THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Energy Infrastructure for Road Transport Electrification

Modeling Hydrogen Supply, Electric Vehicle Charging, and Grid Constraints

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CHALMERS UNIVERSITY OF TECHNOLOGY

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Abstract

This thesis analyzes the interactions that occur between electricity and road transportation systems. It explores the infrastructure required for the indirect electrification of heavy transport using hydrogen as an intermediary energy carrier and the direct electrification of passenger vehicles. Multiple models were developed and applied to study the infrastructural requirements for the supply of hydrogen to refueling stations and the electricity grid capacity required for home charging of electric vehicles (EVs).

A comparison of the different hydrogen supply systems, all of which use electrolysis to produce hydrogen, reveals substantial differences in the costs for supplying hydrogen to refueling stations. For the Swedish case studied, a system in which electricity is supplied from the electricity grid with onsite production at the refueling station is found to be the least-costly option, as compared with centralized hydrogen production with transportation to the station. The most-expensive option is to produce hydrogen using local solar PV and/or wind power instead of connecting to the electricity grid.

A model of the Swedish low-voltage (LV) electricity grid was developed to study the impacts of EV home charging on the LV grid as the share of EVs increases, as well as the ways in which these impacts are influenced by different network tariff designs. The results show that the number of power system violations in the LV grid (defined as exceeding the operational limits for thermal capacity and voltage magnitude) increases as the share of EVs in the vehicle fleet grows. However, the number of occurrences with violations varies significantly across geographic regions in Sweden and across EV charging cases. Even with a high level of EV penetration, some areas have zero violations, while in other areas, violations are recorded already at small EV fleet shares.

Implementing different network tariff designs significantly impacts when and to what extent it is cost-optimal to charge EVs. Thus, there are impacts on the loading of the LV grid and the flexibility that EV charging can provide to the electricity system by adapting to variable electricity spot prices. Cost-minimizing EV charging with no network tariff or a tariff for the monthly peak power demand of individual households during daytime hours provides the highest level of flexibility for EV charging from the electricity systems' perspective, but also the highest loading on the LV grid. Having a network tariff based on the monthly peak power of individual households, including all hours of the day, results in the lowest loading on the LV grid, but also entails the lowest level of flexibility. Combining the results, a trade-off emerges between adapting EV charging to low electricity spot prices and reducing the loading on the LV grid. Implementing a network tariff for the combined peak power of all modeled households provides an alternative that lowers the loading on the grid, yet retains greater flexibility than when the cost is implemented at the household level.

Given that EV charging behavior strongly impacts the loading on the LV grid, different charging strategies in a fully electrified vehicle fleet lead to significant variation in the required transformer capacity and, thereby, the extent of LV grid reinforcement.

Keywords: *Transport electrification, Electric vehicles, Energy systems analysis, Hydrogen supply, Hydrogen refueling infrastructure, Low-voltage grid, Grid congestion, Network tariffs*

List of publications

The thesis is based on the following appended papers, which are referred to in the text by their assigned Roman numerals:

- **I.** T. Lundblad, M. Taljegard, & F. Johnsson. "Centralized and decentralized electrolysis-based hydrogen supply systems for road transportation – A modeling study of current and future costs". *International Journal of Hydrogen Energy*, Volume 48, Issue 12, pp. 4830–4844, 2023, doi: 10.1016/j.ijhydene.2022.10.242.

- **II.** T. Lundblad, M. Taljegard, N. Mattsson, E. Hartvigsson, & F. Johnsson. "An open data-based model for generating a synthetic low-voltage grid to estimate hosting capacity". *Sustainable Energy, Grids and Networks,* Volume 39, 101483, 2024, doi: 10.1016/j.segan.2024.101483

- **III.** T. Lundblad, E. Perotti, M. Taljegard, & F. Johnsson. "The role of network tariffs in steering electric vehicle charging and household peak power demand", doi: 10.2139/ssrn.6360789. *Submitted for publication.*

- **IV.** T. Lundblad, M. Taljegard, N. Mattsson, E. Perotti & F. Johnsson. "Assessing the impact of fleet electrification on low-voltage grids: the role of network tariffs in mitigating power system violations", doi: 10.2139/ssrn.6366416. *Submitted for publication.*

Author contributions

Therese Lundblad is the principal author of **Papers I–IV** and performed the modeling, analysis, and writing for all four papers. Professor Filip Johnsson and Assistant Professor Maria Taljegård contributed to the discussions and editing of **Papers I–IV**. Dr. Niclas Mattsson contributed to the method development and discussion in **Papers II** and **IV**. Dr. Elias Hartvigsson contributed to the method development and discussion in **Paper II**. Dr. Elisabetta Perotti contributed to the method development, discussion, and editing of **Papers III** and **IV**.

Other publications, not included in the thesis:

- T. Lundblad, M. Taljegard, & F. Johnsson. “Indirect electrification of transport – a study of hydrogen supply systems for heavy road transportation”, *35th International Electric Vehicle Symposium and Exhibition (EVS35)*, Oslo, Norway, June 11-15, 2022

- T. Lundblad, M. Taljegard, F. Johnsson, & N. Mattsson. ”Impacts from electric vehicle charging strategies on low voltage grids”, *42nd International Energy Workshop*, Bonn, Germany, June 26-28, 2024.

- P. Anchustegui, T. Lundblad, M. Taljegard, & A. Nordelöf. ”Climate and economic impacts from reinforcement of the distribution grid due to different EV charging strategies”, *38th International Electric Vehicle Symposium and Exhibition (EVS38)*, Göteborg, Sweden, June 15-18, 2025.

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Therese Lundblad

Göteborg, 9th of March 2026

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1 Introduction

Transportation accounts for approximately one-third of the energy demand in the European Union (EU), and its energy supply is currently dominated by fossil fuels, the use of which entails substantial greenhouse gas (GHG) emissions [1]. Thus, electrification of the transportation sector has been identified as a crucial step towards achieving climate targets, assuming that it is combined with a low-carbon electricity supply [2, 3]. Two main pathways exist for the electrification of the transport sector: indirect electrification; and direct electrification. Indirect electrification occurs when electricity is used to produce a so-called *electrofuel*, which is used in the vehicle, either through its conversion back to electricity in a fuel cell and the employment of an electric motor or by using the electrofuel in an internal combustion engine (ICE). Direct electrification of transportation means that electricity is charged directly to the vehicle and stored in a battery. This stored energy is subsequently used to propel the vehicle using an electric motor in a battery electric vehicle (BEV). Direct electrification is typically associated with higher efficiency, while indirect electrification has the advantages of faster refueling time, greater range, and the possibility for long-term storage of fuels [4, 5]. However, a drawback of direct electrification is the higher demand for battery capacity, for which material extraction and processing raise challenges regarding environmental burdens and limited resource availability. Nonetheless, direct electrification is the preferred method, when feasible, due to its substantially higher efficiency. However, for vehicle segments where this is not possible (for example, due to restrictions related to weight, range or charging time), indirect electrification via hydrogen (the simplest electrofuel) is a complementing technology, enabling transport without tailpipe GHG emissions in situations where direct electrification is not an option [5, 6].

For heavy road transport, electrification is proceeding slowly, with electric buses making up 23% and electric trucks making up only 4.2% of the vehicles sold in Europe in Year 2025 [7]. For hydrogen, the share of hydrogen-fueled buses sold in Europe in Year 2025 was 0.5%, and the share of trucks fueled by hydrogen was 0.06% [7]. In addition to electrification, efficient transport logistics for the flow of goods are needed to decarbonize this sector, while fulfilling other sustainability goals [8]. For passenger cars, the share of electric vehicles (EVs) is increasing in several countries [9]. In Year 2024, EVs accounted for 21% of new registrations of passenger vehicles in Europe, when considering both BEVs and plug-in hybrid electric vehicles (PHEVs) [9].

Regardless of whether electrification is direct or indirect, there is a need for a supporting infrastructure, in order to enable the transition. For indirect electrification, a refueling infrastructure, in the form of hydrogen refueling stations, is required. The hydrogen needs to be produced at the refueling station or produced at a central location and transported to the refueling station. Direct electrification relies on the availability of an electricity grid and charging infrastructure. As the number of EVs increases, so also do the loads arising from EV charging in the electricity grid. Almost 90% of the distribution system operators (DSOs) in Sweden are expecting an increased demand for grid capacity, in part due to electrification of the transportation sector [10].

As indicated above, an electrified road transportation system typically has some type of onboard energy storage in vehicles, in the form of hydrogen tanks or batteries. This enables flexibility in the electricity demand, which has the potential to have many benefits for the electricity system, typically related to more efficient use of resources [11]. One benefit of a flexible electricity demand is the ability to counteract the intermittency of electricity production associated with renewable electricity generation [11]. Another benefit is the possibility to reduce the need for grid reinforcements by lowering the peak demand exerted on distribution grids [11, 12]. However, in order to accomplish this, there is a need to communicate to customers when electricity should be used and when it should not. Typically, communication is through a price signal, where the price signal is designed in such a way that it promotes the desired behavior. Furthermore, when multiple price signals are in place, it is important to understand the nature of their combined incentives.

The work in this thesis contributes to the field by studying the electrification of the transportation sector from a techno-economic perspective. Studies of both indirect and direct electrification are included, and the emphasis is on the infrastructure needed to supply electricity to hydrogen refueling stations and for the home charging of passenger EVs. By highlighting the impacts on infrastructure, this study could identify potential barriers before they occur, thereby enabling lower costs and more efficient resource use. In addition, this thesis explores the possibility of using network tariffs, which are paid by consumers to the DSO for use of the local electricity grid, as a price signal to reduce the load on the distribution grid.

1.1 Aim and research topic

The overall aim of the thesis is to analyze the interactions between electricity and transportation systems as the electrification of transportation progresses. This thesis focuses on exploring the infrastructure required for the indirect electrification of heavy transportation and the direct electrification of passenger vehicles. The work is motivated by the increase in the number of electrified vehicles and a lack of knowledge regarding how this increase affects the electricity system.

This thesis is based on the four appended papers (**Papers I–IV**) and this introductory essay. **Paper I** investigates the infrastructure for indirect electrification. **Papers II**, **III**, and **IV** investigate direct electrification and the required infrastructure, with the focus on the capacity of a low-voltage (LV) grid to host large-scale home charging of EVs and how this is impacted by electricity price signals, such as network tariffs. The appended papers are designed to:

- Compare centralized and decentralized hydrogen supply systems, as well as standalone and grid-connected systems, in terms of their cost-efficiencies (**Paper I**);
- Present and validate a method for modeling the LV grid using open data, so as to enable modeling of the ways in which EV charging impacts the residential Swedish LV grid (**Paper II**);
- Study how cost-optimal EV charging depends on the design of network tariffs (**Paper III**); and
- Assess how different EV charging cases and the presence of a network tariff influence the peak power and power system violations (defined as exceeding the operational limits for thermal capacity and voltage magnitude) that are likely to appear in LV grids (**Paper IV**)

1.2 Contents of the papers

Paper I compares different electrolysis-based systems for supplying hydrogen to refueling stations. Previous studies have studied different supply systems, but not using the same methodology. Therefore, centralized and decentralized electricity grid-connected systems are compared alongside a standalone system in a cost-minimizing linear optimization model.

Paper II develops and applies a model for residential LV grids that generates a synthetic LV grid for Sweden from open data. This model can be used to run grid simulations covering areas for which grid capacities are not publicly available. For the few similar models that exist, validation data are usually not publicly available, which means that the accuracy and transferability of the model results are unsatisfactory. Therefore, the model used in this work is calibrated and validated against real-world data, and the accuracy of the generated grid is discussed in this paper.

Paper III develops and applies a cost-minimizing linear optimization model for EV charging in which both electricity spot prices and network tariffs can be considered at the same time. The modeling investigates how different network tariff designs based on peak power (also known as ‘power tariffs’, ‘capacity charges’, or ‘demand charges’) influence the cost-optimal charging of electric vehicles (EVs) and the peak power demand of households.

Paper IV combines the models developed in **Papers II** and **III** to assess how different EV charging cases and the presence of a network tariff influence the issues that are likely to emerge in LV grids as the EV fleet share expands. The studied network tariff enables the reduction of the burden on the LV grid using a simple price signal, rather than an all-knowing actor controlling the charging of each individual vehicle. The study quantifies the increase in load when the EVs are added and which factors influence the magnitude of the increase. It also quantifies the power system violations (defined as exceeding the operational limits for thermal capacity and voltage magnitude) that are likely to appear in LV grids.

The work presented in this thesis was carried out in the period of 2021–2026.

1.3 Structure of the thesis

This introductory essay outlines some of the key findings of the four papers within the context of the overall aims of the thesis. Chapter 2 provides background information on the infrastructure needed for direct and indirect electrification of transportation, as well as a brief overview of the different components of the retail price of electricity. Chapter 3 summarizes previous work on supplying hydrogen to refueling stations, as well as the modeling of distribution grid impacts from EV charging and power tariffs. Chapter 4 explains the models used in this work and the context in which they evolved, as well as giving an overview of the modeled cases for both hydrogen supply and EV charging. Chapter 5 presents and discusses the key results from this work. Chapter 6 summarizes the main conclusions, while Chapter 7 identifies topics for future studies.

2 Background

This section provides background information on the technologies and systems studied. It includes descriptions of: hydrogen production and distribution (Section 2.1); the voltage levels in the electricity grid (Section 2.2); and the different components of the retail price of electricity (Section 2.3).

2.1 Hydrogen production and distribution

Indirect electrification using hydrogen as an energy carrier has been identified as a possible solution in the transition to a decarbonized heavy freight transportation system [6, 13–15]. However, as the power of fast chargers for electric trucks has increased, and increases, the segment in which hydrogen was earlier expected to fill a purpose shrinks. Hydrogen and other electrofuels remain as options for other transport segments. If hydrogen is to be used as a transport fuel, there is a need for it to be produced and distributed in an efficient manner. Although hydrogen is scarcely used for transportation at present, it is employed extensively in industry. Hydrogen can be produced from a variety of sources, with steam methane reforming (SMR) of natural gas currently accounting for the largest share of production, followed by oil reforming and coal gasification. These processes rely on feedstocks that are associated with significant GHG emissions. When it comes to hydrogen for supplying the energy transition, production through water electrolysis using electricity from renewable sources is an option [16–18].

To enable a shift to hydrogen-fueled heavy transport, it will be crucial to introduce a network of hydrogen refueling stations for which the hydrogen supply must be both reliable and cost-efficient. In the European Union (EU), the alternative fuels infrastructure regulation (AFIR) states that hydrogen refueling stations should be deployed every 200 km in the trans-European transport network (TEN-T) [19]. A global overview of the current trend in relation to the installation of hydrogen refueling stations has been carried out by Samsun et al. [5]. They have shown that the number of hydrogen refueling stations is growing, although they conclude that an accelerated rate of new installations is needed to meet the target numbers (for example, the previously mentioned EU target of refueling stations placed every 200 km) in the coming years [5].

2.2 The voltage levels in the electricity grid

The basic layout of an electricity system involves electricity generation that is connected to end-consumers via an electricity grid that consists of power lines, cables, and transformers (that connect the different voltage levels). This electricity grid can be delineated based on the different voltage levels, as different voltage levels in the grid serve different purposes. Figure 1 shows an overview of the common voltage levels in the different parts of the electricity grid. The *transmission grid* transports a large amount of electric energy over long distances, from the large centralized electricity generators to the *distribution grid* [20]. This transmission is carried out at the highest voltage levels in the grid, to reduce losses [20]. The distribution grid consists of two parts, the regional grid and the local grid. The regional grids connect the transmission grid to the local grids, so their function is similar to that of a transmission grid, although due to techno-economic factors, transmission occurs at a lower voltage level [21]. *Local grids*, have the primary purpose of distributing electricity from the regional grid to end-users [21]. In Year 2024, 149 DSOs owned and operated local grids in Sweden [12]. Depending on the power demand at a specific location, customers, and thus electrified transportation, can connect to different parts of the distribution grid. Simply put, the higher the power demand, the higher the voltage level at which the connection is made. To determine if the distribution grid has the capacity to handle the emerging loads from electrified transport, further analysis is needed. The study of direct electrification of passenger vehicles included in this work models the part of the local grid referred to as the *LV grid*, as shown in Figure 1, as this is the level at which households connect to the electricity grid. It also includes the transformer down to this voltage level.

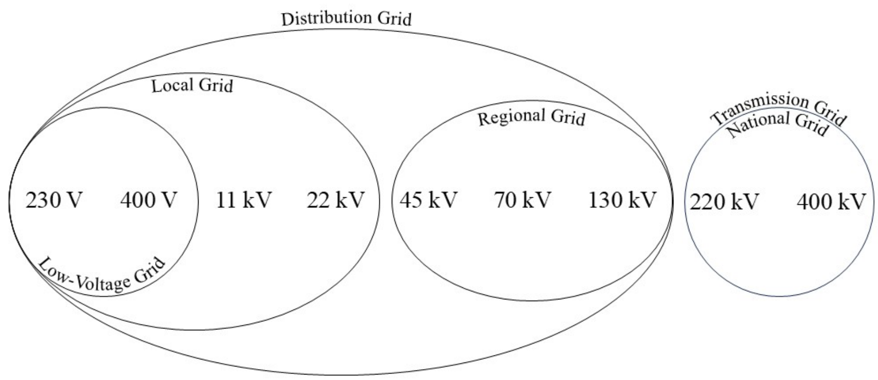

Figure 1. *Schematic overview of the voltage levels in the different parts of the electricity grid. The modeling performed in this thesis focuses on the part labeled "Low-Voltage Grid".*

2.3 The components of the retail price of electricity

The retail price that consumers pay for electricity has three main components: the wholesale electricity price; network tariffs; and taxes and levies. The wholesale electricity price, which is also referred to as the energy cost or the purchase cost, is related to the electricity spot price. The electricity spot price describes the balance between the system's aggregated demand and generation, and varies on a 15-minute basis in northern Europe [as of 30th of September 2025, before which date it was cleared on an hourly basis] [22]. In Sweden, many consumers pay wholesale electricity prices that are affected by electricity spot prices, either within a pricing system that is indirectly affected by the varying prices or by directly paying the spot price at the time that the electricity is consumed [23]. In January 2026, 60% of Swedish electricity provision subscriptions had an electricity price that was based on the monthly average spot price, and approximately 14.5% of subscribers paid the spot price directly [24].

Network tariffs, which are designed to cover the costs associated with network losses and grid investments, are typically collected by transmission system operators (TSOs) and DSOs [25]. According to a report published by the EU Energy Regulators Association (ACER) [25], the most-common network tariff designs across the EU are fixed, volumetric, and power tariffs, or combinations thereof. Fixed tariffs do not vary according to user behavior, although they may depend on factors such as the connected power capacity and other technical characteristics. Volumetric charges are calculated per unit of energy withdrawn from or injected into the grid, and are typically used to recover costs associated with network losses and system services. Power-based tariffs, on the other hand, are based on the contracted or connected power capacity, the annual or multi-year peak demand or generation, and are commonly employed to recover costs related to infrastructure maintenance and upgrades [25]. Power tariffs are sometimes referred to as 'capacity charges' or 'demand charges'. Several European countries, including Sweden, are gradually shifting towards more power-based tariff designs in line with ACER's recommendations [25].

3 Previous work

This section summarizes the results from previous research related to hydrogen refueling stations (Section 3.1), methods for modeling EV charging impacts on distribution grids (Section 3.2), how different EV charging strategies impact the distribution grid (Section 3.3), and studies of the demand response to power tariffs (Section 3.4).

