



LUND UNIVERSITY

Quantifying the Grid Impact of Electric Vehicles

A Probabilistic Case Study of Southern Sweden

Callanan, Alice

2026

Document Version:

Publisher's PDF, also known as Version of record

[Link to publication](#)

Citation for published version (APA):

Callanan, A. (2026). *Quantifying the Grid Impact of Electric Vehicles: A Probabilistic Case Study of Southern Sweden*. [Doctoral Thesis (compilation), Division for Industrial Electrical Engineering and Automation]. Department of Biomedical Engineering, Lund university.

Total number of authors:

1

General rights

Unless other specific re-use rights are stated the following general rights apply:

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

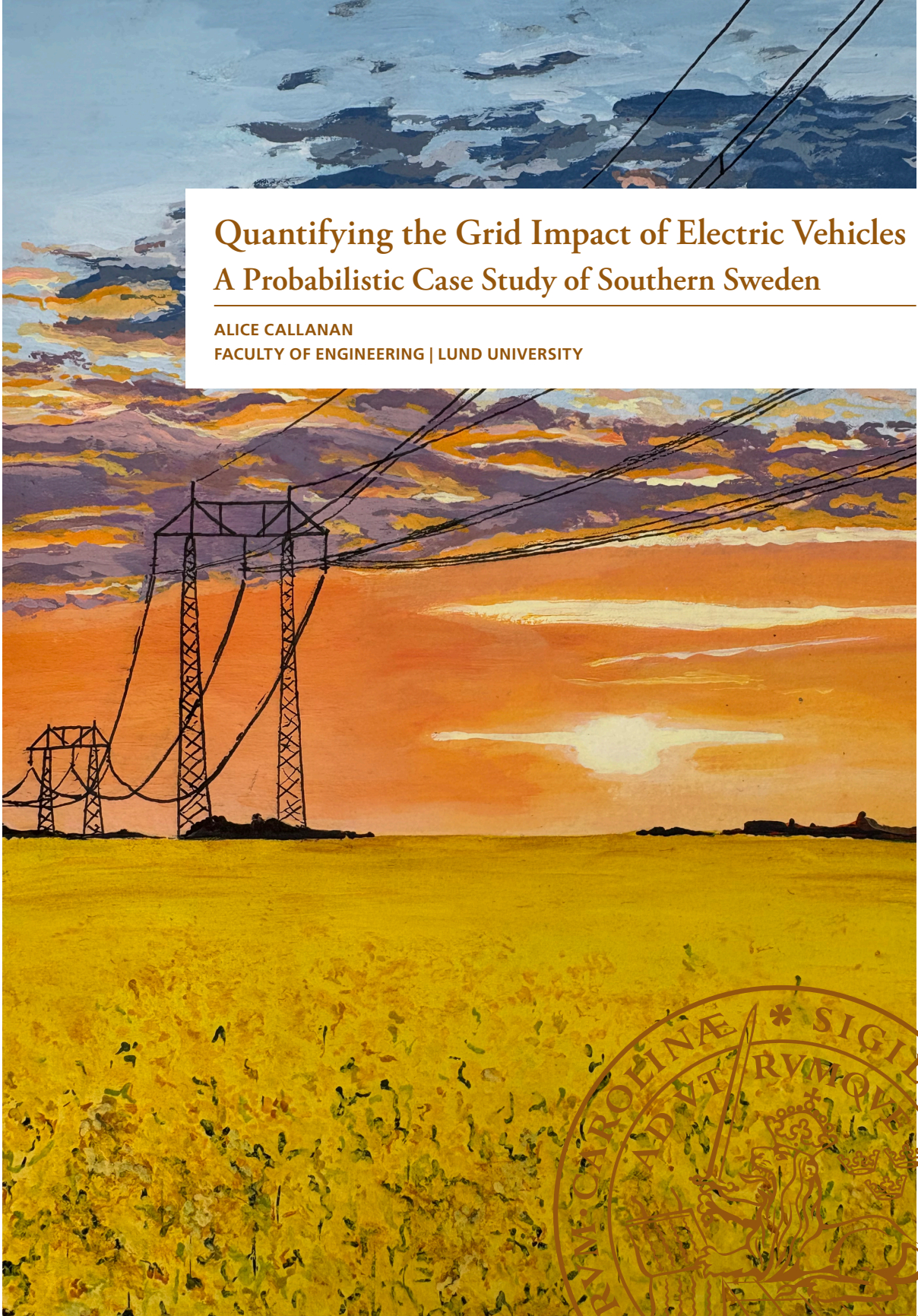
Read more about Creative commons licenses: <https://creativecommons.org/licenses/>

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

LUND UNIVERSITY

PO Box 117
221 00 Lund
+46 46-222 00 00



Quantifying the Grid Impact of Electric Vehicles A Probabilistic Case Study of Southern Sweden

ALICE CALLANAN

FACULTY OF ENGINEERING | LUND UNIVERSITY



Quantifying the Grid Impact of Electric Vehicles

A Probabilistic Case Study of Southern Sweden

by Alice Callanan



LUND
UNIVERSITY

Thesis for the degree of Doctor of Philosophy

Thesis advisors: Prof. Olof Samuelsson, Dr. Francisco J. Márquez-Fernández

Faculty opponent: Prof. Lina Bertling Tjernberg

To be presented, with the permission of the Faculty of Engineering of Lund University, for public criticism in the M:B lecture hall (M-building, LTH) at the Div. Industrial Electrical Engineering and Automation on Wednesday, the 13th of May 2026 at 09.00.

