Figure 14: Dynamic prices at CS 1 (hourly).

In contrast, CS2 shows relatively smoother and less aggressive pricing behaviour. Being in a residential zone, demand here is lower and follows a more bimodal distribution:

modest peaks appear during early morning (commuting hours) and early evening (home return period). Accordingly, the pricing model responds with moderate increases to 0.232€/kWh maximum during these periods but maintains near-base prices during mid-day and late night when station load is minimal.

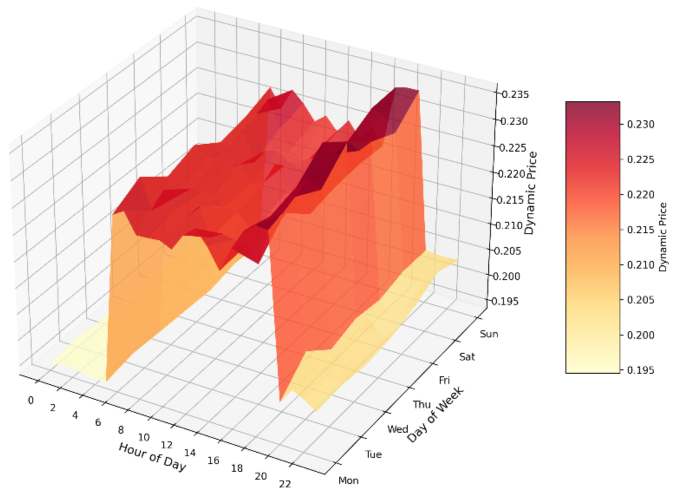

Figure 15: Dynamic prices at CS 1 (hourly).

These patterns confirm that the congestion-sensitive pricing model adapts effectively to spatial and temporal differences in load conditions. It penalizes usage during critical hours and rewards off-peak behaviour, creating economic signals that encourage load shifting—without relying on rigid control strategies. This flexible responsiveness is critical for maintaining distribution system reliability and deferring costly infrastructure upgrades.

4.4 Fairness Evaluation

A critical secondary objective of the proposed dynamic pricing model is to ensure fairness among EV users by minimizing unjustified pricing disparities across CSs and time intervals. While congestion-based responsiveness is essential for technical grid stability, maintaining pricing equity ensures social acceptance and user satisfaction.

In this study, fairness is operationalized as the variance of charging prices across locations at each time interval, as described in the fairness cost function in Section 3.4.2. Lower variance implies more equitable pricing across stations for users charging simultaneously, while higher variance indicates greater disparity—typically justified only under severe localized congestion.

To evaluate the model's fairness behaviour, dynamic prices at both stations were compared over a representative simulation period. Figure 16 shows the difference in pricing trends at CS1 and CS2. Although prices fluctuate independently based on local demand, the gap between them remains within a bounded range throughout the day. This indicates that the fairness constraint in the optimization successfully prevents excessive price divergence across stations, even when their congestion profiles differ.