3.1 Comparisons of hydrogen supply systems

The supplying of hydrogen to refueling stations has been evaluated in several studies [26–34]. Hydrogen production can be located at the site of the refueling station, i.e., in a decentralized system, or it can be centrally located in combination with a distribution system that transports hydrogen from the production site to the refueling station [29]. For hydrogen that is produced through electrolysis, the production cost is heavily dependent upon the cost of electricity, and the estimates of the levelized cost of hydrogen (LCOH) available in the literature are heavily based on historical electricity price data. A future electricity system with high shares of variable renewable electricity (VRE) production could generate more-severe fluctuations in electricity prices, thereby altering the conditions for hydrogen production. Tang et al. [27] have compared electrolysis-based hydrogen production at refueling stations in Sweden that are run in island mode (i.e., not connected to the electric grid), using dedicated wind and solar power units with a similar, albeit grid-connected, system; and they have concluded that grid connection tends to achieve a lower LCOH. However, since Tang et al. [27] assumed a constant hydrogen demand using historical spot market prices for the electricity supplied to the electrolyzer, these prices may not be representative of a future electricity system that contains a higher share of VRE.

An economic analysis of a standalone wind-powered system for supplying hydrogen to refueling stations in Sweden has been conducted by Siyal et al. [26]. They have concluded that such a setup could help reach the goal of a fossil-free transport sector in Sweden, although the setup investigated was not compared with other systems for hydrogen production. Göcek and Kale [31] used a techno-economic analysis to assess the feasibility of a hydrogen refueling station powered by either a wind-photovoltaics (PV)-battery or wind-battery system located on the island of Gökçeada in Turkey. They have pointed out that such systems could be feasible for the chosen site and that a hybrid wind-PV-battery system yields a lower LCOH than a wind-battery system [31]. Janssen et al. [28] studied off-grid hydrogen production facilities in different European countries. They found that electrolyzer systems that use both wind power and solar PV to power an electrolyzer have the lowest costs in nearly all of the countries studied. They conclude that with projected cost reductions, off-grid hydrogen production from renewable sources could yield a cost similar to that of conventional hydrogen production [28]. That study did not target the transport sector, and hydrogen compression and storage were not included. Furthermore, the study did not consider hydrogen production systems that are connected to an electric grid with renewable electricity. Nistor et al. [33] performed a techno-economic study of a hydrogen refueling station in the UK, focusing on the short-to-medium-term representation of the technology and costs, comparing a wind-powered system run in island mode with a similar grid-connected system. For the grid-powered system, a fixed electricity price was used. They found that the grid-connected and standalone wind-powered systems had a similar LCOH; however, the grid-connected system had a larger share of the cost as operational costs, while the island-mode system had a larger investment cost. The authors of that study expressed the need for further investigation of the tradeoffs that occur between installed wind power capacity and hydrogen storage size [33].

Ulleberg and Hancke [34] have studied hydrogen production in a Norwegian context using two small-scale production cases that employ water electrolysis. In the first case, local hydropower was used to power an electrolyzer onsite, while the second case looked at a hydrogen refueling station, comparing onsite hydrogen production with a centralized supply system. They observed lower costs for hydrogen production in the second case, largely attributable to increased utilization [34]. In that study, optimization was not performed, and no estimations were made of how severely their defined cases would be affected by changes in the electricity system composition and any consequent changes in electricity prices.

Although the abovementioned studies have provided valuable insights into the cost of hydrogen production for the transport sector, studies that evaluate multiple hydrogen supply systems are lacking. For those situations in which there is more than one supply system, the previous studies have been limited to modeling their costs using historical electricity price profiles. A future electricity system with high shares of VRE production would likely generate more-severe fluctuations in electricity prices, thereby altering the conditions for hydrogen production [35].

In summary, there is a need to investigate the conditions for hydrogen production in a future electricity system with larger shares of non-dispatchable electricity generation. Therefore, this work compares three different hydrogen supply systems using the same method, in both a current and a future cost setting in **Paper I**.

3.2 Modeling the distribution grid impacts of electric vehicles

In order to model the distribution grid impacts of electric vehicles, a representation of the distribution grid is needed. Currently, it is often difficult to have access to grid capacities relevant to a larger geographic area, since the operation of electricity grids, especially distribution grids, is typically split among multiple actors, and national security considerations limit access to the data. Some previous studies have performed case studies and subsequently extrapolated the results to a larger area [36]. Due to the lack of real grid capacities, some studies (e.g., Veldman et al. [37]) have used typical reference grids. An alternative method deployed in many previous studies is to develop a synthetic grid based on information regarding the number of customers in an area and the grid design principles [38–45]. As an example, Amme et al. [38] have combined local grid planning principles and GIS data, considering line congestion and voltage limitations, to generate a plausible, distributed representation of all the medium-voltage (MV) grids [here defined as voltage levels of 10 kV and 20 kV] in Germany. Using this methodology, a deviation of approximately 10% from real network data was achieved [38]. However, those authors did not consider the LV grid and its capacities.

Once there is a representation of grid capacities, loads can be added to the grid using multiple methods. Thereafter, it can be evaluated whether the operational limits of the grid are exceeded. Reviews of the methods and tools for estimating the numbers of EVs and amounts of solar PV that can be hosted by the capacities of current LV grids – hereinafter referred to as the *hosting capacity* – have been presented by Umoh et al. [46] and Carmelito and Filho [47]. An additional review of the calculations of hosting capacity has been presented by Abideen et al. [48]. All of these publications describe methodologies for the evaluation of hosting capacity, along with their strengths and weaknesses. The reviews have characterized previous studies based on the types of methodologies used for predicting how new loads influence electricity grids. Three types of methodologies for adding new loads have been identified: deterministic simulations; stochastic methodologies; and time-series methods [47]. In the reviews of Umoh et al. [46] and Mulenga et al. [49], the evaluation criteria for the determination of hosting capacity have been addressed. Both studies have concluded that most previous studies of hosting capacities have used the same three performance indices: voltage magnitude; line or cable loading; and transformer loading. In addition, some studies have included additional evaluation criteria, such as losses and voltage imbalance [50–53].

Zhu et al. [51] have assessed the EV hosting capacities of two Australian MV and LV grids using stochastic time-series analysis, building their analysis on a model that was first presented by Nacmansson et al. [40]. They used the known capacities of the MV grid network and approximated the LV grid capacities based on data, which included the number of customers per transformer and the local design principles used for grid development in the area, in order to derive a synthetic LV grid representation [40]. The loads were simulated using a stochastic time-series analysis run with a 1-minute resolution over a 24-hour day [51]. The household load profiles with 1-minute resolution were created by interpolating data with a 30-minute time resolution [51]. They found that the hosting capacity needed to be estimated for different types of networks, and concluded that different components can be limiting factors [51]. No estimation was performed on a larger regional level (e.g., encompassing several MV grids), and no data on how accurate the estimations of LV grid capacities are were presented in that study.

As the real-world capacities of the Swedish LV grid are not openly available, **Paper II** develops the Reference Electricity Grid Analysis model (REGAL), which extends the grid model introduced by Hartvigsson et al. [39]. The REGAL model is validated against real-world data and published in an open repository under a permissive open-source license. The model is further described in Section 4.3 and in **Paper II**.

Assessments of hosting capacity rely heavily on the definition of when the grid's operational limits are exceeded, as modeling is performed to find the amount of a technology that can be added before such conditions are met. Although the methodology presented in **Paper II** is described as being suitable for assessing hosting capacity, the modeling in **Paper IV** goes beyond the description of hosting capacity. As it is possible to overload components to some extent, the work presented in **Paper IV** performs grid simulations with 25% to 125 % of the current vehicle fleet being electrified. For some areas, the number of vehicles added goes beyond the hosting capacity of the grid. For other areas, the hosting capacity is greater. Exceeding the hosting capacity allows an understanding of how frequently and to what extent the operational limits may be exceeded at different EV fleet shares, thereby providing additional information compared to only performing simulations with fleet shares up to the point at which the first exceedances of the operational limits are seen.

3.3 Different electric vehicle charging strategies and the distribution grid

The charging of EVs can be unidirectional or bidirectional. Bidirectional charging means that electricity can also be transferred from the vehicle to the household or to the electricity grid [also known as V2X when referring to feeding electricity back into any type of system, or vehicle-to-grid (V2G) when feeding electricity back to the grid]. Furthermore, charging can be controlled or uncontrolled. Previous studies have shown that uncontrolled charging of EVs, typically corresponding to the EV owners starting to charge directly when arriving at the home location, can increase the load during hours of the day that already have high loads, thereby imposing an additional stress on the electricity grid [54, 55]. However, if a controlled charging strategy is applied, such as that responding to a price signal, there is potential to mitigate the impact on the grid, as well as to provide services to the electricity grid [37, 54–63]. However, if the strategy for control is solely based on a single price signal, the burden on the grid may increase due to the EVs acting on the same price signal and, therefore, all charging at the same time [37, 54, 64].

Veldman et al. [37], in an energy systems modeling study, investigated how different EV charging strategies affect distribution grids in the Netherlands. They considered three different charging strategies for EVs: cost-minimized charging; peak load-minimized charging; and uncontrolled charging. They allocated EVs to transformers in a set of typical MV distribution networks, including the transformers acting from the MV to LV level, in the Netherlands, to estimate the distribution grid impacts. They concluded that cost-minimized charging would lead to high load peaks in the distribution grid, which would require grid reinforcement. The peak-load minimized charging significantly reduced the need for grid reinforcement, as compared with cost-minimized charging. They concluded that the high load peaks in the cost-minimized scenario were due to all the EVs acting on the same price signal, thereby collectively shifting their charging to the same time and, thereby, increasing the peak demand [37]. However, the peak-load minimizing scenario simply minimized the peak power of the household when deciding how to charge the EVs; it did not consider the cost of charging and how it might vary with time.

Zaferanlouei et al. [61] modeled the impacts of different EV charging strategies in a Norwegian case study of a grid that included 32 transformers [from the MV to LV level] and 856 consumers, with an average of 1.3 vehicles per consumer. They used an optimal power flow model with non-linear power flow constraints and considered three different charging scenarios: direct charging; cost-minimized charging without grid constraints; and cost-minimized charging with grid constraints (such as cable/transformer capacity and voltage deviation). They found that for the studied grid, the capacity limit when using a direct charging scenario was in the range of 18%–27% of the EVs in the total vehicle fleet. Above this range, thermal violations began to occur. Their cost-minimized charging scenario allowed for higher EV penetration levels than in the direct charging scenario, achieving up to 36% EVs before thermal violations began to occur. However, only the scenario that took grid constraints into account could handle up to 100% EVs in the studied grid without grid reinforcements. They concluded that to achieve 100% EVs, measures corresponding to such a scenario (e.g., applying a scheduling mechanism) would have to be applied or the distribution grids would have to be strengthened [61]. However, they assumed that the grid constraints were known when performing the optimization, and that an all-knowing actor scheduled the loads of the EVs.

Smart charging algorithms, and the cost-minimized charging examples above, typically schedule home charging to coincide with periods of the lowest wholesale prices, thereby lowering the market-based cost of purchased electricity for the user, while requiring a spot price-based contract for the vehicle owner. This entails spreading the demand to times when the level of electricity generation is high and/or the demand for electricity in general is low [65]. However, wholesale electricity prices do not reflect local grid congestion, which means that even if the vehicle owner charges according to the electricity spot price, there could be insufficient grid capacity for additional loads, despite the price for electricity being low.

The abovementioned studies provide important insights into how different EV charging scenarios can impact the local grid. Some of these studies have considered charging scenarios with different grid constraints, in order to reduce the burden on the local grid. However, previous studies that have looked at reducing the burden on the distribution grid have either considered known grid capacities and performed the optimization of EV charging within those capacity limits [61], or not considered current grid capacities but then optimized charging to only reduce the peak power of households without considering the spot price of electricity [37]. Although some groups have considered a variable spot price for electricity, few studies have analyzed how a price signal in the form of a power tariff can be included in the optimization of charging, alongside the electricity spot prices, so as to reduce the burden on the distribution grid. Therefore, the present study implements different EV charging scenarios based on an optimization process, including different price signals, to an LV grid model that includes all residential LV grids in Sweden.

3.4 Demand response to power tariffs

Velovski et al. [66] studied how electricity pricing and network tariffs impact energy communities and the consequential impacts on the local grid. They found that including a power component in the network tariff mitigated the peak loads imposed on the local grid [66]. However, they did not study power tariffs in detail or use multiple tariff designs, instead focusing on the roles of the energy communities. Azutalam et al. [67] evaluated different network tariff designs, two of which included a cost for the monthly peak power. They concluded that for residential customers with solar photovoltaics (PV) and batteries, the two tariffs that included a power tariff, reduced the peak demand in households, as compared with other tariffs.

Saele [68] has studied the customer impacts of changing from a volumetric network tariff to a power tariff. Using historical load data to compare how different network tariff designs affect different customers, they have shown that tariff designs based on peak power reallocate the costs between customers, as compared with volumetric charges. In that study, customers with a low utilization rate experience an increase in costs, although the conclusion drawn is that a more-detailed study on which customer groups are impacted is needed [68]. They conclude that power tariffs resemble more closely the impacts that customers have on the distribution grid [68]. An analysis conducted by the Massachusetts Institute of Technology found that power-based network tariffs significantly lower the levelized EV charging costs for EV owners and curb the aggregate demand peaks, whereas pure volumetric tariffs lead to higher charging costs and no reduction in the demand peak [69].

Some studies have looked at historical load data to understand how network tariffs have impacted user behavior [70, 71]. For example, van Zoest et al. [71] examined the impact of power tariffs on demand flexibility among commercial customers. They analyzed the measured load patterns of 1,161 small-to-medium (meaning a connection size of 35–63 A) commercial customers before and after the introduction of a power tariff. When clustering the customers according to their consumption patterns, differences in the responses to the power tariff were seen. van Zoest et al. [71] showed that the strongest responses to the power tariff occurred in two clusters, both displaying a high periodicity in their electricity demand. The first of these two clusters had customers with a high electricity demand and electrical fuse size, while the other had customers with small fuse sizes, indicating that the periodicity, rather than the fuse size, was an indication of the response [71]. The clusters that had a weak response to the power tariff were dominated by loads from shared areas in residential buildings, where the loads typically relate to the usage of lights, elevators, laundry rooms, etc., with a large share of the load being constant and inflexible [71].

El Gohary et al. [70] evaluated power tariffs as a means to lower the peak demand on distribution grids. They used historical demand data for both residential and commercial customers to compare the timing of the demand peaks for individual customers and the system peak demand. They have shown that there are large temporal gaps between when individual and system-level peaks occur, indicating that the tariff signals for customers to limit their demand for electricity even during times when the loading on the grid is not at its peak [70]. Furthermore, they conclude that the peaks that are critical to the distribution grid are few and strongly related to the outside temperature, while the tariff targets daily behavior [70]. Both of these factors mean that customers are encouraged to change their behaviors in ways that provide little value to the distribution grid. El Gohary et al. [70] conclude that in order to reflect the costs that users impose on the grid, the maximum system peak should be included in the design.

A study by Lanot and Vesterberg [72] looked at the price elasticity of the electricity demands of households when they face a network tariff based on the monthly peak power. They show that the price elasticity is low, meaning that only small changes to the electricity demand occur. This was true despite the authors of the study judging the incentive to be very large, possibly due to the total electricity costs being low compared to other expenses [72]. They found that access to detailed information about the household's consumption through the company website did not increase the demand response. Lanot and Vesterberg [72] also showed that basing the tariff on the monthly peak power gives a weak incentive to change the demand at the end of the month.

Abdelmotteleb et al. [73] modeled a network tariff design in which a part of the cost is fixed, with the remainder of the cost being based on customers' contributions to peak power during peak hours, in a study that focused on the impacts of network tariffs on active customers. They suggested that this peak power cost should be implemented for hours with loads that exceeded a predefined threshold. They modeled the reactions of four customer groups in a simple 2-bus network with cost-minimization, assuming that the customer satisfied their load but can invest in distributed energy resources [73]. Abdelmotteleb et al. [73] concluded that this network tariff outperformed traditional tariffs in that it yielded higher economic efficiency for the system. However, their study assumed a fixed wholesale price of electricity and had limited representation of other tariff designs, and the grid infrastructure.

Brown et al. [74] emphasized that in addition to cost-reflectiveness and fairness in tariff design, graduality is important when changing a network tariff. This is due to the long lead times inherent to investments in end-use technologies [74]. Gradually shifting tariffs ensures that customers are not shocked by sudden bill increases, and enables them to increase predictability in the cost savings that investments can generate [74]. This underscores that not only the nature of the tariff design is of importance but also how it is implemented.

Raassina et al. [75] performed a questionnaire-based survey of 566 DSO customers with EVs (fully battery electric and plug-in hybrids), to assess consumer attitudes towards controlling when EV charging occurs under different network tariff structures. A majority of the survey respondents (71%) charged their vehicles directly upon arrival at their home location. However, the study showed that power tariffs increase the share of customers willing to control when they charge their EVs to 79% from 44% with the current fixed tariff. Furthermore, they showed that excluding weekends from the power tariff slightly increased the share to 82% of customers with EVs [75].

As van Zoest et al. [71] identified flexibility and intermittency of load as determining whether adaptation to power tariffs occurs, the potential exists for EV charging to be impacted more powerfully by power tariffs than traditional household loads. As EVs are typically parked for much longer than they need to charge, there is an inherent flexibility to the EV charging demand [76]. This might explain the willingness to shift EV loads observed by Raassina et al. [75]. This is strengthened by the study of Ovaere and Vergouwen [77], in which they evaluated the impact on the distribution grid of introducing power tariffs. They noted a 1%–3% reduction in peak power for an average household, while a household with an EV reduced its peak power by 5% [77]. Ovaere and Vergouwen [77] describe how real-time pricing of the purchase price of energy can have a negative impact on the loading on the local grid, although the addition of a power tariff can counteract that, as it introduces a cost for the loading of the distribution grid.

The previous work presented lays the foundation for mapping the interplay between network tariffs and their impacts on the loads exerted on the local grid. However, there is a lack of studies on the optimization of loads with different tariff designs, to identify the behaviors that the different network tariff designs incentivize. Furthermore, there is a need to understand the trade-offs for flexible loads between adapting to the spot price in electricity price areas and lowering the burden on local grids. Although the ways in which traditional household loads may respond to power tariffs are not explicitly incorporated in the modeling in this study, the work presented in this section is used for the discussions of the impacts of existing tariff structures and optimal power tariff designs.

4 Method

This section includes a brief description of the characteristics of the models, data, and modeled cases in this work. The studies described in this thesis were performed by developing and using three separate models, for which an overview of the key features is given in Section 4.1. Some of the key concepts of the models include energy conservation and linear optimization. The first model used in this work is a cost-minimizing linear optimization model for hydrogen refueling stations (described in Section 4.2), which was developed to compare the cost-efficiencies of different systems designed to supply hydrogen to refueling stations, as applied in **Paper I**. **Paper II** develops the Reference Electricity Grid Analysis model (REGAL), which extends the grid model introduced by Hartvigsson et al. [39]. The REGAL model is described in Section 4.3 and is a simplified form of a power system model for a larger geographic region. In this work, considerable changes have been made to the model, so as to serve new purposes and increase the level of accuracy when analyzing the research questions in this thesis. Section 4.4 describes how the output of the REGAL model is used to determine the need for grid reinforcement. In **Paper III,** an additional cost-minimizing linear optimization model is developed and applied, in which logged EV charging data, hourly electricity spot prices, and different network tariff designs are used as inputs to a linear cost-minimization model that minimizes the EV charging costs. This model is described in Section 4.5. **Paper IV** uses the output of the model developed in **Paper III** and implements the generated EV charging profiles in the REGAL model.