Organization LUND UNIVERSITY Div. Industrial Electrical Engineering and Automation Box 118 SE-221 00 LUND Sweden		Document name DOCTORAL DISSERTATION	
Author(s) Alice Callanan		Date of disputation 2026-05-13	
		Sponsoring organization	
Title and subtitle Quantifying the Grid Impact of Electric Vehicles: A Probabilistic Case Study of Southern Sweden			
Abstract The electrification of the transportation sector is a central strategy for decarbonization, yet it raises concerns about the capacity of existing electric power grids to meet increasing demand. This thesis investigates the interaction between large-scale electrified vehicle fleets and the electric power system under the assumption of full transport electrification. The focus is on assessing the readiness of the existing sub-transmission grid to accommodate increased power demand, in contrast with previous research that has focused mainly on lower voltage levels. A probabilistic load-flow simulation framework is developed and applied to a full-scale grid model of Skåne in southern Sweden. The framework quantifies the aggregated energy and power requirements of fully electrified fleets of passenger cars, long-haul trucks, and heavy construction equipment. These loads are then integrated into a full-scale grid model covering sub-transmission and transmission levels. The results indicate that the sub-transmission grid is largely capable of accommodating the aggregated charging demand under normal operating conditions, although localized bottlenecks require reinforcement. While smart charging strategies successfully reduce peak power demand from vehicle fleets, the thesis reveals that this benefit does not always translate into a proportional reduction in grid congestion. Importantly, the impact of charging loads is often "dampened" by existing background loads and local grid conditions. This finding challenges the assumption that high charging peaks inevitably lead to grid congestion and underscores the need to couple transport models with realistic grid simulations to assess the impact of new loads on grid capacity accurately.			
Key words Electric vehicles, Grid capacity, Probabilistic load flow, Transport electrification			
Classification system and/or index terms (if any)			
Supplementary bibliographical information		Language English	
ISSN and key title		ISBN 978-91-985111-0-9 (print) 978-91-985111-1-6 (pdf)	
Recipient's notes		Number of pages 160	Price
		Security classification	

I, the undersigned, being the copyright owner of the abstract of the above-mentioned dissertation, hereby grant to all reference sources the permission to publish and disseminate the abstract of the above-mentioned dissertation.

Signature _____

Date 2026-03-31

Quantifying the Grid Impact of Electric Vehicles

A Probabilistic Case Study of Southern Sweden

by Alice Callanan



LUND
UNIVERSITY

The cover illustration is painted by Erika Thörn.

Funding information: The thesis work has been supported by the Swedish Electromobility Centre through the project ACTUAL Grid and Road Simulation for E-mobility, which is gratefully acknowledged.

© Alice Callanan 2026
Paper I © 2023, IEEE
Paper II © 2025, The Authors
Paper III © 2025, The Authors
Paper IV © 2025, IEEE
Paper V © 2025, IEEE
Paper VI © 2026, The Authors

Faculty of Engineering, Div. Industrial Electrical Engineering and Automation

ISBN: 978-91-985111-0-9 (print)
ISBN: 978-91-985111-1-6 (pdf)
CODEN: LUTEDX/(TEIE1103)/1-160/2026

Printed in Sweden by Media-Tryck, Lund University, Lund 2026



Media-Tryck is a Nordic Swan Ecolabel certified provider of printed material. Read more about our environmental work at www.mediatryck.lu.se

MADE IN SWEDEN 

Abstract

The electrification of the transportation sector is a central strategy for decarbonization, yet it raises concerns about the capacity of existing electric power grids to meet increasing demand. This thesis investigates the interaction between large-scale electrified vehicle fleets and the electric power system under the assumption of full transport electrification. The focus is on assessing the readiness of the existing sub-transmission grid to accommodate increased power demand, in contrast with previous research that has focused mainly on lower voltage levels. A probabilistic load-flow simulation framework is developed and applied to a full-scale grid model of Skåne in southern Sweden. The framework quantifies the aggregated energy and power requirements of fully electrified fleets of passenger cars, long-haul trucks, and heavy construction equipment. These loads are then integrated into a full-scale grid model covering sub-transmission and transmission levels. The results indicate that the sub-transmission grid is largely capable of accommodating the aggregated charging demand under normal operating conditions, although localized bottlenecks require reinforcement. While smart charging strategies successfully reduce peak power demand from vehicle fleets, the thesis reveals that this benefit does not always translate into a proportional reduction in grid congestion. Importantly, the impact of charging loads is often "dampened" by existing background loads and local grid conditions. This finding challenges the assumption that high charging peaks inevitably lead to grid congestion and underscores the need to couple transport models with realistic grid simulations to assess the impact of new loads on grid capacity accurately.