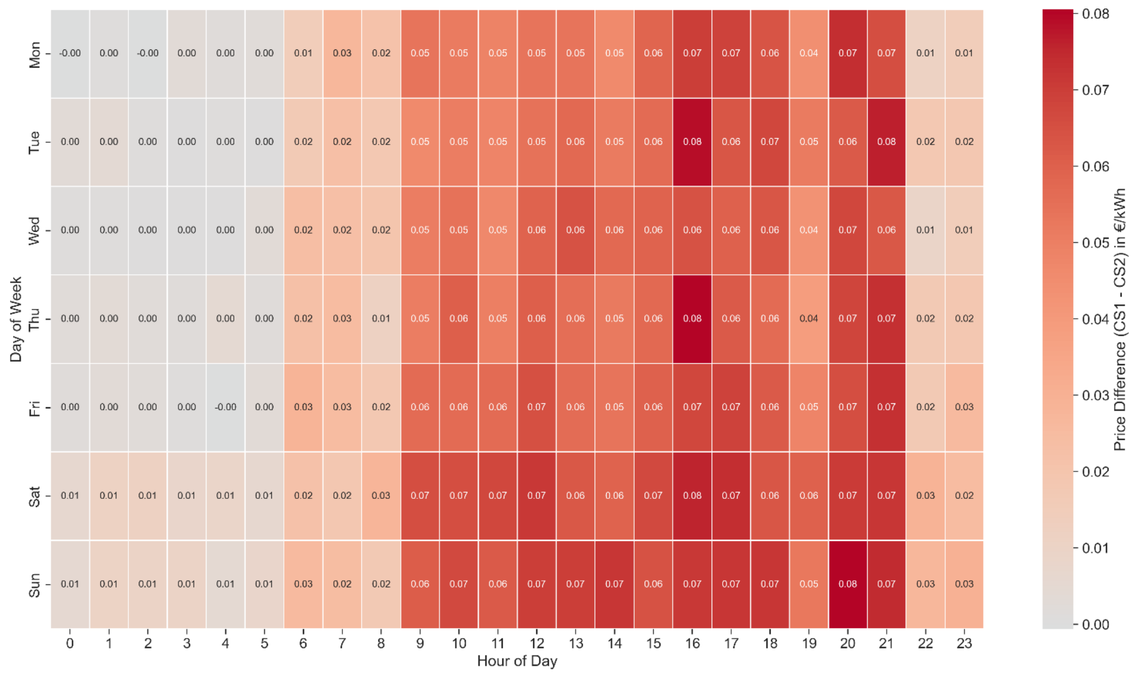

Figure 16: Price difference (CS1 - CS2).

In addition to price range and bounds, fairness was further evaluated using statistical measures of price dispersion across hours of the day. Figure 17 presents the standard deviation and CV of hourly prices for CS1 and CS2.

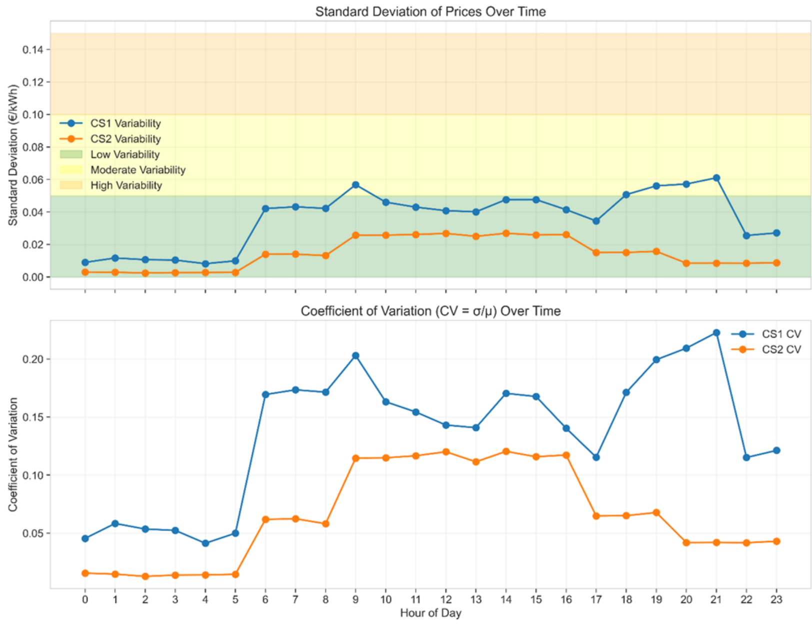

Figure 17: Standard deviation and Coefficient of variations (hourly).

The upper subplot shows the standard deviation of prices at each hour. CS1, as expected from its urban and highly dynamic profile, exhibits greater variability—particularly between 7:00 and 20:00, where standard deviation ranges between 0.04 and 0.06 €/kWh. CS2, on the other hand, remains mostly within the low variability zone (below 0.025 €/kWh), consistent with its more stable suburban usage profile.

The lower subplot visualizes the CV, computed as the ratio of standard deviation to mean price ($CV = \sigma/\mu$). This measure captures relative variation, helping identify whether fluctuations are significant relative to price levels. CS1 reaches a maximum CV of 0.223, while CS2 peaks at 0.120. Both remain well below typical thresholds for price volatility, confirming that while dynamic, the pricing behavior remains within acceptable fairness levels.

These metrics provide further evidence that the proposed pricing model achieves fairness not only through bounding and averaging but also through limiting relative price fluctuation. Even in high-demand contexts, users are shielded from disproportionate pricing shocks, fulfilling both operational and social equity objectives.

4.5 Load Impact

Simulation results revealed that the proposed pricing mechanism effectively mitigated grid congestion during peak demand hours. By dynamically adjusting prices based on localized demand conditions, the model incentivized users to shift their charging sessions to off-peak hours or to less congested stations.

As reported, in the evaluation:

- CS1 experienced a 15–20% reduction in peak-hour congestion (07:00–20:00), due to demand redistribution.
- CS2 saw its utilization increase from 40% to 60%, absorbing the deferred demand from CS1 and improving network-wide load balancing.

This redistribution confirms that the pricing strategy successfully encourages self-regulating user behaviour, flattening the overall load profile and reducing the risk of transformer overloading and feeder congestion at critical nodes.