The work of this thesis uses a dataset of logged EV data, described in Section 4.6. Section 4.7 describes the different modeled cases in **Papers III** and **IV**. For details of the models and assumptions, see **Papers I–IV**.

4.1 Scope of the three models

The three models, one for indirect electrification and two for direct electrification of road transportation, are inherently different in terms of how they function and the systems with which they deal. Table 1 provides an overview of the key features of the three models developed and applied in this thesis. The hydrogen refueling station model and the EV charging model are linear optimization-based energy systems models, while the REGAL model is a simplified power system analysis model used for grid simulation. Most of the work in this thesis focuses on the Swedish context. However, for the refueling station model, additional model runs representing western Spain, Ireland, and Croatia-Slovenia-Hungary are also included in **Paper I**. More information can be found in the descriptions provided in Sections 4.2, 4.3, and 4.5, as well as in the relevant papers.

Table 1. *Overview of the key features of the models included in this thesis.*

	The hydrogen refueling station model	**The REGAL model**	**The EV charging model**
Paper(s)	**I**	**II** and **IV**	**III** and **IV**
Syntax	GAMS	Julia	GAMS or Julia
Type of model	Cost-minimizing linear optimization	Grid simulation	Cost-minimizing linear optimization
Temporal scope and resolution	Run over 1 year with 1-hour timesteps, present day and future cases	Run over 1 year with 10-minute (**Paper II**) or 15-minute (**Paper IV**) timesteps, representation of the current grid with different fleet shares of EVs	Run over 1 year with 10-minute, 15-minute or 1-hour timesteps
Geographic scope and resolution	Representing a hydrogen refueling station with conditions for Sweden, western Spain, Ireland, and Croatia-Slovenia-Hungary	All of Sweden, divided into squares of 1×1 km^2	All of Sweden, divided into four different electricity price areas
Main inputs	Costs and technical properties of components, hourly electricity price, hourly demand, and hourly electricity generation from solar PV and wind turbines	Distributed data for the numbers of inhabitants, apartments, and single-family dwellings, number of vehicles, costs, and technical properties of components, national grid regulations, driving patterns, household load profiles, and fleet share of EVs	Electricity prices, network tariff costs, household loads, and logged EV data for energy demand, times when the vehicle is at the home location, and battery sizes of the vehicles
Main outputs	Investments in components, total system cost, hourly hydrogen production, and levels in hydrogen storage	Synthetic representation of the LV grid, frequency (i.e., how often), amplitude (i.e., by how much), and timing of exceedances of the operational limits of the LV grid, and what types of operational limits are exceeded	Peak power of individual households, aggregated peak power of all modeled households, and time distribution of home charging for individual vehicles

4.2 The hydrogen refueling station model

Paper I of this work compares the costs and efficiencies of three electrolysis-based hydrogen supply systems for heavy road transportation: a decentralized, off-grid standalone system for hydrogen production from wind and solar power (Dec-Sa); a decentralized system connected to the electricity grid (Dec-Gc); and a centralized grid-connected electrolyzer with hydrogen being transported to refueling stations (Cen-Gc) (Figure 2). A cost-minimizing optimization model was developed in which hydrogen production systems are designed to meet the demand at refueling stations at the lowest total cost for two timeframes: one with current electricity prices, and one with estimated future prices. The two timeframes also come with different assumptions regarding costs and efficiency levels (detailed in **Paper I**) for components such as electrolyzers and hydrogen storage tanks. In **Paper I**, Year 2019 is used as the base for the current case, and an estimation for Year 2050 is used as the future case. In addition to this, **Paper I** includes modeling of Years 2015 to 2020. For those years, the costs and efficiencies of components in Year 2019 are used, combined with varying electricity price profiles derived from Nord Pool [78]. This introductory essay further introduces results obtained using electricity prices for the period of 2021–2024.

The model was developed and applied to compare the system efficiency levels and costs of hydrogen delivery for the three hydrogen supply systems, and included the electricity source, energy conversion to hydrogen, and the distribution and storage of hydrogen. Optimization was carried out to satisfy an exogenous hydrogen demand profile at the lowest total cost. Although the methodology could be applied to any region, the electricity price area SE3 in Sweden was chosen as the main case, so the results presented in this thesis are for this region only. In addition, three regions (Ireland, Croatia-Slovenia-Hungary, and western Spain) were modeled to determine how system costs are influenced by different electricity system compositions, as well as by different potentials for wind and solar power generation. The results for these additional regions are presented in **Paper I**.

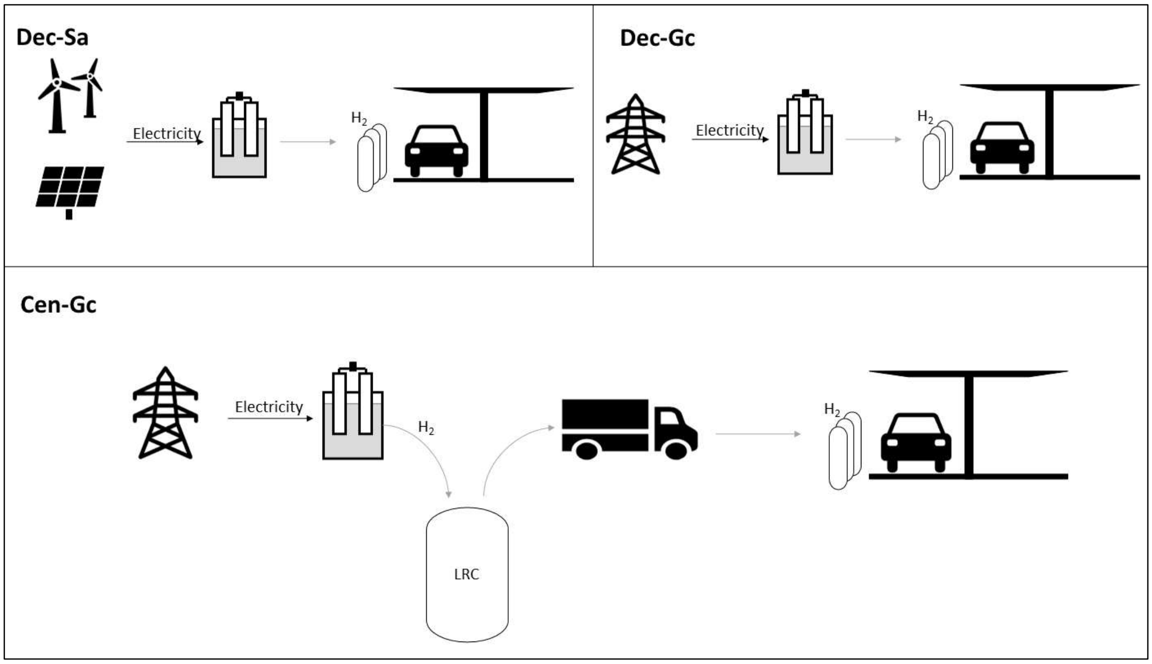

Figure 2. *Visualization of the hydrogen supply systems investigated in this work. For the Dec-Sa and Dec-Gc systems, hydrogen production occurs onsite at the refueling station, while the Cen-Gc system requires the transportation of hydrogen to the refueling station. LRC, Lined rock cavern (storage).*

Compared to other studies of hydrogen refueling systems, the current analysis examines multiple system setups with the same assumptions, whereas most of the previous studies were limited to one supply system (e.g., [26, 28]). Furthermore, the few studies that included multiple supply systems considered only one electricity price profile (as in [27, 33]). As the price for electricity was concluded to comprise a substantial part of the cost of hydrogen production [79], this work considers multiple electricity price profiles and investigates if and how these profiles alter the results obtained for the system setup and operation.

4.3 The REGAL model

The REGAL model uses open data to create a synthetic LV grid representation, which enables grid simulations of geographic areas for which the grid properties are not known. This synthetic grid can then be used to simulate the ways in which new technologies, in this case, large-scale home-charging of EVs, affect the LV grid, and whether the operational limits of the grids would be exceeded. The REGAL model was developed for Sweden, whereby the country was divided into squares of 1×1 km^2, herein termed *grid cells*, based on publicly available demographic data. Only residential loads are considered in the model, so unpopulated grid cells are excluded. This results in almost 105,000 populated grid cells for Sweden, for which the population is shown in Figure 3.

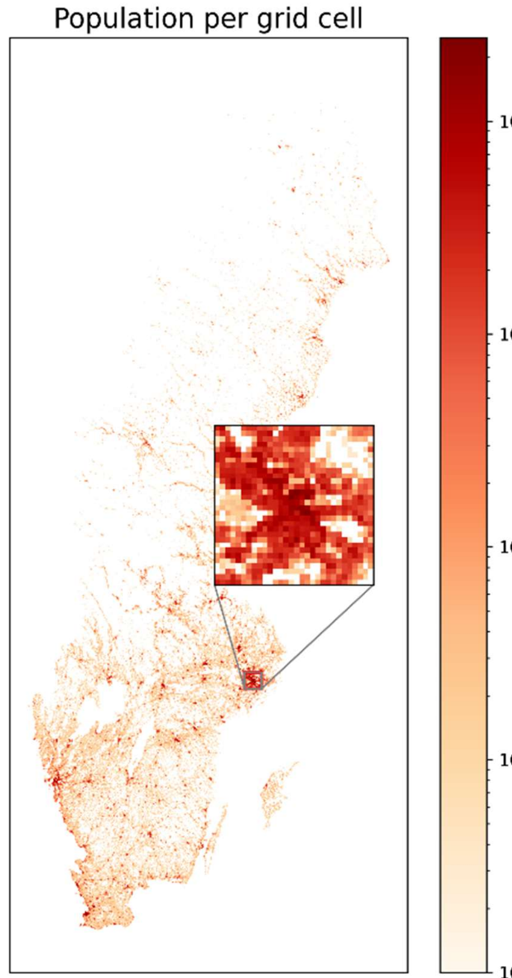

Figure 3. *Population per grid cell for Sweden. The zoomed subplot represents the Stockholm region.*

An overview of the modeling framework used in **Paper IV** is shown in Figure 4. It consists of two models: the REGAL model (presented in **Paper II**), and the EV charging model (presented in **Paper III**). In the figure, modeling blocks are striped, key input data are shown in white, and key output data are shown in orange. The REGAL model consists of three main modeling blocks that for each grid cell: (1) generate a synthetic LV grid; (2) perform grid simulation when adding EV charging to the residential load; and (3) evaluate power system violations and load changes. The addition of loads and grid simulation and the evaluation of power system violations [Steps (2) and (3)] are performed iteratively with randomly assigned load profiles. In the REGAL model, a power system violation is defined as occurring when the operational limits of the grid are exceeded. The violations are classified as: *voltage*, where a violation occurs if the voltage magnitude fluctuates more than what is allowed according to national regulations; or *thermal*, where a violation occurs when the thermal capacity of a component is exceeded. The REGAL model considers thermal violations that occur in both transformers and cables. Other outputs from the model include the lowest voltage (both the lowest value recorded in any iteration and the mean value over the different iterations) and the maximum transformer loading in each grid cell. The lowest voltage is assumed to be located at the end of the longest feeder, as no electricity-generating technologies are added in this model version. More information about the EV charging model is presented in Section 4.5 and in **Paper III**.

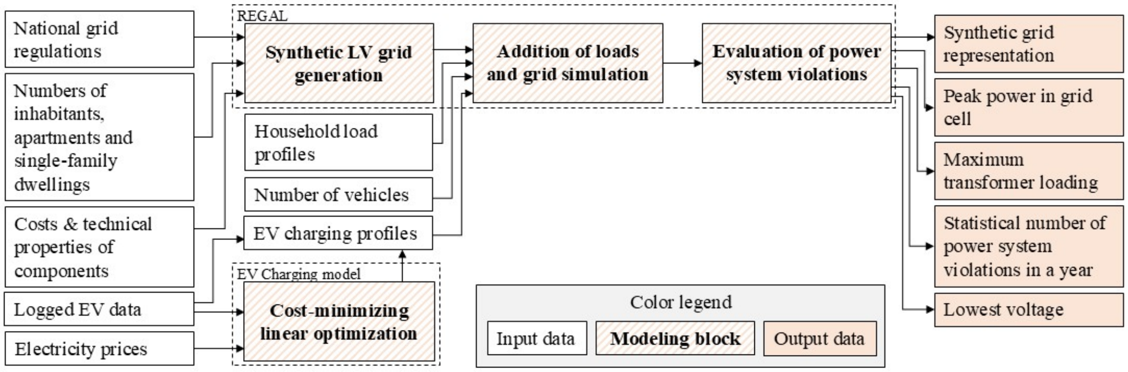

Figure 4. *Overview of the modeling framework used in **Paper IV**, including the main modeling blocks in the REGAL model and the EV charging model. The EV charging model is used to generate EV charging profiles, which can then be used to run the REGAL model. Thus, the EV charging profiles represent both input data to the REGAL model and output data from the EV charging model.*

A reference dataset of real grid capacities was collated as part of the work of this thesis. The reference dataset consists of real-world data supplied by several Swedish DSOs, representing both large and small operators. This dataset was used to calibrate model parameters and validate the geographic scope for which the model is suitable for analysis. The dataset covers 9,477 out of the 104,853 grid cells applied in this work. The data per grid cell consist of: (i) the annual electricity demands for residential and commercial customers; (ii) the number of transformers with different capacities; and (iii) the cable lengths. A comparison of the generated synthetic grid and the reference dataset can be found in **Paper II**. Compared to other studies of how EVs affect the distribution grids in Sweden, the research presented in this work captures a larger geographic area, enabled by the generation of a synthetic LV grid.

The model code is available online under a permissive open-source license [80]. Further, the repository contains the input data needed to run the model. However, as all load profiles cannot be shared openly, only a partial dataset with manipulated values is provided. The openly available version of the model generates the same synthetic grid representation as that described in this thesis and produces comparable results. Minor numerical differences may occur because the underlying data have been modified to ensure anonymity. The mathematical formulations and methodological choices in the REGAL model are described in detail in **Paper II**, and the development of EV charging profiles is described in Section 4.5 and in **Paper III**. The modeled EV charging cases are described in Section 4.7.

In relation to studies involving smaller geographic areas with real grid capacities, the synthetic grid representation of a large geographic region increases the likelihood that the general conclusions drawn will be correct, although it reduces the accuracy levels for specific areas. Therefore, the work included in this thesis is useful for drawing general conclusions about, for example, differences between charging strategies, as well as for carrying out analyses from a societal perspective rather than answering specific questions about future loads in a grid cell.

Compared to the model version presented by Hartvigsson et al. [39], changes have been made to most parts of the model, including the input data, data conversion, grid topology, adjustment factors, process for selection of component capacities, how loads are added to the grid, and how violations are evaluated.

4.4 Estimating the need for grid reinforcements

In addition to the modeling included in the appended papers, this introductory essay includes grid simulations with the REGAL model conducted for a system in which 100% of the current vehicle fleet is assumed to be electrified, in order to quantify the grid reinforcements needed to meet the new demand with EV charging. So far, only increasing the transformer capacity based on the transformer loading has been included. Modifications to a determined grid cell to meet the new load are done in one of two ways:

1. One or more additional transformers are added to the existing capacity to meet the new load; or
2. An existing transformer is replaced by a new transformer of a higher capacity to meet the new load.

A visual representation of the reinforcement decision logic is depicted in Figure 5. The determination must both ensure that the new load is covered and minimize the economic impact of the transformer changes. In addition to these two criteria, conversations with DSOs have provided an additional criterion for when a replacement is done and when a new transformer is added. This extra criterion is that a new transformer must always be added instead of replacing an existing transformer when the current capacity of the transformer is 800 kVA or higher. Due to these requirements, a transformer is replaced with a larger one when: (a) there is only one transformer in the reviewed grid cell; (b) the capacity of the transformer to be replaced is <800 kVA; and (c) a transformer of sufficient capacity exists. If the largest available transformer capacity is not sufficient for replacement, an additional transformer is introduced instead. When estimating the demand for new transformer capacity in a grid cell, a maximum transformer loading of 60% is assumed. No transformer replacement or addition is performed when the required demand for added capacity is less than 10 % of the rated capacity of the current transformer. Following this logic, the required transformer reinforcement for a specific grid cell in the REGAL model can be determined.

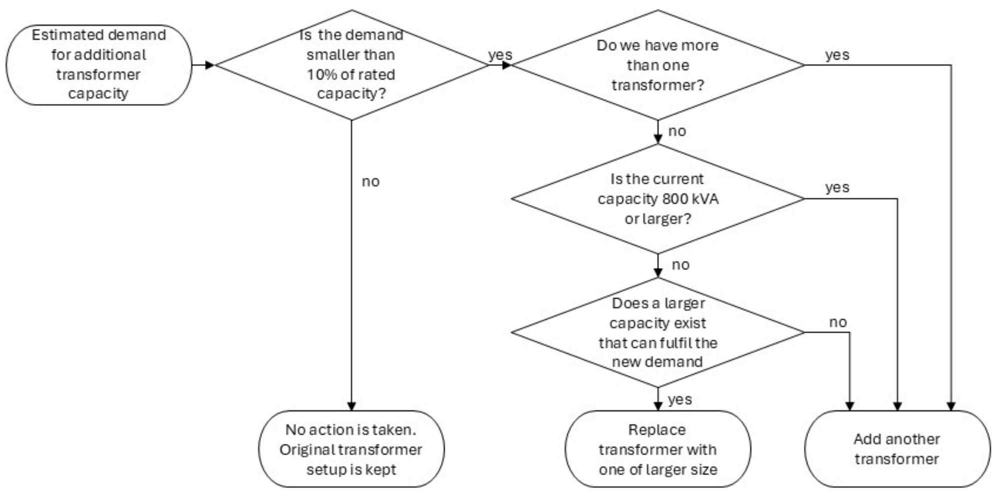

Figure 5. *Decision logic tree for areas in which there is a need for additional transformer capacity, and a choice is to be made between replacing an existing transformer with one of a larger size or introducing an additional transformer to the area.*

4.5 The electric vehicle charging model

A cost-minimizing linear optimization model for EV charging, hereinafter referred to as the *EV charging model*, was developed within **Paper III** to compare cost-optimal EV charging, assuming different network tariff designs in combination with electricity prices that vary according to the spot price. The purpose of the model is to study both the temporal distribution of charging and the peak power that an electrified vehicle fleet might introduce to the local grid. The EV charging model minimizes the cost of EV charging, while ensuring that the energy demand for driving is met in all timesteps for each vehicle, subject to different constraints related to the network tariff designs. In particular, the model considers network tariffs based on peak power, also known as *power tariffs*. The components included in the cost calculation and the constraints vary between the modeled cases.

The EV charging model is solved using GAMS with a Gurobi solver, and the code is available in a public repository [81]. The model optimizes the charging of 188 EVs and runs over 1 year with a 15-minute timestep, resulting in 35,040 timesteps. The 15-minute time resolution is chosen because this is the time interval for variable electricity price contracts in many European markets as of September 30th 2025, and thus is the highest temporal resolution at which household demands are recorded and available on a large scale. The model ensures that the driving demand of each vehicle is met at every timestep.

Household electricity loads, other than EV charging, are used as an input to the optimization model. One household is assumed to have one vehicle when combining the EV and conventional household loads for the optimization. In the runs performed for **Paper III**, 188 individual household load profiles for a full year with a 15-minute temporal resolution from a region in western Sweden were used. The household load data were gathered from the 1st of April 2024 until the 31st of March 2025. The profiles are obtained from both single-family houses and apartments, and use different heating technologies. Due to the computational demands of the optimization, an average household load profile was created from the household load profiles, so as to represent an average household. This means that, with only one model run, the incentive is to shift EV charging to times when the overall household load is low.

The maximum home charging power was set to 6.9 kW (corresponding to a 10 A, 3-phase connection). Other common home charging power levels are 11 kW, or even 22 kW in some cases. A low, yet currently commonly used, charging power level is selected because of the tendency of the optimization model to focus excessively on charging during periods with the lowest cost, despite there being very small price differences. This ensures a reasonable average charging power, although the peak charging power assumed at the home location may be lower than the measured charging power in the real-world data. Thus, the low maximum home charging power level ensures that the peak power increases only up to a level that is reasonable when adding EV charging to the household demand.

4.6 The electric vehicle dataset

The logged EV data are from a dataset presented by Kobayashi et al. [76] that originally included 334 vehicles distributed across 55 EV models. The logging was performed in Sweden between Years 2022 and 2025 using GPS-based equipment plugged into the vehicle's OBD port [76]. The vehicles were randomly selected and distributed across all of Sweden. In this study, 188 of the 334 logged vehicles were selected, as these vehicles had both one full year of measurements and few faulty measurements. The logged data used in this study are: energy demand for driving per timestep; charged energy per timestep; and the share of each timestep during which the vehicle is at its home location. All EV charging profiles have a temporal resolution of 15 minutes over 1 year and include only charging at the home location. Each EV is assumed to have a battery capacity that is in line with the estimation made in the logging conducted by Kobayashi et al. [76], and a charging efficiency of 95%. The individual battery capacities, sorted by size, are shown in Figure 6.

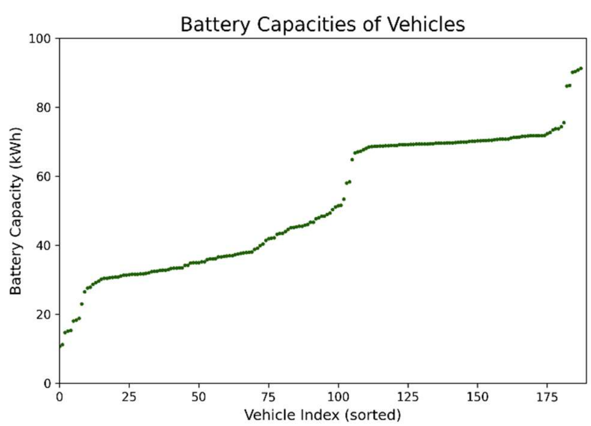

Figure 6. *Battery capacities of the studied vehicles, sorted according to size.*

The logging of data was complemented by a survey to the vehicle owners, which entailed questions regarding if the vehicle is used for commuting, whether the household lives in a single-family dwelling or in an apartment, the number of vehicles in the household, and the type of electricity contract held by the household. It also contained general information questions about the main driver of the vehicle, including age and gender. Figure 7 shows the charging options at the home locations of the 188 vehicles used for the work in this thesis. By far the most-common charging option is to have a private wallbox. Three other options, i.e., normal socket, shared wallbox, and public charging station, have a similar number of respondents. Four participants in the sample have no charger available at their home location. About 33% of the 188 EV owners live in apartments, and the remainder live in single-family households. For the 188 vehicles included in the modeling, approximately 30% of households have an electricity price contract whereby they directly pay the spot price of electricity. However, in the full dataset of 334 vehicles, the corresponding share is 35% of households. This is significantly higher than the 14.5% of households that do so in the general Swedish population [24]. Here, it should be noted that both the available charging option types and the possibility of choosing an electricity price contract are strongly dependent upon the type of housing. For example, many people living in apartments do not have the option to choose the electricity price contract that applies to their main charging location.

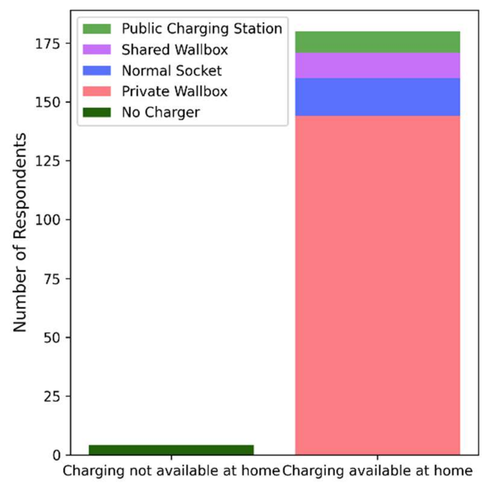

Figure 7. *Charging options at the home location for the 188 vehicles included in this study.*

Figure 8 shows whether the household of the EV owner has one or more vehicles. About 40% of the EV owners in this study have only one vehicle in the household. For households with more than one vehicle, they were asked to specify whether the EV logged in the study is the primary vehicle of the household, if another vehicle is the primary vehicle, or if the vehicles of the household have no order in which they are prioritized for use. For households with more than one vehicle in the household, the most-common answer was that the EV used in the study is the primary vehicle of the household.

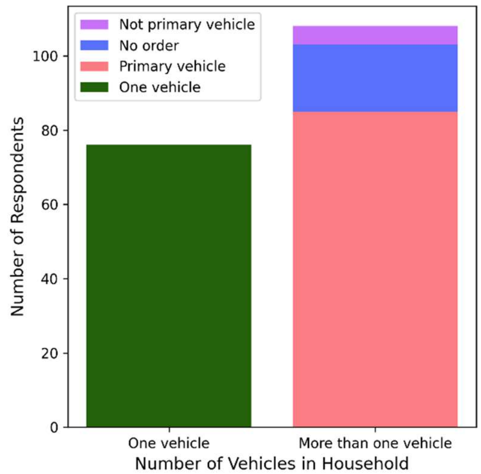

Figure 8. *Number of households/respondents that have either one vehicle or more than one vehicle, as well as the priority assigned to the EV by the owner, if the household has more than one vehicle.*

The logged vehicles were selected to be representative of current EV owners, spanning all of Sweden and including both households living in apartments and single-family dwellings. For the modeling in this thesis, the logged vehicles are used to model the whole vehicle fleet, including those vehicles that are not currently electrified. However, the extent to which they are representative of future EVs remains uncertain, as there may be both technical and behavioral changes.

4.7 Modeled cases for electric vehicle charging

The logged charging patterns collected by Kobayashi et al. [76] are compared for four different modeled cases, one with no power tariff and three with different power tariff designs (**Paper III**). The four modeled cases differ with respect to the design of the power tariff applied and, therefore, with regards to the equations (presented in **Paper III**) included in the optimization. Out of the four modeled cases in **Paper III**, two were introduced to the REGAL model in **Paper IV**. However, the results in this thesis include all of the modeled cases. The modeled EV charging cases and the names assigned to them in **Papers III** and **IV** are summarized in Table 2. For the vehicles studied, approximately 30% of the EV owners had an electricity contract whereby they were directly paying the spot price, whereas in the modeling, it is assumed that this is the case for all vehicle owners to study the combined incentive of spot prices and network tariffs. The five cases studied in this thesis are as follows:

(i) *Logged charging*, a reference case based on logged charging profiles.
(ii) *No tariff*, where the modeling considers an electricity spot price but no power tariff.
(iii) *Daytime tariff*, where the modeling considers an electricity spot price, as well as a time-differentiated power tariff, where only the peak power level that occurs between 7 am and 8 pm is included in the power tariff. This is inspired by the power tariffs implemented by Jönköping Energi, Telge Nät, and Växjö Energi [82–84]. Outside of these hours, no cost is assumed to be associated with the peak power in this case.
(iv) *All hours tariff*, where the modeling considers an electricity spot price, as well as a power tariff, where all hours of the day are included. This tariff is inspired by the power tariffs implemented by Ellevio, Göteborg Energi Nät, Malung-Sälens Elverk, Partille Energi, and Varberg Energi [85–89].
(v) *Dynamic tariff*, where the modeling considers an electricity spot price, as well as a power tariff that reflects the combined load, rather than only the peak power of the individual household. Thus, it is applied to the combined peak power of all 188 households and EVs together, rather than the peak power of individual households.

Table 2. *Summary of the modeled cases in* ***Papers III*** *and* ***IV****. The electricity costs are shown, as well as the hours of the day included in the power tariff.*

Case name in **Paper III** and thesis	Case name in **Paper IV**	Spot price	Power tariff	Hours included in the power tariff
Logged charging	Logged charging	-	-	-
No tariff	Cost-minimized charging	Yes	No	-
Daytime tariff	-	Yes	Yes	7 am to 8 pm
All hours tariff	Cost-minimized charging with power tariff	Yes	Yes	All hours
Dynamic tariff	-	Yes	Yes	All hours

The *Daytime* and *All hours* cases are based on a mapping of the power tariffs in use in Sweden during the Fall of Year 2025, which can be found in **Paper III** and represent tariff designs that are currently commonly used. Of the two cases, it is more common to have a daytime tariff, although the hours defined as daytime vary between the different DSOs. The dynamic tariff is not implemented at present, but rather is an attempt to study further what would be the cost-optimal behavior if the tariff were to consider the moment with the highest loading on the local grid, thereby steering the behavior according to the dimensioning case for the local grid. An alternative to the implemented *Dynamic tariff* could be to create a price signal with an hourly or 15-minute resolution that reflects the expected load in the local grid, similar to how electricity spot prices work for a price area. This could discourage electricity use during times when the load is typically high, and shift it towards times when the load is low. However, as the most-critical time typically defines the needed grid capacity, it could be argued that such a price profile would be less-closely related to the cost of maintaining and expanding electricity grids, as costs would be incurred for using the electricity grid at times that are not dimensioning the needed grid capacity.

5 Results and discussion

Electrified transportation is increasingly prevalent. The results presented in this section provide insights into the infrastructure needed to supply the necessary hydrogen and electricity for charging and refueling as the number of electrified vehicles increases. The results reveal the differences between different hydrogen supply systems and EV charging cases in terms of the infrastructure needed. In addition to presenting and discussing the main results from this thesis, this section discusses the optimal power tariff design and some of the main limitations of the developed models, and reflects on the contributions of this work.

Section 5.1 presents the results related to indirect electrification. In particular, it compares centralized and decentralized hydrogen supply systems, as well as standalone and grid-connected systems, in terms of cost-efficiency.

Some of the results relating to direct electrification are given in Sections 5.2–5.5. Section 5.2 shows how the peak power asserted on the LV grid can increase with a fully electrified vehicle fleet. Section 5.3 looks at how the operational limits of the grid may be exceeded, and Section 5.4 identifies the grid reinforcements that may be needed to accommodate the charging of EVs. Finally, Section 5.5 looks at how different network tariff designs impact the flexibility of EV charging.

The last two sections (Sections 5.6 and 5.7) discuss the limitations of the modeling framework used to study the home charging of EVs and what aspects need to be considered when designing a power tariff.

5.1 Cost-efficient hydrogen supply systems for refueling stations

Three hydrogen supply systems were evaluated in **Paper I** using the hydrogen refueling station model, to gain insights into the cost of supplying hydrogen to the road transport sector. The results obtained from the modeling show that different setups for producing and providing hydrogen to refueling stations are associated with different costs. Figure 9 shows the LCOH values for the different hydrogen supply systems (see Figure 2) for the two studied timeframes, assuming the current (Year 2019, the reference year used in **Paper I**) and future costs for both investments and electricity. The electricity costs shown in Figure 9 include the costs for electricity that is used for hydrogen production and compression. The results show that the lowest costs for delivering hydrogen at a refueling station in southern Sweden are in the range of 2.2–3.3 €/kgH_2, and are achieved with the decentralized, grid-connected (Dec-Gc) system. For the centralized hydrogen supply system, Cen-Gc, somewhat lower costs are achieved for the production and storage of hydrogen, although the additional cost for hydrogen transportation brings the total cost to 3.7–4.8 €/kgH_2, which is 31% higher for the current case and 41% higher for the future case, as compared with the Dec-Gc system.

The decentralized standalone (Dec-Sa) system is associated with the highest LCOH, mainly due to the higher costs for storage and electricity production, as shown in Figure 9. For all the tested systems, lower costs are achieved in the future cases than in the case corresponding to the present conditions, as shown in Figure 9. This is due to the assumed reduction of investment costs and the higher energy efficiency of electrolyzers. For the grid-connected systems, these assumptions are also the main contributors to the lower cost for this system, although electricity price variations also affect the hours during which hydrogen is produced and, thereby, the electricity costs.

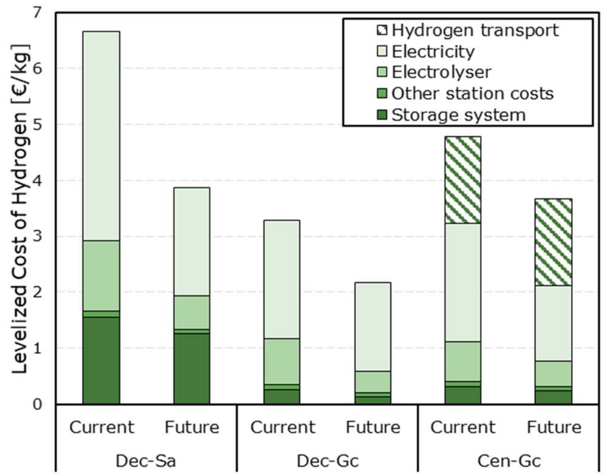

Figure 9. *Levelized costs of hydrogen delivery for the three hydrogen supply systems (Dec-Sa, Dec-GC, Cen-GC) and the two timeframes (Current, corresponding to Year 2019; and Future, corresponding to approximately Year 2050) investigated in this thesis. Source:* ***Paper I****.*

Figure 10 shows the hydrogen production costs assuming the hourly electricity prices for different years when using the hydrogen refueling station model for the decentralized, grid-connected supply (Dec-Gc) system, i.e., the system which gives the lowest LCOH. This means that the results for Year 2019 and the future case are the same values as the ones shown in Figure 9, although the results for Year 2019 are referred to as *the current case* in Figure 9. The results in **Paper I** include the individual years for the period of 2015–2020, and a future case, which means that the results obtained using the electricity price profiles for the period of 2021–2024 included in Figure 10 are new, and they are not included in **Paper I**. The new cases only use an updated electricity price profile, which means that no changes were made to the costs and efficiencies of the different components in the hydrogen supply system. However, the model can choose the capacities of the electrolyzers and hydrogen storage to minimize the LCOH.

There are differences in LCOH values between the modeled years, since these strongly depend on the electricity price. For most years, similar capacities were seen for the model's investments in electrolyzers and storage units, which means that the results differed only in terms of electricity costs. However, for Year 2022, when electricity prices were high in general, but were also more volatile than in the preceding years, a substantial difference is evident in the supply system setup compared to the other years. Year 2022 sees larger investments in both electrolyzer capacity and hydrogen storage, to enable the shifting of hydrogen production to hours with lower electricity prices. As the other years do not have such high electricity prices, the increased investments in storage capacity seen for Year 2022, as compared to other years, might not be reasonable from the cost perspective. However, it should be noted that even for the Year 2022 case with the largest storage capacity, the storage covers the demand for only approximately 2 days and 7 hours, which means that only the highest electricity price periods are avoided, rather than the production being shifted by several weeks or months. From a security-of-supply perspective, the storage capacities derived in the cost-optimal solution are rather small compared to the demand. To ensure continuous operation during hours without an electricity supply, larger storage units are needed. However, the value of self-sufficiency is not considered in the optimization model. Furthermore, it does not include any buffer in the storage capacity that would allow trucks to refuel at different times than those laid out in the assumed pattern. For this reason, the cost figures presented in this thesis should be seen as the lowest possible average LCOH under the given assumptions related to costs and efficiencies.

The different cost-optimal solutions for different years illustrate the difficulties associated with deciding which system will be cost-optimal in the near future based on historical data. Considering the results presented in **Paper I** and comparing them to the additional years included in the updated version of Figure 10, the outcomes are different due to the different patterns of electricity prices in the past years. At the time that **Paper I** was written, electricity prices up until Year 2021 were available, and the last two years (2020 and 2021) were not seen as being representative due to the COVID-19 pandemic, which was the rationale for using Year 2019 as the basis for the studies of current costs in **Paper I**. It was obviously not known that the coming years would create a new geopolitical energy landscape with Russia's invasion of Ukraine in 2022, increased CO_2 prices and increased connectivity to continental Europe, which dramatically affected the Swedish electricity prices in that year. Although the electricity prices differ between the years, the decentralized grid-connected system still has the lowest LCOH for all the studied years. The future case from **Paper I** differs from the current case in terms of having highly volatile, albeit lower, electricity prices, and lower investment costs, as compared with the current case. However, those are not the only changes that impact the investments. At the time of the study, there was a weaker focus on reliability and energy security than today, aspects that are not captured in the current model, highlighting the difficulty in capturing future scenarios in a simple linear optimization model. The difficulties associated with predicting costs, demands, and the policy landscape complicate the interpretation of the results of investment decision modeling, such as those performed in **Paper I**.

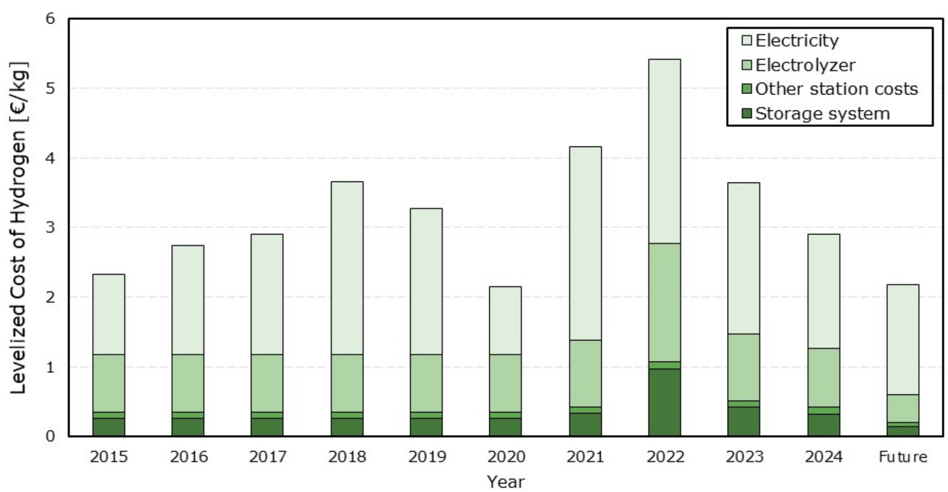

Figure 10. *Hydrogen production costs using different electricity price profiles for the decentralized grid-connected hydrogen supply (Dec-Gc) system. The results shown are from **Paper I** (period of 2015–2020 and the future estimation) and new results derived for this introductory essay (period of 2021–2024).*

As there are uncertainties regarding the cost of the hydrogen supply, the results described in **Paper I,** as well as the new results presented here, should be regarded as estimates of the differences between different types of hydrogen supply systems, rather than as estimates of the hydrogen supply costs in absolute terms. In addition, the estimates for the future case should not be regarded as predictions, but instead as a comparison of today's electricity system and future systems with more-volatile electricity prices.

The results presented in this work represent optimized solutions with perfect foresight. Therefore, it is likely that real-world refueling stations would need larger storage systems than those presented in this study, as there needs to be some element of flexibility in a cost-optimal solution. In addition, the hydrogen will be sold at a price that ensures a profit margin. The real price of hydrogen delivery will, to a significant extent, depend on the extent of utilization of the hydrogen refueling station. This means that the market penetration level will affect the profitability of introducing hydrogen refueling stations. Thus, real-world conditions will increase the costs of the hydrogen supply systems, and these increases may differ according to the type of hydrogen supply system.