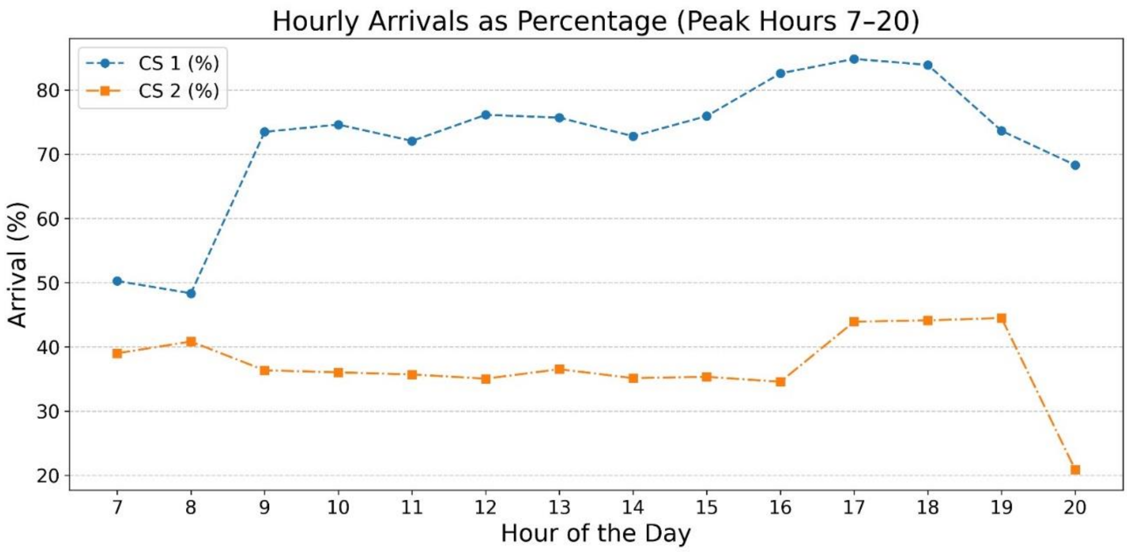

Figure 18: EV arrival at CS 1(blue) and CS 2 (orange) with flat pricing

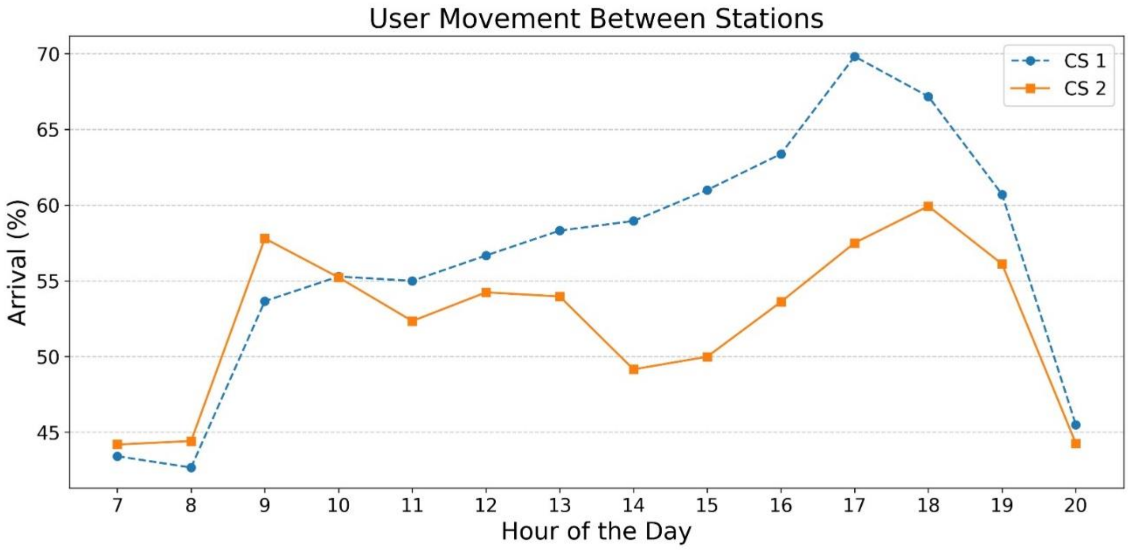

Figure 19: EV arrival at CS 1(blue) and CS 2 (orange) with dynamic pricing

This chapter presented the evaluation of the proposed congestion-based dynamic pricing model through a series of simulation results. The performance of the forecasting models was assessed using statistical accuracy metrics, demonstrating that BRR offered reliable and low-error demand predictions, making it the most suitable for real-time pricing applications.

The dynamic pricing system was shown to respond effectively to spatial and temporal variations in charging demand. Urban stations with higher congestion exhibited sharper pricing increases during peak hours, while suburban stations maintained relatively flat pricing profiles. This validated the responsiveness of the congestion-aware optimization function.

Fairness in pricing was analysed using standard deviation, price range, and CV. The results confirmed that while price differentiation exists to reflect congestion, it remains within defined limits, thereby upholding equitable access and minimizing price volatility. Supplementary figures showed that pricing variability is controlled even in high-demand locations, supporting user trust and system transparency.