The hydrogen refueling station model is a simple model that has several limitations. As an example, the model optimization conducted in this work is designed to minimize the total system cost, which does not necessarily provide the optimal system configuration, as there may be important design factors other than costs. For example, an advantage of the Dec-Sa system is that is not valued in the model is its self-sufficiency and lack of sensitivity to technical changes in the other parts of the electricity system. Another potential advantage of such a system is the possibility to establish refueling stations in areas where the electricity grid capacity cannot accommodate a grid-connected solution, or in areas where development of the grid is more costly than is assumed in this study. A centralized system, such as the Cen-Gc system, could also be an option in areas that have limitations related to grid capacity, since for a production site in a centralized system, especially one with distribution through hydrogen pipelines, there is more freedom with regards to the placement of the hydrogen production site. This means that hydrogen refueling stations could be placed in areas with poor grid availability and still have access to a supply of clean hydrogen, as long as the refueling station is connected to the network of hydrogen pipelines.

The work of **Paper I** was performed in Years 2021 and 2022. Since then, battery technologies have been extensively developed, and the number of electric trucks has increased, providing a stronger case for direct electrification of heavy transport. Although the AFIR states that hydrogen refueling stations must be deployed such that there is a maximum distance of 200 km between the stations along the TEN-T network, the Swedish environmental protection agency has announced that economic support will not be given to hydrogen refueling stations during Year 2026 [19]. They claim that development of other parts of the value chains is needed before it becomes relevant to provide support for hydrogen refueling stations [19]. Regardless of the extent of usage of hydrogen in road transport, the production and storage principles for hydrogen remain the same for other sectors. In **Paper I**, it is concluded that the demand profile for hydrogen has a limited impact on the system setup. Therefore, the results presented in the paper could be relevant for sectors other than road transport.

5.2 Increase in peak power with a fully electrified vehicle fleet

To study what happens in the local grid as EV charging is added, EV charging profiles were added alongside household loads to the REGAL model. The resulting peak power in each grid cell was compared to a model run with the same residential profiles but excluding EV charging. In total, 1,000 different iterations of selecting load profiles for households and vehicles were performed, and the results were averaged over the different iterations. In **Paper III**, the change in household peak power was evaluated when EV charging was cost-minimized with different network tariff designs. Here and in **Paper IV**, we advance the modeling one step further by adding the EV charging profiles generated in **Paper III** and the household load profiles to each grid cell according to how many apartments, single-family dwellings, and cars are present, and then iterate the different load combinations to ensure that the results are stable, regardless of which profile is randomly selected for each household and vehicle.

Histograms of the increases in peak power from home charging of EVs per grid cell, when assuming that 100% of the current vehicle fleet is electrified, are shown in Figure 11 for the five cases compared with the model run with no EVs. The median increase is indicated as a dashed line. In **Paper IV**, three EV charging cases were compared (the *Logged charging*, *No tariff,* and *All hours tariff* cases, albeit under different names, as presented in Section 4.7), although the results in Figure 11 show all the tariff cases from **Paper III**. From Figure 11, it can be concluded that the increase in peak power varies significantly across the different grid cells and charging cases. The lowest increase in peak power is seen with the *All hours tariff* case (the median corresponds to an increase of approximately 10%, and the maximum is an increase of 130%). Although the optimization performed in **Paper III** showed a similar peak load for individual households for the *Dynamic tariff* and *All hours tariff* cases, the increase in peak load for the grid seen in Figure 11 is larger for the *Dynamic tariff* case (than for the *All hours tariff* case) when added to REGAL, with a median increase of 30% and a maximum increase of 180%. This outcome may be due to the optimization in the EV charging model, which assumes that there is always one vehicle per household, as well as the REGAL model having up to 2.5 vehicles per household; this means that the vehicle charging is optimized according to a situation where they are a substantially smaller share of the aggregated load. In spite of this, the *Dynamic tariff* case still gives the second-lowest increase in the peak power asserted on the LV grid, followed by the *Logged charging* case, where the median increase in peak power is slightly above 60%, while the highest increase with this case is almost 160%. For the *No tariff* and *Daytime tariff* cases, the increases in peak power are the highest, with a median increase of approximately 80% and a maximum increase of 480% for both cases. The *Daytime tariff* case has slightly higher values, but the difference is small.

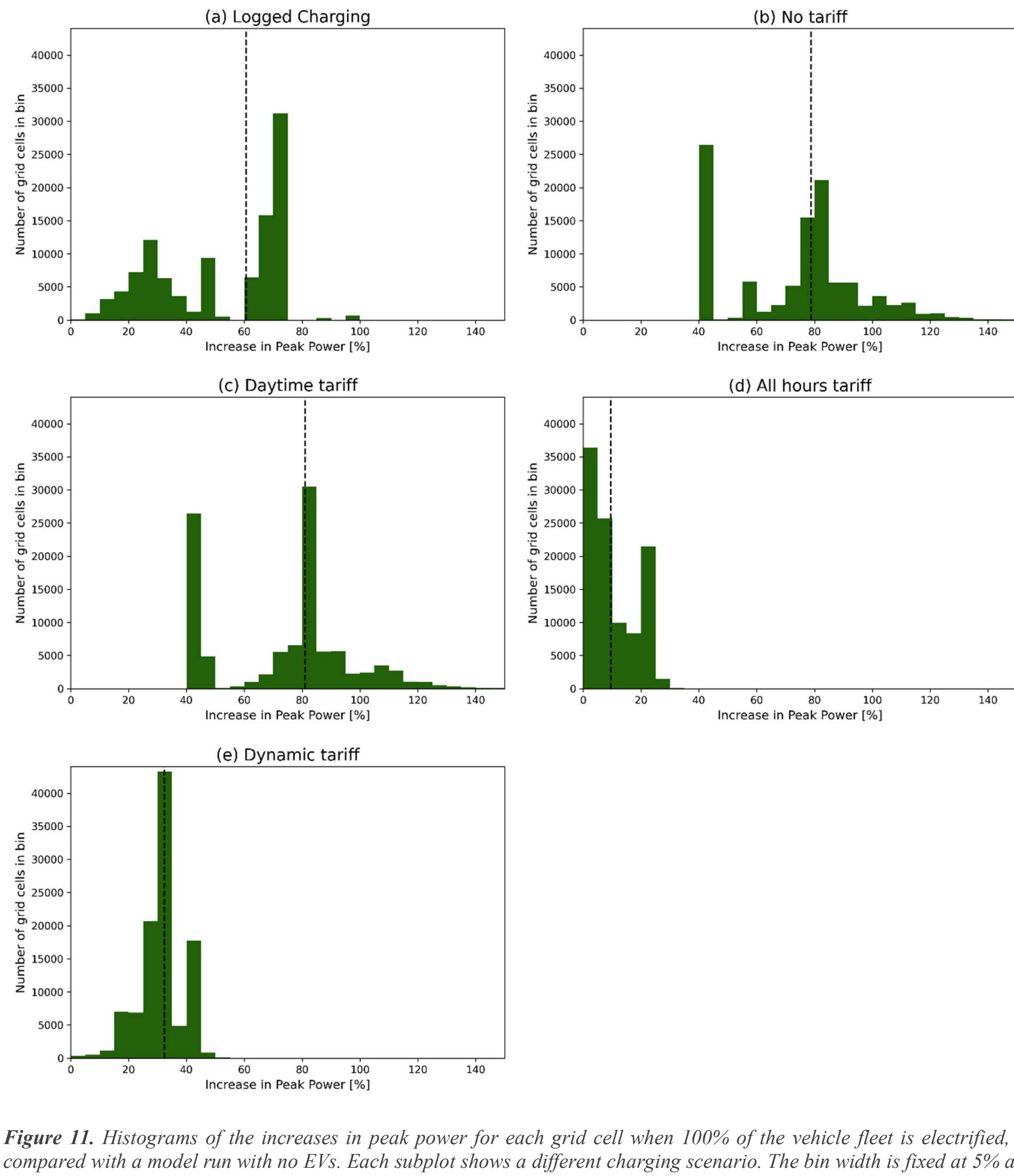

Figure 11. *Histograms of the increases in peak power for each grid cell when 100% of the vehicle fleet is electrified, as compared with a model run with no EVs. Each subplot shows a different charging scenario. The bin width is fixed at 5% and all 103,515 grid cells in Sweden are included. The results are taken from* ***Paper IV*** *(subplots a, b, and d, although with different names for the cases) and new results derived for this introductory essay (subplots c and e).*

5.3 Is the current grid capacity exceeded?

The benefit of having a synthetic grid representation is that the load estimations shown in the previous section can be positioned in relation to the likely capacity of the grid in each grid cell. If the operational limits of the LV grid are exceeded, that is defined as a violation in this study. Figure 12 shows the share of grid cells for which, statistically, one or more violations occur on average in a year. It shows how the share of grid cells with power system violations increases as the share of electrified passenger vehicles increases for the different charging cases (with each symbol in the figures corresponding to one model run). Figure 12a-c show each type of violation separately, while Figure 12d shows all types of violations, i.e., thermal and voltage violations together (see Eq. [2] in **Paper IV**). The pattern observed in Figure 12, whereby the increase in the share of grid cells with violations is non-linear, is related to the different levels of excess capacity in the grid components and the fixed threshold for when a grid cell is considered to have violations.

As expected, among the charging cases, the *No tariff* and *Daytime tariff* cases give the largest shares of grid cells with violations. The results for the two cases are very similar, as charging outside the hours included in the *Daytime tariff* has the same conditions as the *No tariff* case. In the case with the *All hours tariff*, almost no violations occur even with a high penetration of EVs, which means that the number of violations is substantially lower in this case than in the other cases.

In general, more grid cells experience voltage violations than the two types of thermal violations. Voltage violations also occur at smaller fleet shares of EVs. The second-most-common type of violation is thermal violations in the transformer, while only a small share of grid cells experience thermal violations in the cables. Therefore, the trend for the results for any type of violation generally follows the trend seen for the voltage violations. However, there are exceptions. For example, with the *Logged charging* case when EV fleet shares are greater than 50% and smaller than 100%. In that range of fleet shares, the share of grid cells achieving any type of violation is larger than the share having voltage violations. This is due to a group of grid cells having a number of violations close to the threshold for a grid cell to be considered to have violations for both thermal violations in the transformer and voltage violations, meaning that the grid cells exceed the value for the threshold when all violation types are combined. This reveals a weakness for this type of figure, where a set limit is imposed as to when grid cells are considered to have a violation or not.

The severity of violations depends on both the amplitude (by how much the operational limits of the grid are exceeded) and the frequency (how often the operational limits are exceeded). Figure 13 indicates how the frequency of violations varies between the different cases at different shares of EVs in the vehicle fleet. It shows the average numbers of 15-minute timesteps that have a violation per grid cell, with the violations averaged across all grid cells and iterations with different randomizations of the addition of household and EV charging profiles. Figure 13a-c shows each type of violation separately, while Figure 13d shows all types of violations, i.e., thermal and voltage violations together (see Eq. [2] in **Paper IV**). A non-linear increase in the number of power system violations occurs with an increase in the share of EVs in the passenger vehicle fleet, regardless of the charging case. Figure 13 shows that the increase in the average number of timesteps with violations initially progresses slowly, whereas it accelerates as the fleet share increases.

When the increase in the share of grid cells with violations is small (Figure 12), although the number of violations increases in Figure 13, the increase in the number of violations occurs in grid cells that already have violations. This is seen, for example, between fleet shares of 75% and 125% with the *No tariff* case, where the number of violations increases in Figure 13d, while the increase in the share of grid cells with violations is much smaller in Figure 12d. In some grid cells, no power system violations occur even at high EV fleet shares.

The number of timesteps with violations averaged over all grid cells is the highest for voltage violations. However, as the number of grid cells achieving thermal violations in the transformer (Figure 12a) is substantially lower, the number of violations in the grid cells that exceed the transformer capacity is higher. This means that the voltage violations may be affecting more grid cells, but for the grid cells that see thermal violations, the number of violations is higher.

For the *No tariff* and *Daytime tariff* cases, the coincidence between EV charging and the residential load is low, whereas the coincidence of charging between vehicles is high, as they all act on the same price signal. This means that as the EV fleet share increases, the EVs introduce demand peaks to the grid. This explains why these cases show the strongest increases in both Figures 12 and 13 as the share of EVs in the vehicle fleet increases. The *Logged charging* case shows a lower coincidence between charging of the different vehicles, but a high coincidence with the household load. Because of this, the *Logged charging* case follows the trend seen in the *No tariff* and *Daytime tariff* cases as long as the household load is dominating in the grid. However, the low coincidence seen for EV charging means that the peaks from the EV charging are not as high for the *Logged charging* case, even with high shares of EVs.

The *Dynamic tariff* and *All hours tariff* cases have similar values for the number of violations, yet more grid cells are impacted in the *Dynamic tariff* case. This is due to many grid cells having a number of violations that are close to the threshold. This may have limited practical implications, as it is possible to have a loading of a grid component that is higher than the rated capacity for a limited time.

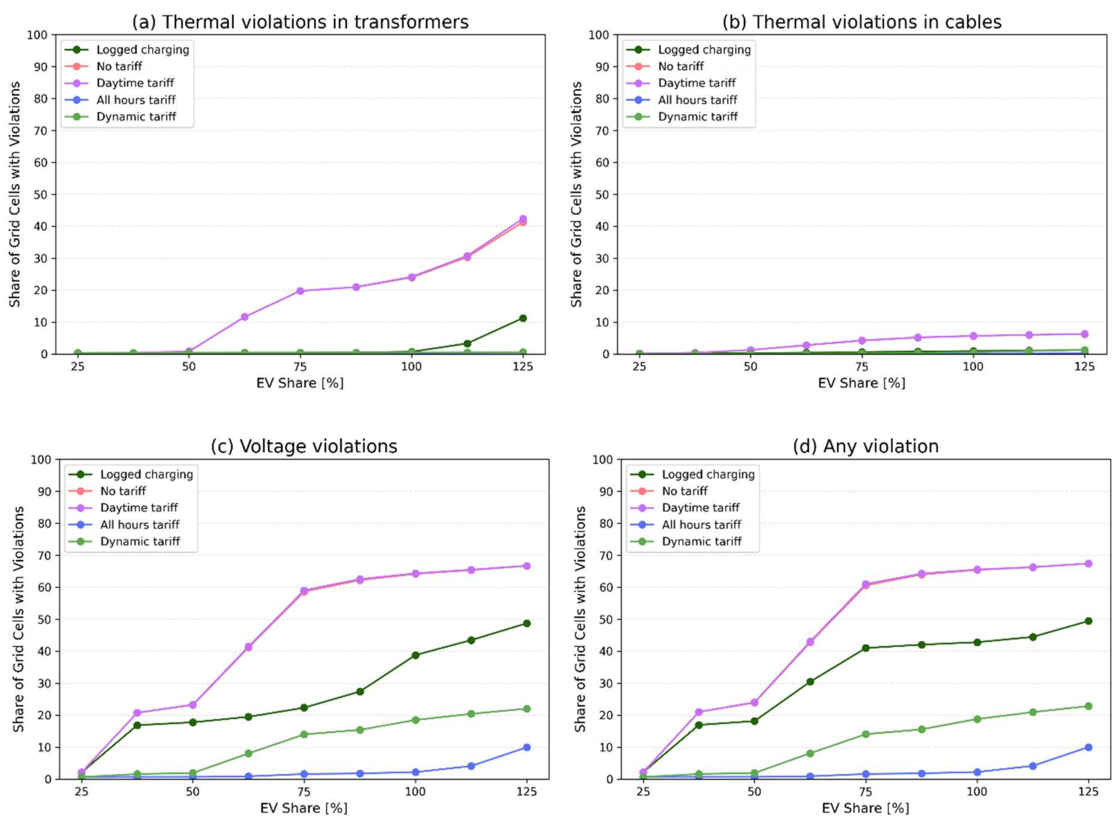

Figure 12. The shares of grid cells with power system violations for the different EV charging cases for the different shares of EVs investigated in this work. Both thermal and voltage violations are included. Whether or not a grid cell has a violation is defined by Eq. [3]. The results are from ***Paper IV*** *(subfigure (d), Logged charging, No tariff, and All hours tariff cases, although under different names, as declared in Table 2) and new results derived for this introductory essay [(a), (b), and (c), as well as Daytime tariff and Dynamic tariff in (d)].*

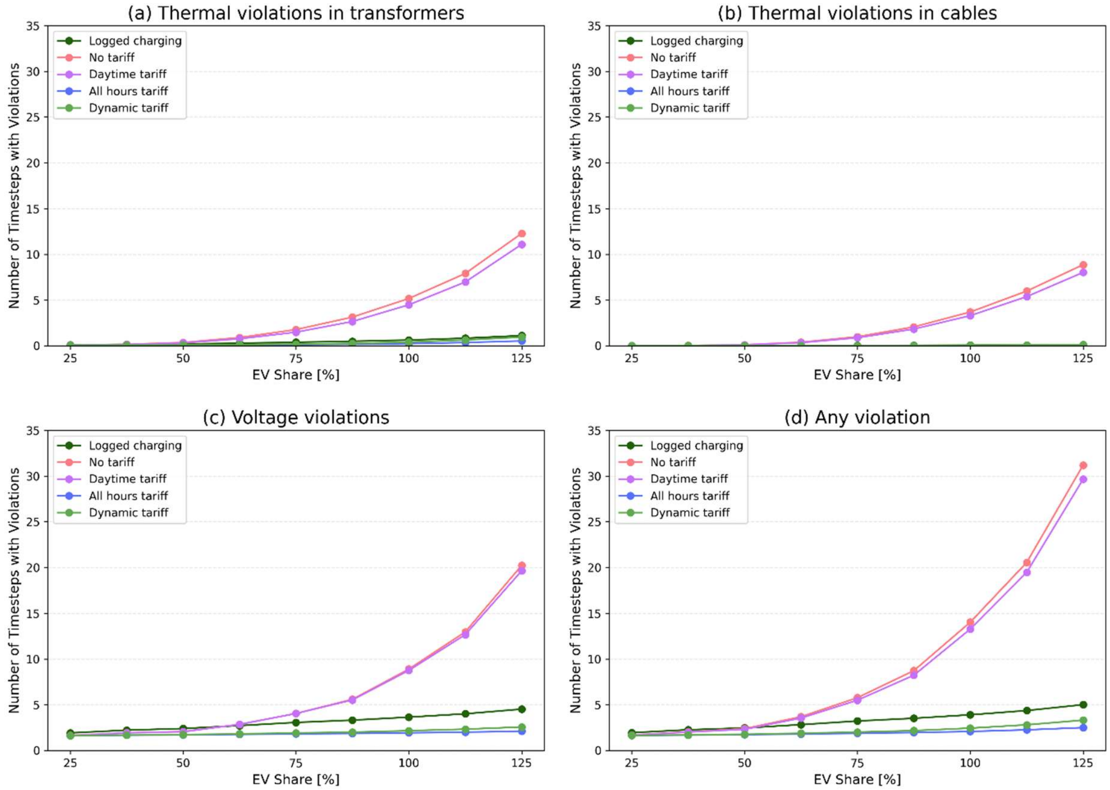

Figure 13. *The average numbers of 15-minute timesteps with power system violations per grid cell for the five charging cases and the different fleet shares of EVs (Eq. [2]). Shown are the averages over the numbers of iterations and cells. Both thermal and voltage violations are taken into consideration. The results are from* ***Paper IV*** *(Logged charging, No tariff, and All hours tariff cases, although under different names, as declared in Table 2) and new results derived for this introductory essay (Daytime tariff and Dynamic tariff).*

Figure 14 shows how the transformer loading changes associated with different EV fleet shares. For each grid cell, the maximum transformer loading in all iterations and timesteps is recorded, and the figure presents the values averaged across the grid cells. With low EV fleet shares, the highest maximum transformer loading is seen with the *Logged charging* case, since it has the highest coincidence with the household load. As the share of EVs increases, the highest transformer loading is seen with the *Daytime tariff* and *No tariff* cases. These cases are shown in **Paper III** to have a coincidence of EV charging that is substantially stronger than the other cases. This means that they are introducing large demand peaks due to the EVs concentrating their charging to the same timesteps due to low electricity spot prices.

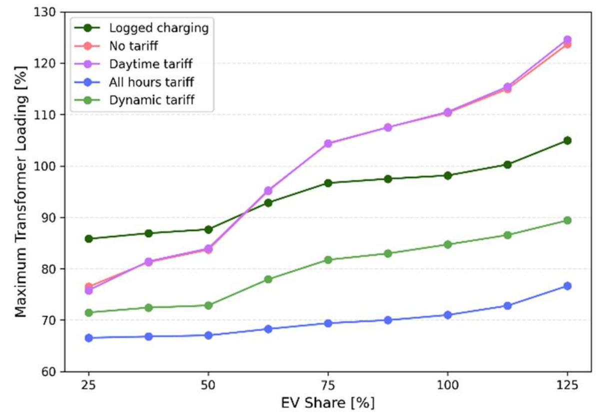

Figure 14. *Maximum transformer loading for the different charging cases and the different fleet shares of EVs. Shown are the maximum values in any iteration averaged over the grid cells.*

The work presented in **Paper IV** explores in greater detail the frequency and amplitude of the exceedances of grid capacity (compared to, for example, Zaferanlouei et al. [61] and Veldman et al. [37]). Thus, information other than that exceedances happen at certain levels of EVs in the vehicle fleet is available. This is a better starting point from which to explore the measures that could be taken to alleviate these issues.

Large differences in the loading of the LV grid are seen with the different cases, despite the household loads being the same in all the studied cases. This means that applying the appropriate power tariffs solely to the optimization of EV charging has the potential to reduce substantially the loading seen on the LV grid, regardless of its impact on the remainder of the household load. This is true when comparing to both the current logged charging patterns and to cost-minimized charging without a power tariff. However, the EV charging does not reduce the loading on the LV grid when optimized according to the *Daytime tariff*, which means that the choice of tariff design matters.

Since the results show that only optimizing the EV charging is sufficient to impact significantly the peak power asserted on the local grid, an alternative to imposing power tariffs on all household loads is to adopt an approach whereby EV charging is cheaper for the EV owner if an actor can control the charging so as to prevent it from introducing load peaks to the local grid. This would ensure that the loading on the grid is not increased by EV charging, while avoiding the need for each household to understand and act on a price signal. However, such a system could be viewed as intrusive, as the EV owner would cede control over the charging of their vehicle. Furthermore, it would not provide guidance for other household loads that may be flexible.

5.4 The need for grid reinforcements

In addition to mitigating the violations seen in the LV grid by altering the charging patterns for EVs using different price signals, the violations could be alleviated by grid reinforcements. To study the need for grid reinforcements, model runs with a fully electrified vehicle fleet (fleet share 100%) are studied for the different EV charging cases, to compare the need for exchanging components to accommodate the needed loads. Specifically, the needed transformer capacity is analyzed, and the need for additional transformers and replacement of transformers is quantified for each of the EV charging cases. Using the logic presented in Section 4.4, Table 3 shows an overview of the number of grid cells in need of increased transformer capacity, and some key values for the necessary replacements. As shown in the table, the load on the transformers in the LV grid caused by the introduction of EVs varies with the different EV charging cases. The number of transformers needed ranges between approximately 400 with the *All hours tariff* and 41,300 with the *Daytime tariff*. This means that there are substantial differences in the need for grid reinforcements between the different EV charging cases.

Figure 15 shows the estimated number of transformers of each size needed to reinforce the LV grid. Figure 15a shows the number of transformers, while Figure 15b shows the total capacity provided by each transformer size, with both having the different transformer capacities represented by different shades. From the figure, it can be concluded that the highest number of transformers and the highest total capacity are needed when EVs charge according to the *No tariff* case or *Daytime tariff* case. Although there is a greater need for transformers with small capacities in Figure 15a, the capacity provided by the larger transformers is greater in Figure 15b. The lowest number of transformers and the lowest capacity are needed in the *All hours tariff* case, followed by the *Dynamic tariff* case. When comparing Figure 15a and Figure 15b, it should be noted that the *Logged charging* scenario stands out in that it has a higher share of the total transformer capacity provided by transformers with low capacity.

When comparing the *All hours tariff* and the *Dynamic tariff*, both of which show low numbers of violations (Figure 13), the *Dynamic tariff* has a much higher number of grid cells in which the transformer capacity is exceeded to such a magnitude that the transformer needs to be replaced, according to Table 3. When comparing the total capacities for the new transformers, a smaller difference is seen. Combining this with the distribution between the capacities in Figure 15 for the two cases reveals that the higher number of transformers mainly consists of transformers with the two smallest capacities, while most of the grid cells that need larger transformers for the reinforcements do so in both cases. The high number of small transformers introduced is further underlined by the mean exceedance of transformer capacity (seen in Table 3) for the *Dynamic tariff* case, being the closest to the limit of 10% set in Section 4.4. This means that the results could be amenable to the logic used for deciding when transformers are replaced. This would be beneficial to explore further in future work, to ensure that the results are not sensitive to small changes in the limits set for when transformers are replaced. This becomes especially important when using a synthetic grid representation, as there are uncertainties related to the initial transformer estimations.

Table 3. *Key values for the extent of exceedance of transformer capacity in grid cells when using different charging strategies.*

	Logged charging	***No tariff***	***Daytime tariff***	***All hours tariff***	***Dynamic tariff***
Number of grid cells for which the transformer capacity needs to be increased	34,641	38,951	39,378	318	17,465
Share of grids for which the transformer capacity needs to be increased	33%	38%	38%	0%	17%
Exceedance of rated transformer capacity averaged over the grid cells in which the capacity is exceeded	24%	32%	33%	19%	13%
Number of new transformers added to reinforce the grid	34,777	40,837	41,293	372	17,559
Total capacity of new transformers [MVA]	1,900	6,680	6,784	320	984
Number of transformers replaced in the grid	17,371	8,018	8,492	15	23
Total capacity of transformers replacing others [MVA]	525	825	877	4	6

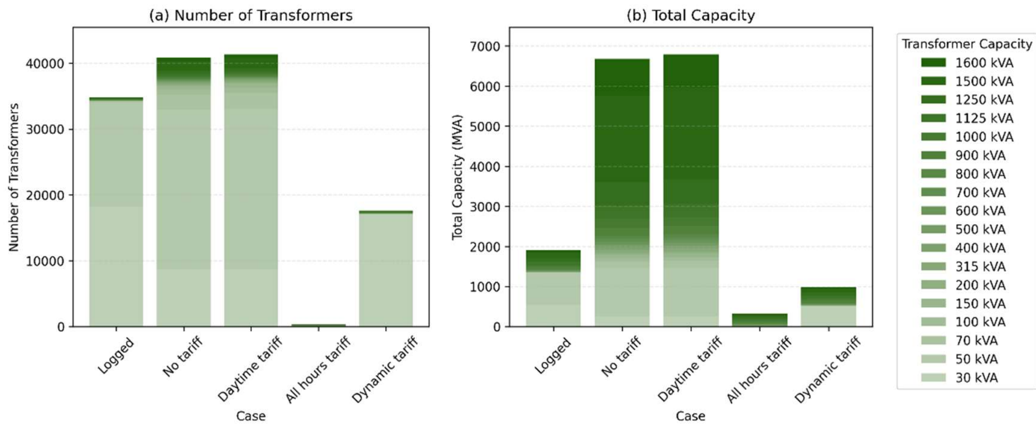

Figure 15. *Grid reinforcements needed due to the replacement or addition of transformers in terms of: (a) number of transformers of different capacities; and (b) total capacity in MVA added, both of which are per transformer capacity (which is shown in kVA).*

Although these results provide an initial estimation of the needed grid reinforcements in terms of what transformer capacity might be needed with respect to the loads introduced by EVs, more research is needed to identify the factors that drive the need for reinforcements. The numbers are rough estimates, highly dependent upon both the accuracy of the synthetic representation and the logic used to determine if additional transformer capacity is needed. Despite these weaknesses, they clearly indicate that the ways in which EVs are charged heavily influence the needed reinforcements.

5.5 How network tariff design impacts electric vehicle charging flexibility

The previous results on how the loading on the local grid varies with different power tariff designs is a consequence of that the power tariffs determine when it is cost-optimal to charge EVs. The loading on the grid varies between the power tariff cases, despite the spot prices for electricity being the same, showing that the power tariff design influences when it is cost-optimal to charge EVs. The *No tariff* case represents a case in which the vehicles can charge in a fully flexible manner from the energy system point of view, which is defined as adapting to times with low wholesale electricity prices. This means that the vehicles in this case contribute the most to balancing the demand and generation in the electricity price area. The difference in the cost of purchased electricity with and without power tariffs can, therefore, be seen as a proxy for the decreased flexibility in EV charging caused by the implementation of power tariffs, since it describes how the different tariff structures limit the possibilities for EVs to charge during periods with low electricity prices.

The distribution of the annual cost for purchased electricity for each EV is shown in Figure 16. The results are presented in **Paper III** and are obtained from running the EV charging model. Figure 16 only includes the purchase costs, i.e., those costs related to the spot price, so the results for the network tariff cost are not shown. The results shown are for Year 2024 and electricity price area SE3, and each subplot shows a different case. The mean cost of purchased electricity is shown as a dashed line. A large variation in the cost is evident across the different vehicles modeled. Figure 16 shows that the *All hours tariff* case limits to the greatest extent the possibility to charge at the lowest spot prices, making it the most-limiting scenario in terms of flexibility for the electricity system in a larger area. The second-most-limiting power tariff is the *Dynamic tariff*, although it does so to a significantly lesser degree.

The average annual cost of purchased electricity related to wholesale prices for Year 2024 is in the range of €7–€35 (excluding network tariffs and taxes), depending on the modeled case and electricity price area. Compared to the *No tariff* case, the average cost of purchased electricity is increased by: 220% in the *All hours tariff*; 105% in the *Dynamic tariff* case; and 45% in the *Daytime tariff* case. In absolute terms, the increases are in the range of €4–€25 per year, meaning that although the percentage increase is substantial, the costs are relatively low in absolute terms.

The results in **Paper III** show an average power tariff cost of €150–€160 per year and household, depending on the power tariff case applied. Further, consumer costs also include taxes. This means that the cost of purchased electricity represents a relatively small fraction of the total retail price of electricity. It should also be noted that in a real-world case, the cost of the power tariff would likely be substantially higher, due to the application of an average household load profile with lower peaks rather than an individual household profile. Furthermore, the network tariff in Sweden typically contains costs in addition to the power tariff, which are not included in this estimation. Moreover, the cost of purchased electricity is likely to be higher, to cover the costs and uncertainties for the electricity trading company.

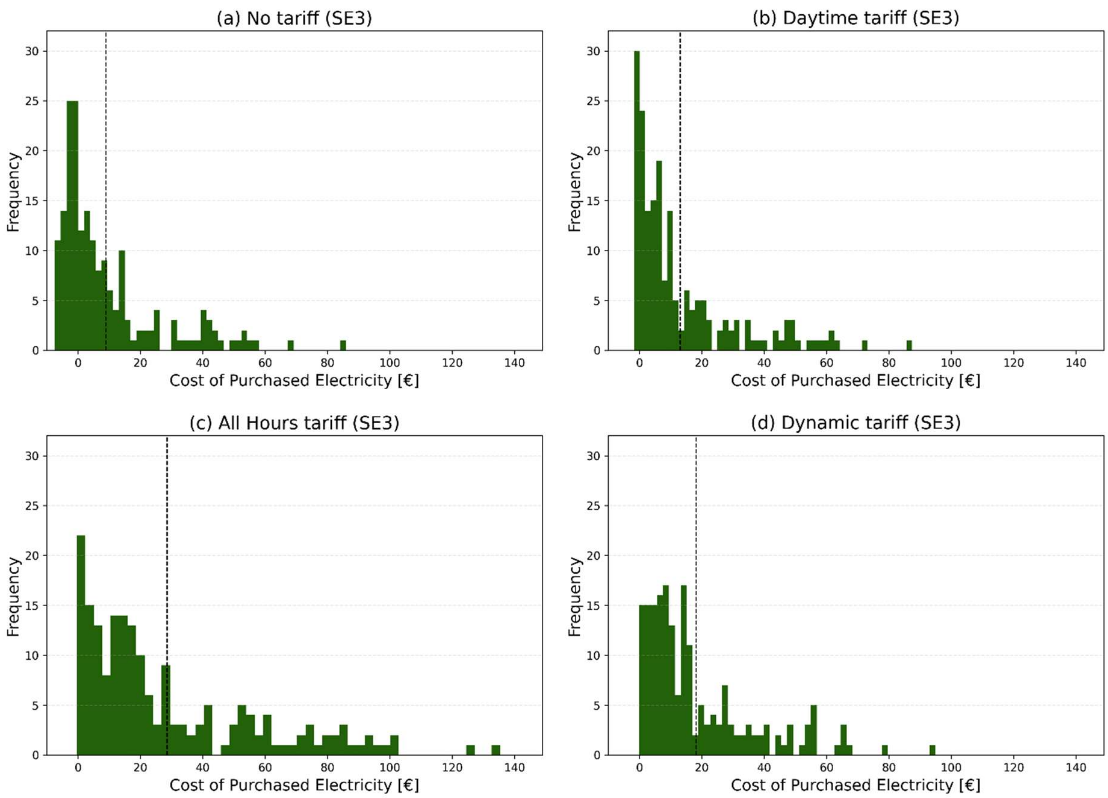

Figure 16. Distributions of the cost of purchased electricity for charging each EV in the different power tariff cases for one electricity price area (SE3) for Year 2024. The cost for an average vehicle is shown as a dashed line. Panels a-d show the different modeled cases. Source: ***Paper III.***

Cost-minimizing linear optimization, such as in the EV charging model, means decision-making as if one actor minimizes the total cost. As the reality consists of multiple actors making decisions based on more criteria than the cost, this might not produce realistic charging patterns. In order to further study charging behaviors, an alternative to this modeling approach might be to use an agent-based model, in which vehicle owners are treated as individual actors and can choose to charge or not based on a predefined set of criteria. The results from such modeling might be suitable for further exploring likely charging behaviors for vehicle owners and could therefore complement this study.

The EV charging model assumes perfect foresight, the absence of any behavioral constraints (other than whether or not the vehicle is at the home location), and no technical issues with, for example, the charging equipment. Furthermore, it requires no redundancy in the state of charge and assumes that the vehicle is always plugged in when parked at the home location. These are all factors that, if real conditions were instead considered, would limit the charging flexibility. Assuming perfect foresight means knowing exactly when and how much driving is going to happen, as well as the electricity prices for the whole modeling period showing perfect adaptation to the electricity prices. This is far from the current real-life situation, where, for example, only the coming day’s electricity prices are known. Owing to these limitations, it does not predict likely charging behaviors, rather it is an attempt to study which behaviors are incentivized by different cost structures.

Electricity price profiles are currently implemented as a fixed parameter, meaning that EV charging does not influence the electricity spot prices. In a situation where EVs are being implemented on a large scale, the vehicles' charging behaviors may influence the electricity spot price such that the price increases during current low-price hours to such an extent that EV charging is shifted to other hours. While this has not been considered in the current study, it warrants further exploration. However, as traditional loads and electrified industries are likely to be associated with much greater electricity demands in Sweden, the impact of this assumption is expected to be low.

Fully allowing vehicles to follow the electricity spot price, as in the *No tariff* case, induces large peaks to the LV grid, yet has the lowest purchase costs for electricity. This shows that there is a tradeoff between flexibility from the price area perspective and reducing the burden on the local grid. The exceedances of the current grid capacity seen when adding EV charging to the LV grid could be seen as constraints on charging flexibility or as an estimation of the needed reinforcements to the grid that would allow for the load seen with flexible EV charging fully driven by differences in the spot price of electricity. The implemented power tariffs restrict the flexibility seen with EV charging, thereby hindering the ability to adapt EV charging to, for example, the availability of renewable electricity generation. An alternative could be to reinforce the grid to allow for the larger power peaks seen when EVs charge flexibly. Therefore, an interesting area of future study could be to quantify further the economic and environmental burdens of expanding the distribution grid, as compared to the benefit of providing flexible loads.

5.6 Limitations of the modeling framework used for studying direct electrification

Models, such as those used in this thesis, use imperfect assumptions to simplify the real-world systems that they aim to represent. Using a synthetic grid representation, for example, comes with certain advantages and drawbacks. The use of a synthetic grid representation allows for grid simulation in those cases where detailed information on the state of the grid is not publicly available. However, when possible, more-accurate results will naturally be achieved with real grid capacities. This means that a model such as REGAL can provide initial indications as to where and when problems will occur in the grid when adding, for example, EV charging (as is done in this work), although the model will seldom make predictions that are accurate for a small geographic area (such as 1 km^2).

The development of the REGAL model described in this thesis involves validation of the model against the calibration dataset with information provided by electricity grid operators. Validation was carried out on both the grid cell level and on groups of grid cells. For a given population density, some grid cells will have a larger transformer capacity in the REGAL model than is evident from the data provided by the grid operators, and some grid cells will have a smaller capacity. When the transformer capacity in the model is smaller than in reality, the average number of timesteps with violations will be overestimated, whereas in a grid cell with a larger transformer capacity, the average number of timesteps with violations will be underestimated. As the dimensioning of transformers has been calibrated to have a close-to-zero deviation, while ensuring that the errors are as small as possible on the grid cell level, this issue could, to some degree, cancel itself out. Although the grid capacities derived from the REGAL model have been validated and calibrated on a general level, the level of accuracy on a cell level remains low (as can be seen in **Paper II**). This means that the estimations of violations at the cell level might be inaccurate. This increases the uncertainty linked to the estimations of violations, as compared to using the real grid capacities and loads in an area. However, the methodology was chosen because it enables an overview of the issues that are likely to arise as the vehicle fleet is electrified. As shown in

Paper IV, the regionally distributed input data vary significantly between different grid cells, which means that the conclusions drawn from the modeling of a smaller geographic area might not be transferable to other regions. Thus, being able to model an entire county also comes with advantages when the goal is to study general trends.

Papers II and **IV** place little emphasis on the estimations of cable capacities and the associated violations. This is due to two things: first and most importantly, few violations are seen due to thermal limitations in the cables. Second, the cable calibration data are less-descriptive for both the used cable capacities and topology. For these reasons, the model accuracy cannot be determined with the same precision as for the transformers. Cables have been calibrated to have an accurate distribution between the selected cable capacities and the amounts of each cable capacity. Furthermore, the per-cell data for the longest feeder, the number of feeders, and the number of parallel cables have been compared to examples from real grids. This means that, although the accuracy has not been quantified to the same extent as for the number of transformers and the transformer capacities, the assumptions in the model have been compared to real-world data and have been found to be reasonable estimates. To develop the estimations of grid topology further, it may be possible to develop the model using GIS data to adapt the synthetic grid topology to the existing road infrastructure, such as the road network, or the locations of buildings.

The version of the REGAL model used in this work only considers residential loads, which is a weakness of the model. This means that neither commercial nor industrial loads are included. However, further work is being undertaken to expand the model to include these loads. Nonetheless, the presented model version was deemed sufficient to answer the studied questions, as home charging is by definition introduced in homes. However, dimensioning the grid exclusively for residential loads means that the model does not take into account the spare transformer capacity linked to commercial or industrial needs. Excluding these loads may overestimate or underestimate the available grid capacity, depending on the coincidence of EV charging and the loads not included in the model.