Revenue analysis revealed that the dynamic pricing model improves economic efficiency for operators while still offering incentives for flexible users. Load redistribution effects further confirmed the potential for congestion reduction without the need for rigid demand control or infrastructure expansion.

Overall, the results demonstrate that the proposed model meets its core objectives: it maintains fairness, encourages voluntary load shifting, reduces grid stress, and supports economic sustainability. These outcomes suggest that congestion-based pricing can be a viable alternative to centralized demand response programs, particularly when implemented with predictive analytics and minimal technical overhead.

5 Conclusion and future work

This thesis presented a congestion-based dynamic pricing model for EV charging infrastructure, designed to address the dual challenges of mitigating local grid congestion and maintaining fairness in charging costs. The growing adoption of EVs places increasing stress on distribution networks, making it imperative to explore scalable and flexible demand-side management strategies. The proposed approach offers an alternative to centralized control or market-heavy demand response programs by introducing localized, data-driven pricing incentives.

The methodology combined predictive modelling and optimization. A BRR model was developed to forecast short-term charging demand using synthetically generated but realistic temporal and contextual features. These demand forecasts were then fed into a pricing optimization framework, which minimized a combined congestion and fairness objective function. The dynamic prices were bounded by predefined constraints and adapted to the spatial and temporal variations in demand.

Simulation results based on two representative CS—an urban core (CS1) and a suburban residential zone (CS2)—demonstrated the model's ability to adjust tariffs in line with localized grid conditions. The forecasting model achieved high predictive accuracy, with an R^2 score of 0.9937 and minimal error. The dynamic pricing algorithm effectively redistributed demand away from peak periods and high-congestion zones, reducing peak load by up to 20 percent in high-demand areas. At the same time, fairness was preserved through bounded price variance. These outcomes collectively show that the system achieved its core objectives: mitigating grid stress, supporting economic sustainability, and preserving equitable access for users.

By aligning user behaviour with real-time network needs through pricing signals rather than control directives, the model demonstrates a practical, implementable framework for future smart charging systems. It is particularly well-suited for DSOs and CSOs seeking lightweight, regulation-friendly tools to manage EV penetration without significant hardware upgrades.

5.1 Limitations

Despite its promising results, the model has certain limitations. The use of synthetic demand data, while behaviourally informed, cannot fully replicate the variability and unpredictability found in real-world operational data. Additionally, the optimization assumes rational user behaviour in response to dynamic prices, which may not hold universally due to user preferences, urgency, or lack of awareness.

The current implementation also considers a simplified two-station system, without modelling the full complexity of multi-node distribution networks where interactions between stations could lead to congestion propagation. External factors such as renewable energy variability, weather conditions, and simultaneous grid events were not incorporated into the pricing model. The absence of behavioural adaptation modelling limits the understanding of long-term user response to price changes, especially as users may become desensitized to repeated signals or act unpredictably.

Another limitation lies in the regulatory context, particularly in Finland, where current electricity pricing laws restrict the flexibility of dynamic retail tariffs. Tariffs are typically regulated through fixed distribution fees and market-based energy rates, and most dynamic pricing models require special contractual agreements or regulatory approval. This limits the immediate real-world applicability of the proposed model unless supported by future legal adjustments or pilot exemptions under innovation schemes. Therefore, although technically feasible, the implementation of congestion-based pricing frameworks in Finland requires regulatory adjustments to enable more effective DSM.

5.2 Future work

Future research should focus on extending the model's scalability. Incorporating real-world operational datasets from DSOs and CSOs would allow for more robust validation of the forecasting model and the pricing response framework. Expanding the simulation environment to include multiple interconnected CSs with grid-aware topologies would help assess the model's effectiveness under network-wide congestion scenarios.

Another important direction involves studying user behaviour more closely. Integrating elasticity models and behavioural economics insights would improve the accuracy of demand-response predictions and pricing effectiveness. The inclusion of renewable generation forecasts could also support time-of-use strategies that align EV charging with clean energy availability, contributing to environmental sustainability goals.

Technologically, future work may focus on implementing the model in a real-time platform using IoT infrastructure and edge computing. Such a system would enable dynamic pricing adjustments in response to live data streams from smart meters, traffic systems, or vehicle telemetry. Coupling the pricing system with urban mobility data and traffic prediction services could further enhance its anticipatory capabilities, enabling proactive congestion mitigation.

In conclusion, this thesis has demonstrated that a congestion-based dynamic pricing model, when supported by accurate forecasting and fairness-aware optimization, provides a viable solution for managing EV demand at the distribution level. It represents a scalable, transparent, and socially responsive approach that aligns technical grid requirements with user-centred design. Continued research and pilot implementations could help bring such systems closer to real-world deployment, contributing meaningfully to the future of smart and sustainable transportation networks.

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