The optimization of EV charging in the EV charging model (later added to the REGAL model) is performed with a general household load profile, rather than the load of a specific house to which the EV is added. This has the benefit that it is necessary to run the EV charging model only once, which allows each vehicle to prioritize charging during times when the loads placed on the local grid are likely to be high. However, it has the drawback that the EV charging might not be well-adapted to the specific household to which it is added. Furthermore, the EV charging profiles do not consider the grid connection size of a home. As houses typically have a fixed fuse size for their connection to the electricity grid, and there are EV chargers that can take this into account, the present work may have overestimated the maximum power levels of individual households when adding EV charging. Thus, allowing for the integration of individual household loads and EV charging into the optimization would increase the accuracy of the results, albeit at the expense of dramatically increased computational time.

Using the logged EV data to create charging profiles and implementing them throughout Sweden entails assuming that they are representative of households that do not have an EV at the present time. As the survey of the vehicle owners shows that the EVs in the study are mostly used either as the household's only vehicle or its primary vehicle, this may not reflect accurately a secondary vehicle in the household. As many of the grid cells in the REGAL model have more than one vehicle per household, this might not be representative. Although the EV fleet share has increased in the past year, EVs are not the dominant technology with respect to cars. Therefore, the people who are choosing to own an EV might not be representative of the general population. For example, they may have a driving or charging behavior that is different from those who do not choose to own an EV.

As there are violations seen in this study that are due to voltage drops below the given thresholds, a limitation of the study is that no residential solar PV generation is included in the model. As local electricity production within a grid cell, most commonly achieved through the installation of solar PV, increases the voltage, the inclusion of solar PV in the model could alleviate some of the voltage violations seen in this study. It is not obvious how to represent solar PV in the model, since it is obviously not known which households within a grid cell will install solar PVs. Thus, it might be necessary to perform multiple iterations with PV installments being introduced for different customers in the LV grid when assessing the violations; however, this would drastically increase the computational time and model complexity. Similar benefits could be achieved through bidirectional charging, as this could also feed electricity back into the LV grid. In order to alleviate grid stress, this would require communication between the grid operator and the system that controls EV charging. It would be beneficial to explore this in a future study; however, it might require more-complicated control algorithms for charging and optimization within the grid simulation, thereby significantly increasing the computational complexity.

5.7 What to consider when designing a power tariff

There is a need for DSOs to collect the revenue needed to operate, maintain, and expand the local grid. If the costs are to be paid by the customers using this grid, the costs must somehow be distributed between different customers. In this context, three different principles are described in Section 2.3: fixed tariffs (where the cost is independent of the variations in the customer's electricity consumption); volumetric tariffs (where the cost depends on the level of energy consumption); and power tariffs (where the cost depends on the peak power level of the customer).

Optimality is subjective, as a tariff could be evaluated based on a number of factors, such as its transparency, whether it is non-discriminatory, how cost-reflective it is, its predictability, its simplicity, if it leads to efficient network use, and how much it restricts freedom as to when electricity is used. Depending on which actor is considered, the degrees of importance of these factors might vary substantially. Furthermore, the definition of when these factors are met can vary. For example, what is considered a fair distribution of costs between customers may vary between different customer groups. In addition to this, some of the factors could be contradictory.

For customers who have a low electricity demand, the peak power could easily be determined by a few unusual events during which multiple appliances are used within a short timeframe. Thus, it matters over what timeframe the peak is measured. For example, the hourly peak is likely to be substantially lower than the peak measured over intervals of 10 minutes or shorter. Most of the current power tariffs mapped out in **Paper III** use an average of the peaks that occur at different times, for example, an average of the three highest peaks on an hourly basis that occur on three different days. The more peaks that are included and the longer the timespan over which they are measured, the less severely they are impacted by short-term events. The variability for low-demand customers could be tackled by either including a peak power level under which no cost is asserted, or by applying a lower cost up to a certain power level. Such a system is being implemented in Finland, where only the peak power above 8 kW is subject to a power tariff [90]. Another possible solution might be to introduce a progressive cost, although this might be more complex for customers to understand.

Another aspect of fairness is that many actions aimed at reducing the peak power may be associated with significant investment costs. This may mean that low-income households have no choice but to stay with expensive technologies, such as direct heating, because the investment cost for an alternative technology, such as a heat pump, may be too high. This means that there is a risk that low-income households will be charged higher power tariff costs than households with higher incomes. Therefore, if the desired outcome is for the peak power asserted on the local grid to decrease, there may be a need for complementing policies that target energy efficiency measures for low-income households. This has been highlighted by Schittekatte and Meeus [91] in their evaluation of distribution tariff designs. They wrote that "There is a fear that active consumers investing in distributed energy resources (DER) might benefit at the expense of passive consumers" [91]. As different types of customers may have different levels of flexibility, some may have an easier time being active customers. For example, Göteborg

Energi Nät AB has an exemption from their power tariff for apartment-dwelling customers, as they have been identified as currently having a weaker possibility to shift their loads, such that power tariffs are not expected to impact their peak demand [92]. The large differences in loads on the LV grid seen in this study, despite only EV charging being controlled, may indicate that it is sufficient to assign a power tariff to specific loads that are flexible.

In Sweden, power tariffs have been introduced at large scale over the past few years (as can be seen in the summary of current tariffs presented in **Paper III**). The rollout has been rapid, with several of the tariff designs shifting the major pricing mechanism to peak power in a single instance. This goes against the recommendation of graduality set out by Brown et al. [74], and could be part of the explanation for the numerous critical articles and letters to the editor in newspapers describing how customers are surprised or angered by increased tariff costs, or do not understand why the cost for the network tariff can be high at times when wholesale prices are low (some examples can be found in [93–98]). In March 2026, the government announced that they are planning to change the current policy so that power tariffs will no longer be mandatory from the start of 2027 [99]. They have asked the Energy Markets Inspectorate to propose a new recommendation for tariff design that makes tariffs more similar between different regions, and that is simple, fair, and transparent. The government decision suggests there may be reason to exclude customers with a low electricity demand [99].

In the past few months, after the writing of **Paper III**, some new power tariffs have been introduced or announced by DSOs in Sweden in addition to the ones reviewed in the paper. Although most tariffs are based on the monthly peak power, E.ON have announced that their new power tariff will be based on the daily peak power during daytime in winter [100], thereby likely shifting the incentive from pushing down the extreme peaks within the month to moving daily loads to times outside their definition of daytime. Although this might not allocate costs between consumers according to their impact on the grid as effectively as having a tariff on a monthly basis, Saele [68] has proposed that it may be easier to understand for customers. Another recent example is a pilot study conducted in Gotland, in which nodal pricing is tested in a part of the local grid. They are currently trying an implementation in which the network tariff is differentiated both in time and between different transformer stations [101]. The pilot includes five substations that include both residential and commercial customers, and is looking at how customers react to a bi-hourly price signal, published the day before, describing the predicted local loading on the grid [101]. This could be seen as implementation of a dynamic tariff. The design is being constantly evaluated, and results from the pilot are expected to be published during 2026.

The reason to include a network tariff in the REGAL model, as performed in this work, is to generate a general price signal for the actors connected to the grid, so as to lower the peak power imposed on the LV grid without communicating with all the individual actors. Including this in the optimization alongside the electricity spot price means that the EV charging model incorporates the tradeoff between buying cheap electricity and having a low peak power in the household. **Paper III** shows that the cost related to the power tariff is much higher than the cost of the purchased electricity, which means that the cost-minimization in the EV charging model primarily focuses on keeping the peak power low and then, within that limit, minimizing the cost of purchased electricity. From the results of this study, it seems that some power tariff designs successfully mitigate the creation of new load peaks and avoid unnecessary stresses in the LV grid. However, some of these designs do so at the cost of the flexibility that EVs could provide to the electricity system.

El Gohary et al. [70] have shown that there are temporal gaps between when the individual peak powers of households and the system aggregated load peak occur. This is further strengthened by the differences seen between the *All hours tariff* and *Dynamic tariff* cases studied in this work. This means that a power tariff imposed at the household level that has the same cost at all hours that are included in it may limit the flexibility of households at times when the grid is not congested. From the system perspective, there may be times when the desired response from customers in the grid is counteracted by power tariffs.

For example, if the frequency or local voltage in the grid increases, the desired reaction could be to increase the load from EVs and other flexible loads to alleviate the stress on the grid. As the power tariffs, except for the *Dynamic tariff* case, do not vary in line with the current grid condition, but instead discourage the increase in peak power, they would then counteract the desired behavior. Inflexible power tariffs may encourage customers to maintain a low peak power even during hours when the grid is not congested, thereby limiting the flexibility of variable loads, even when doing so does not alleviate grid stress. An alternative would be to create a price signal that communicates to the customers to lower their peak power only during times that are critical. However, that may be both more complicated to implement for the grid operator and difficult for the customers to comprehend.

The previous studies of demand responses to network tariffs presented in Section 3.4 show that customers in general display a weak response to network tariffs despite the cost being high. However, as Zoest et al. [71] have identified flexibility and intermittency of load as determining whether adaptation to power tariffs occurs, it seems likely that EV charging could be a load that is more adapted to network tariffs. Furthermore, most of the studies presented here use historical load data. As digitalization and automatization progress, the possibility emerges for more-advanced control mechanisms to steer the electricity demand going forward. Removing the need for manual control has the potential to strengthen further the flexibility of electricity use. This could mean that the response to the price signal is bolstered. In such a case, aligning price signals with the desired behavior (and studies such as the present one) increases in importance. After approximately one year with power tariffs for all hours, the DSO Ellevio claims that they have seen a reduction in the peak load in the local grids of 2%–3%[102]. They claim that their customers with EVs have lowered their peak load even more [102]. They report that a majority of their customers have the same tariff costs as with the previous pricing mechanism, although reallocation between some of the customers has been seen [102].

The network tariffs studied in this thesis are found to heavily influence the cost-optimal charging of EVs. Applying the network tariff to the optimization of EV charging is seen to have a strong impact on the loading imposed on the local grid, despite other household loads being fixed. It is shown that the cost for the network tariff is much greater than the cost for purchasing electricity, which means that the price signal of network tariffs is strong. Creating an optimal tariff that reduces the burden on the local grid is not a simple task, as it should provide a fair distribution of costs between customers, yet be simple enough for customers to understand and act upon. Furthermore, it should signal when action is and is not needed, avoiding limiting electricity usage at times when the grid is not congested. In addition to the tariff design, the rate of implementation and complementary subsidies should be considered, to enable customers to act on the price signal. Therefore, it remains important to evaluate continuously the network tariffs from the perspectives presented in this thesis, as new models for network tariffs are introduced.

6 Conclusions

The work of this thesis analyzes the interactions between electricity and transportation systems as transportation becomes increasingly electrified. It focuses on exploring the infrastructure required for the indirect electrification of heavy transportation and the direct electrification of passenger vehicles. Multiple models have been developed and applied to study the impacts on the infrastructural requirements for hydrogen supply systems and the electricity grid capacity needed for home charging of EVs.

Three hydrogen supply systems were compared, to gain insights into the cost of supplying hydrogen to refueling stations. The model results show LCOH values in the range of 2.2–6.7 €/kgH_2 in Sweden. The lowest cost is achieved with the decentralized grid-connected supply system, and the highest cost is achieved with the decentralized standalone system not connected to the electricity grid. From the comparison of the decentralized and centralized grid-connected hydrogen supply systems, it can be concluded that, with the given assumptions, a centralized production system is approximately 30%–40% more expensive than a decentralized grid-connected system in Sweden. Although slightly lower costs for hydrogen production and storage are achieved in the centralized system, the additional cost for hydrogen transport to the refueling station results in a higher total cost. Thus, the higher cost for hydrogen transport offsets the advantage of having access to large-scale hydrogen storage. It should be noted, however, that the results from the optimization model show the lowest possible cost with the given input data, meaning that the actual costs are likely to be higher than the model results.

The work on direct electrification of transport focuses on the modeling of home charging of passenger EVs. In this work, a method for modeling how EV charging impacts the LV grid using open data was developed, resulting in the REGAL model. The REGAL model was presented and validated against a large dataset of real-world grid capacities. Thus, this study shows that open data describing the population and distribution of dwellings in Sweden can be used to estimate the electricity grid capacities for the entire residential LV grid. In addition, a cost-minimizing linear optimization model for the home charging of EVs was developed and applied to study how different network tariff designs impact the cost-optimal charging of individual EVs and household peak power demand. In particular, network tariffs based on peak power, also known as 'power tariffs', were considered. This model was also used to generate EV charging profiles that were subsequently used to represent EV charging in the REGAL model.

The influences of different power tariff designs on the cost-optimal home charging of individual EVs and household peak power demand were modeled and compared to the logged charging of 188 EVs. The power tariff designs considered were: (i) no power tariff; (ii) a monthly cost for household peak power; (iii) a cost for monthly household peak power during daytime; and (iv) a dynamic tariff based on the monthly combined peak power of all households. The results show that power tariffs significantly influence when in time and to what extent it is cost-optimal to charge EVs, indicating that power-based tariffs can be an effective tool for managing the loads of LV electricity grids. The results obtained from running the different cases in the REGAL model show that fully electrifying the vehicle fleet increases the peak power exerted on the LV grid in all cases: by 51% in the Logged charging case; by 73% with no power tariff or a daytime power tariff; by 30% with a dynamic power tariff; and by 10% with the power tariff on the household level active all hours of the day, on average. These findings suggest that tariff design plays a critical role in aligning EV charging with grid capacity, especially if a larger proportion of the EV owners deploy charging strategies to lower their charging costs.

The results show that there is an increase in the number of power system violations (defined as exceeding the operational limits in terms of thermal capacity and voltage magnitude) in an LV grid that has an increased share of EVs in the vehicle fleet. Initially, the increase in the number of violations with increased fleet share proceeds slowly, though the larger the share of EVs in the vehicle fleet, the greater the increase in the number of violations for each additional vehicle. The number of timesteps with violations varies significantly across different geographic regions in Sweden and across the different EV charging cases. Even with a high level of EV penetration, some grid cells have no violations, while in other grid cells, violations are recorded already at small EV fleet shares. Because how EVs are charged was found to heavily impact the loading on the LV grid, the required transformer capacity and thus the extent of LV grid reinforcement varies significantly with the adopted EV charging strategy under a fully electrified vehicle fleet.

It is shown here that the design of the power tariff impacts the flexibility that EV charging can contribute to the electricity system by adapting charging to times with low wholesale prices of electricity. The power tariff on a household level that includes all hours of the day retains lower flexibility of EV charging compared to the other cases. The highest flexibility in EV charging is seen with the case with no power tariff, and the case with a tariff during the daytime. Combining the results presented in this thesis, a tradeoff can be identified between adapting EV charging to low electricity spot prices and lowering the loading on the LV grid. In general, a power tariff that includes all hours of the day lowers the loading on the LV grid the most, although it achieves less flexibility, and a power tariff that includes fewer hours imposes a higher loading on the LV grid, but also greater flexibility with respect to EV charging. The dynamic tariff provides an alternative that lowers the loading on the grid, yet retains greater flexibility than the power tariff for all hours on a household level.

7 Future work

The integration of electricity and transportation systems is a complex topic, with many issues remaining to be explored in future research studies. Some potential aspects for future research that have been identified during this work are presented below.

- For hydrogen supply systems, the next step in this work is to study sector coupling with industrial applications of hydrogen, to investigate the extent to which production and storage units could be shared. In addition, one could look at what the supply systems for multiple refueling stations might look like, and how optimization is impacted by studying different scopes, such as comparing the optimization of implementation of one and several refueling stations or of a country and a continent. If adopting a larger geographic scope, it would be beneficial to consider also the locations of refueling stations in relation to each other and to road networks.
- The REGAL model could be improved in several ways. It could be expanded to include more loads and more-detailed input data. For example, GIS data could be used to adapt the synthetic grid topology to the existing road infrastructure, such as the road network, or the locations of buildings. Another strategy would be to expand the model to include commercial loads. In addition, the model could be expanded to include more technologies, such as stationary batteries or solar PV. Technologies that inject electricity to the grid could raise the voltage thereby balancing the voltage drops seen due to EV charging.
- The modeling of EV charging in this thesis has been limited to a specific charging power and EV charging based on a limited number of strategies. One way to improve the work could be to study in greater detail how different charging powers affect the EV charging patterns and their impacts on the local grid. Furthermore, EV charging strategies that involve factors other than cost-minimization could be incorporated into the REGAL model to investigate how they impact the LV grid. There might also be benefits associated with introducing cases in which different charging scenarios are combined, to examine their impacts. Although charging is assumed to be unidirectional, it is also possible that V2X would impact both the peak power of households and the loading imposed on the local grid.
- Electrification as a strategy to reduce environmental burden involves transitioning from a fuel-driven system to a material-driven system. The overarching idea is that the tradeoff between the increase in material use and the decrease in fuel use will reduce pressures on ecological systems. However, there are many driving forces and multiple usage patterns, as well as several assumptions that influence the estimations of environmental pressures and their eventual impacts. While these are not evaluated in this work, their existence and the need for further analysis are important to bear in mind and appreciate before drawing conclusions as to which system *should* be developed or which technologies are most-suitable overall.

References

1. European Commission: Shedding light on energy in Europe – 2025. (2025)
2. European Environment Agency: New registrations of electric vehicles in Europe, https://www.eea.europa.eu/en/analysis/indicators/new-registrations-of-electric-vehicles
3. Iea: Transport, (2021)
4. Marchenko, O. V., Solomin, S. V.: The future energy: Hydrogen versus electricity. Int. J. Hydrogen Energy. 40, 3801–3805 (2015). https://doi.org/10.1016/J.IJHYDENE.2015.01.132
5. Samsun, R., Rex, M., Antoni, L., Stolten, D.: Deployment of Fuel Cell Vehicles and Hydrogen Refueling Station Infrastructure: A Global Overview and Perspectives. Energies (Basel). 15, 4975 (2022). https://doi.org/10.3390/en15144975
6. Aryanpur, V., Rogan, F.: Decarbonising road freight transport: The role of zero-emission trucks and intangible costs. Sci. Rep. 14, 2113 (2024). https://doi.org/10.1038/s41598-024-52682-4
7. European commission, European Alternative Fuels Observatory: European Union (EU27): Vehicles and fleet, https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road/european-union-eu27/vehicles-and-fleet
8. Iea: Trucks and buses, https://www.iea.org/energy-system/transport/trucks-and-buses
9. European Environment Agency: New registrations of electric cars in Europe, https://www.eea.europa.eu/en/analysis/indicators/new-registrations-of-electric-vehicles
10. Swedish Energy Markets Inspectorate: Sammanställning av innehållet i distributionsnätsföretagens nätutvecklingsplaner. (2025)
11. Swedish Energy Markets Inspectorate: Measures to increase demand side flexibility in Swedish electricity system - Abbreviated version. (2017)
12. Swedish Energy Markets Inspectorate: Utvecklingen av smarta elnät - Nationell rapport för Sverige 2025. (2026)
13. Iea: The future of hydrogen. (2019)
14. Moriarty, P., Honnery, D.: Prospects for hydrogen as a transport fuel. Int. J. Hydrogen Energy. 44, 16029–16037 (2019). https://doi.org/10.1016/j.ijhydene.2019.04.278
15. European Commission: A hydrogen strategy for a climate-neutral Europe. , Brussels (2020)
16. Li, S., Kang, Q., Baeyens, J., Zhang, H.L., Deng, Y.M.: Hydrogen Production: State of Technology. In: IOP Conference Series: Earth and Environmental Science (2020)
17. Abdalla, A.M., Hossain, S., Nisfindy, O.B., Azad, A.T., Dawood, M., Azad, A.K.: Hydrogen production, storage, transportation and key challenges with applications: A review. Energy Convers. Manag. 165, 602–627 (2018). https://doi.org/10.1016/J.ENCONMAN.2018.03.088
18. Acar, C., Dincer, I.: Comparative assessment of hydrogen production methods from renewable and non-renewable sources. Int. J. Hydrogen Energy. 39, 1–12 (2014). https://doi.org/10.1016/J.IJHYDENE.2013.10.060
19. The Swedish Environmental Protection Agency: Vätgastankstationer, https://www.naturvardsverket.se/amnesomraden/klimatomstallningen/klimatklivet/vatgas/vatgastankstationer/

20. Svenska kraftnät: Sveriges elnät, https://www.svk.se/om-kraftsystemet/oversikt-av-kraftsystemet/sveriges-elnat/

21. Söder, L., Ghandhari, M.: Static Analysis of Power Systems. Electric Power Systems Royal Institute of Technology (2015)

22. Gasparella, A., Koolen, D., Zucker, A.: The Merit Order and Price-Setting Dynamics in European Electricity Markets. (2023)

23. Swedish Energy Markets Inspectorate R2021:08: Sweden's electricity and natural gas market, 2020. , Eskilstuna (2021)

24. Statistics Sweden: Distribution of electricity contracts by bidding zone and contract type. Month 2013M04 - 2025M09, https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__EN__EN0301__EN0301A/SSDManadElAvtalstyp

25. ACER: Getting the signals right: Electricity network tariff methodologies in Europe. , Ljubljana (2025)

26. Siyal, S.H., Mentis, D., Howells, M.: Economic analysis of standalone wind-powered hydrogen refueling stations for road transport at selected sites in Sweden. Int. J. Hydrogen Energy. 40, 9855–9865 (2015). https://doi.org/10.1016/j.ijhydene.2015.05.021

27. Tang, O., Rehme, J., Cerin, P.: Levelized cost of hydrogen for refueling stations with solar PV and wind in Sweden: On-grid or off-grid? ENERGY. 241, (2022). https://doi.org/10.1016/j.energy.2021.122906

28. Janssen, J.L.L.C.C., Weeda, M., Detz, R.J., van der Zwaan, B.: Country-specific cost projections for renewable hydrogen production through off-grid electricity systems. Appl. Energy. 309, 118398 (2022). https://doi.org/10.1016/J.APENERGY.2021.118398

29. Nugroho, R., Rose, P.K., Gnann, T., Wei, M.: Cost of a potential hydrogen-refueling network for heavy-duty vehicles with long-haul application in Germany 2050. Int. J. Hydrogen Energy. 46, 35459–35478 (2021). https://doi.org/10.1016/j.ijhydene.2021.08.088

30. Southall, G.D., Khare, A.: The feasibility of distributed hydrogen production from renewable energy sources and the financial contribution from UK motorists on environmental grounds. Sustain. Cities Soc. 26, 134–149 (2016). https://doi.org/10.1016/j.scs.2016.05.009

31. Gökçek, M., Kale, C.: Optimal design of a Hydrogen Refuelling Station (HRFS) powered by Hybrid Power System. Energy Convers. Manag. 161, 215–224 (2018). https://doi.org/10.1016/J.ENCONMAN.2018.02.007

32. Perna, A., Minutillo, M., di Micco, S., Jannelli, E.: Design and Costs Analysis of Hydrogen Refuelling Stations Based on Different Hydrogen Sources and Plant Configurations. Energies (Basel). 15, 541 (2022). https://doi.org/10.3390/en15020541

33. Nistor, S., Dave, S., Fan, Z., Sooriyabandara, M.: Technical and economic analysis of hydrogen refuelling. Appl. Energy. 167, 211–220 (2016). https://doi.org/10.1016/J.APENERGY.2015.10.094

34. Ulleberg, Ø., Hancke, R.: Techno-economic calculations of small-scale hydrogen supply systems for zero emission transport in Norway. Int. J. Hydrogen Energy. 45, 1201–1211 (2020). https://doi.org/10.1016/J.IJHYDENE.2019.05.170

35. Toktarova, A.: Electrification of the basic materials industry, (2023)

36. Luthander, R., Shepero, M., Munkhammar, J., Widén, J.: Photovoltaics and opportunistic electric vehicle charging in the power system – a case study on a Swedish distribution grid. IET Renewable Power Generation. 13, 710–716 (2019). https://doi.org/10.1049/iet-rpg.2018.5082

37. Veldman, E., Verzijlbergh, R.A.: Distribution Grid Impacts of Smart Electric Vehicle Charging From Different Perspectives. IEEE Trans. Smart Grid. 6, 333–342 (2015). https://doi.org/10.1109/TSG.2014.2355494

38. Amme, J., Pleßmann, G., Bühler, J., Hülk, L., Kötter, E., Schwaegerl, P.: The eGo grid model: An open-source and open-data based synthetic medium-voltage grid model for distribution power supply systems. J. Phys. Conf. Ser. 977, 012007 (2018). https://doi.org/10.1088/1742-6596/977/1/012007

39. Hartvigsson, E., Odenberger, M., Chen, P., Nyholm, E.: Generating low-voltage grid proxies in order to estimate grid capacity for residential end-use technologies: The case of residential solar PV. MethodsX. 8, 101431 (2021). https://doi.org/10.1016/J.MEX.2021.101431

40. Nacmanson, W.J., Zhu, J., Ochoa, L.: Milestone 6: Network Modelling and EV Impact Assessment. , Melbourne (2021)

41. Unterluggauer, T., Hipolito, F., Rich, J., Marinelli, M., Andersen, P.B.: Generation of low-voltage synthetic grid data for energy system modeling with the pylovo tool. Sustainable Energy, Grids and Networks. 41, 101617 (2025). https://doi.org/10.1016/j.segan.2023.101085

42. Mateo Domingo, C., Gomez San Roman, T., Sanchez-Miralles, A., Peco Gonzalez, J.P., Candela Martinez, A.: A Reference Network Model for Large-Scale Distribution Planning With Automatic Street Map Generation. IEEE Transactions on Power Systems. 26, 190–197 (2011). https://doi.org/10.1109/TPWRS.2010.2052077

43. Gonzalez-Sotres, L., Mateo Domingo, C., Sanchez-Miralles, A., Alvar Miro, M.: Large-Scale MV/LV Transformer Substation Planning Considering Network Costs and Flexible Area Decomposition. IEEE Transactions on Power Delivery. 28, 2245–2253 (2013). https://doi.org/10.1109/TPWRD.2013.2258944

44. Mateo, C., Postigo, F., de Cuadra, F., Roman, T.G.S., Elgindy, T., Dueñas, P., Hodge, B.-M., Krishnan, V., Palmintier, B.: Building Large-Scale U.S. Synthetic Electric Distribution System Models. IEEE Trans. Smart Grid. 11, 5301–5313 (2020). https://doi.org/10.1109/TSG.2020.3001495

45. Pisano, G., Chowdhury, N., Coppo, M., Natale, N., Petretto, G., Soma, G.G., Turri, R., Pilo, F.: Synthetic Models of Distribution Networks Based on Open Data and Georeferenced Information. Energies (Basel). 12, 4500 (2019). https://doi.org/10.3390/en12234500

46. Umoh, V., Davidson, I., Adebiyi, A., Ekpe, U.: Methods and Tools for PV and EV Hosting Capacity Determination in Low Voltage Distribution Networks—A Review. Energies (Basel). 16, 3609 (2023). https://doi.org/10.3390/en16083609

47. Carmelito, B.E., Filho, J.M. de C.: Hosting Capacity of Electric Vehicles on LV/MV Distribution Grids—A New Methodology Assessment. Energies (Basel). 16, 1509 (2023). https://doi.org/10.3390/en16031509

48. Zain ul Abideen, M., Ellabban, O., Al-Fagih, L.: A Review of the Tools and Methods for Distribution Networks' Hosting Capacity Calculation. Energies (Basel). 13, 2758 (2020). https://doi.org/10.3390/en13112758

49. Mulenga, E., Bollen, M.H.J., Etherden, N.: A review of hosting capacity quantification methods for photovoltaics in low-voltage distribution grids. International Journal of Electrical Power & Energy Systems. 115, 105445 (2020). https://doi.org/10.1016/J.IJEPES.2019.105445

50. Leou, R., Teng, J., Lu, H., Lan, B., Chen, H., Hsieh, T., Su, C.: Stochastic analysis of electric transportation charging impacts on power quality of distribution systems. IET Generation, Transmission & Distribution. 12, 2725–2734 (2018). https://doi.org/10.1049/iet-gtd.2018.0112

51. Zhu, J., Nacmanson, W.J., Ochoa, L.F., Hellyer, B.: Assessing the EV Hosting Capacity of Australian Urban and Rural MV-LV Networks. Electric Power Systems Research. 212, 108399 (2022). https://doi.org/10.1016/J.EPSR.2022.108399

52. Zuluaga-Ríos, C.D., Villa-Jaramillo, A., Saldarriaga-Zuluaga, S.D.: Evaluation of Distributed Generation and Electric Vehicles Hosting Capacity in Islanded DC Grids Considering EV Uncertainty. Energies (Basel). 15, 7646 (2022). https://doi.org/10.3390/en15207646

53. Fan, S., Li, C., Wei, Z., Pu, T., Liu, X.: Method to determine the maximum generation capacity of distribution generation in low-voltage distribution feeders. The Journal of Engineering. 2017, 944–948 (2017). https://doi.org/10.1049/joe.2017.0470

54. Schachler, B., Heider, A., Röpke, T., Reinke, F., Bakker, C.: Assessing the impacts of market-oriented electric vehicle charging on german distribution grids. In: 5th E-Mobility Power System Integration Symposium (EMOB 2021). pp. 128–136. Institution of Engineering and Technology (2021)

55. Nour, M., Chaves-Ávila, J.P., Magdy, G., Sánchez-Miralles, Á.: Review of Positive and Negative Impacts of Electric Vehicles Charging on Electric Power Systems. Energies (Basel). 13, 4675 (2020). https://doi.org/10.3390/en13184675

56. Dogan, A., Kuzlu, M., Pipattanasomporn, M., Rahman, S., Yalcinoz, T.: Impact of EV charging strategies on peak demand reduction and load factor improvement. In: 2015 9th International Conference on Electrical and Electronics Engineering (ELECO). pp. 374–378. IEEE (2015)

57. Sortomme, E., El-Sharkawi, M.A.: Optimal Charging Strategies for Unidirectional Vehicle-to-Grid. IEEE Trans. Smart Grid. 2, 131–138 (2011). https://doi.org/10.1109/TSG.2010.2090910

58. Heinisch, V., Göransson, L., Erlandsson, R., Hodel, H., Johnsson, F., Odenberger, M.: Smart electric vehicle charging strategies for sectoral coupling in a city energy system. Appl. Energy. 288, 116640 (2021). https://doi.org/10.1016/J.APENERGY.2021.116640

59. Hedegaard, K., Ravn, H., Juul, N., Meibom, P.: Effects of electric vehicles on power systems in Northern Europe. Energy. 48, 356–368 (2012). https://doi.org/10.1016/J.ENERGY.2012.06.012

60. Muratori, M.: Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nat. Energy. 3, 193–201 (2018). https://doi.org/10.1038/s41560-017-0074-z

61. Zaferanlouei, S., Lakshmanan, V., Bjarghov, S., Farahmand, H., Korpås, M.: BATTPOWER application: Large-scale integration of EVs in an active distribution grid – A Norwegian case study. Electric Power Systems Research. 209, 107967 (2022). https://doi.org/10.1016/J.EPSR.2022.107967

62. Steen, D., Tuan, L.A., Carlson, O., Bertling, L.: Assessment of Electric Vehicle Charging Scenarios Based on Demographical Data. IEEE Trans. Smart Grid. 3, 1457–1468 (2012). https://doi.org/10.1109/TSG.2012.2195687

63. Hanemann, P., Behnert, M., Bruckner, T.: Effects of electric vehicle charging strategies on the German power system. Appl. Energy. 203, 608–622 (2017). https://doi.org/10.1016/J.APENERGY.2017.06.039

64. Sandström, M., Huang, P., Bales, C., Dotzauer, E.: Evaluation of hosting capacity of the power grid for electric vehicles – A case study in a Swedish residential area. Energy. 284, 129293 (2023). https://doi.org/10.1016/J.ENERGY.2023.129293

65. Limmer, S.: Dynamic Pricing for Electric Vehicle Charging—A Literature Review. Energies (Basel). 12, 3574 (2019). https://doi.org/10.3390/en12183574

66. Velkovski, B., Gjorgievski, V.Z., Kothona, D., Bouhouras, A.S., Cundeva, S., Markovska, N.: Impact of tariff structures on energy community and grid operational parameters. Sustainable Energy, Grids and Networks. 38, 101382 (2024). https://doi.org/10.1016/J.SEGAN.2024.101382

67. Azuatalam, D., Verbic, G., Chapman, A.: Impacts of network tariffs on distribution network power flows. In: 2017 Australasian Universities Power Engineering Conference (AUPEC). pp. 1–6. IEEE (2017)

68. Saele, H.: Consequences for residential customers when changing from energy based to capacity based tariff structure in the distribution grid. In: 2017 IEEE Manchester PowerTech. pp. 1–6. IEEE (2017)

69. Turk, G., Schittekatte, T., Dueñas Martínez, P., Joskow, P.L., Schmalensee, R.: Designing Distribution Network Tariffs Under Increased Residential End-user Electrification: Can the US Learn Something from Europe? (2024)

70. El Gohary, F., Stikvoort, B., Bartusch, C.: Evaluating demand charges as instruments for managing peak-demand. Renewable and Sustainable Energy Reviews. 188, 113876 (2023). https://doi.org/10.1016/J.RSER.2023.113876

71. van Zoest, V., El Gohary, F., Ngai, E.C.H., Bartusch, C.: Demand charges and user flexibility – Exploring differences in electricity consumer types and load patterns within the Swedish commercial sector. Appl. Energy. 302, 117543 (2021). https://doi.org/10.1016/J.APENERGY.2021.117543

72. Lanot, G., Vesterberg, M.: The price elasticity of electricity demand when marginal incentives are very large. Energy Econ. 104, 105604 (2021). https://doi.org/10.1016/J.ENECO.2021.105604

73. Abdelmotteleb, I., Gómez, T., Chaves Ávila, J.P., Reneses, J.: Designing efficient distribution network charges in the context of active customers. Appl. Energy. 210, 815–826 (2018). https://doi.org/10.1016/j.apenergy.2017.08.103

74. Brown, T., Faruqui, A., Grausz, L.: Efficient tariff structures for distribution network services. Econ. Anal. Policy. 48, 139–149 (2015). https://doi.org/10.1016/j.eap.2015.11.010

75. Raassina, A., Heine, P., Lepistö, J., Äärynen, E., Honkapuro, S.: What a DSO Can Do to Promote EV Smart Charging? In: 2023 19th International Conference on the European Energy Market (EEM). pp. 1–5. IEEE (2023)

76. Kobayashi, Y., Taljegard, M., Johnsson, F.: Assessment of real-world driving patterns for electric vehicles: an on-board measurements study from Sweden. Appl. Energy. 401, 126608 (2025). https://doi.org/10.1016/J.APENERGY.2025.126608

77. Ovaere, M., Vergouwen, M.: Mind the Peak: The Role of Peak Demand Charges and Real-Time Pricing in Residential Electricity Flexibility, (2025)

78. Nord Pool Spot: Elspot prices hourly 2021-2024

79. Rose, P.K., Neumann, F.: Hydrogen refueling station networks for heavy-duty vehicles in future power systems. Transp. Res. D Transp. Environ. 83, 102358 (2020). https://doi.org/10.1016/J.TRD.2020.102358

80. Lundblad, T., Mattsson, N., Hartvigsson, E.: REGAL-public, https://github.com/Atlun/REGAL-public

81. Lundblad, T.: EV toymodel tariffs, https://github.com/Atlun/EV-toymodel-tariffs

82. Jönköping Energi: Priser, https://jonkopingenergi.se/privat/elnat/elnat/priser

83. Telge: Elnätspriser. (2025)

84. Växjö Energi: Elnätsavgift, https://www.veab.se/privat/elnat/elnatsavgift/

85. Ellevio: Elnätspriser privat, https://www.ellevio.se/abonnemang/elnatspriser-privat/

86. Göteborg Energi: Elnätsavgiften, https://www.goteborgenergi.se/privat/elnat/elnatsavgiften#prisvilla

87. Malung-Sälens Elverk: Nättariffer, https://malungselnat.se/elnat/nattariffer/

88. Partille Energi: Elnät, https://partilleenergi.se/elnat/

89. Varberg Energi: Elnätspriser, https://www.varbergenergi.se/privat/elnat/elnatspriser

90. Energiavirasto: Föreskrift om grunderna för bestämning av avgiftskomponenter för eldistributionsprodukter. , Helsingfors (2026)

91. Schittekatte, T., Meeus, L.: Least-cost Distribution Network Tariff Design in Theory and Practice. The Energy Journal. 41, 119–156 (2020). https://doi.org/10.5547/01956574.41.5.tsch

92. Swedish Energy Markets Inspectorate: Ei beviljar Göteborg Energis ansökan om dispens från kravet på effektavgift för lägenhetskunder, https://ei.se/om-oss/nyheter/2026/2026-02-09-ei-beviljar-goteborg-energis-ansokan-om-dispens-fran-kravet-pa-effektavgift-for-lagenhetskunder

93. Flores, J.: Hög elavgift – trots att du laddar bilen när priset är lågt, https://www.dn.se/ekonomi/hog-elavgift-trots-att-du-laddar-bilen-nar-priset-ar-lagt/, (2025)

94. Engvall, J.: Gör om effektavgifterna som är en katastrof för oss som kör elbil, https://www.dn.se/insandare/gor-om-effektavgifterna-som-ar-en-katastrof-for-oss-som-kor-elbil/, (2025)

95. Morin, M.: Är tanken med effektavgift att vi ska sluta med fläskpannkaka?, https://www.dn.se/insandare/ar-tanken-med-effektavgift-att-vi-ska-sluta-med-flaskpannkaka/, (2026)

96. Flores, J.: Ellevios chockavgift slår ut laddstationerna på Orust, https://www.dn.se/ekonomi/ellevios-chockavgift-slar-ut-laddstationerna-pa-orust/, (2026)

97. Flores, J.: Straffavgiften för att ladda elbilen i fjällstugan: 2 200 kronor, https://www.dn.se/ekonomi/straffavgiften-for-att-ladda-elbilen-i-fjallstugan-2-200-kronor/, (2026)

98. Wijnbladh, O.: Fortsatt många klagomål på elnätsbolagens avgifter, https://www.sverigesradio.se/artikel/fortsatt-manga-klagomal-pa-elnatsbolagens-avgifter, (2024)

99. The Government Offices of Sweden: Uppdrag till Energimarknadsinspektionen att upphäva föreskrifter och lämna förslag om en ny utformning av effektavgifterna. (2026)

100. E.ON: Få koll på din effekt, https://www.eon.se/el/elnat/effekt

101. Energicentrum Gotland: Tariff 2.0 – pilottest för kapacitetsbaserade elnätstariffer, https://energicentrum.gotland.se/project/tariff-2-0-pilottest-for-kapacitetsbaserade-elnatstariffer/

102. Ellevio: Kommentar med anledning av energi- och näringsministerns utspel om effekttariffer, https://www.ellevio.se/nyheter/ellevio_tycker/kommentar-med-anledning-av-energi--och-naringsministerns-utspel-om-effekttariffer/