Contents

List of Publications	iv
Populärvetenskaplig Sammanfattning	vi
Acknowledgement	viii
Declaration of the use of Generative AI	x
1 Introduction	1
1.1 Aim and Objectives	3
1.2 Summary of Contributions	4
1.3 Delimitations	5
1.4 Thesis Outline	6
2 Transport Electrification and Grid Modeling	7
2.1 Electrification Trends and Policies	7
2.2 Charging Demand Modeling	10
2.3 Grid Capacity Impact Assessment	11
2.4 Integration of Transport and Power System Models	14
3 Simulation Framework	17
3.1 Charging Demand Models	18
3.2 Grid Simulations	26
4 Estimated Charging Demand and Grid Impact	35
4.1 Aggregated Energy and Power Requirements	35
4.2 Grid Capacity Impact at Sub-Transmission Level	46
5 Discussion and Synthesis	57
5.1 Synthesis of Key Findings	57
5.2 Implications for Industry and Society	59
5.3 Limitations	61
6 Conclusions and Future Work	65
6.1 Conclusions	65
6.2 Future Work	67

References	69
Scientific Publications	75
Paper I: Electromobility Impact on the Power Grid - Base Case for Probabilistic Modelling	75
Paper II: Impact of Aggregated Electric Vehicle Home Charging in the Sub-transmission Grid	83
Paper III: A Data-Driven Probabilistic Framework For Estimating Grid Impacts of EV Charging at Scale	95
Paper IV: Grid Capacity Impact from the Charging of Electrified Long-Haul Trucks	105
Paper V: Charging Requirement and Grid Impact from Electric Heavy Construction Equipment	113
Paper VI: Combined Grid Impact of 100% Electrified Cars, Long-haul Trucks, and Heavy Equipment	121

List of Publications

- I **Electromobility Impact on the Power Grid - Base Case for Probabilistic Modelling**
A. Callanan, O. Samuelsson, and F. J. Márquez-Fernández
IEEE Transportation Electrification Conference & Expo (ITEC), Detroit, MI, USA, 2023, pp. 1–6

Contributions: Alice Callanan conceptualized the study, developed the simulation models, performed the analysis, and wrote the manuscript. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.
- II **Impact of Aggregated Electric Vehicle Home Charging in the Sub-transmission Grid**
A. Callanan, O. Samuelsson, and F. J. Márquez-Fernández
e-Prime - Advances in Electrical Engineering, Electronics and Energy, vol. 13, p. 101066, 2025

Contributions: Alice Callanan conceptualized the study, developed the simulation models, performed the analysis, and wrote the manuscript. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.
- III **A Data-Driven Probabilistic Framework For Estimating Grid Impacts of EV Charging at Scale**
A. Callanan, O. Samuelsson, and F. J. Márquez-Fernández
International Journal of Electrical Power & Energy Systems, vol. 172, p. 111204, 2025

Contributions: Alice Callanan conceptualized the study, developed the simulation models, performed the analysis, and wrote the manuscript. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.
- IV **Grid Capacity Impact from the Charging of Electrified Long-Haul Trucks**
A. Callanan, M. Ingelström, O. Samuelsson, and F. J. Márquez-Fernández
2025 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 2025, pp. 1–6

Contributions: Alice Callanan and Mattias Ingelström conceptualized the study and wrote the manuscript. Alice Callanan developed the simulation models and performed the analysis of the grid impact analysis. Mattias Ingelström developed the simulation models and performed the analysis of the transport simulation. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.

v **Charging Requirement and Grid Impact from Electric Heavy Construction Equipment**

A. Callanan, B. Frank, F. J. Márquez-Fernández, and O. Samuelsson
2025 IEEE Kiel PowerTech, Kiel, Germany, 2025

Contributions: Alice Callanan conceptualized the study, developed the simulation models, performed the analysis, and wrote the manuscript. Bobbie Frank provided support in the acquisition and analysis of the construction machine dataset and reviewed the paper. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.

vi **Combined Grid Impact of 100% Electrified Cars, Long-haul Trucks, and Heavy Equipment**

A. Callanan, F. J. Márquez-Fernández, and O. Samuelsson
Submitted to journal

Contributions: Alice Callanan conceptualized the study, developed the simulation models, performed the analysis, and wrote the manuscript. Olof Samuelsson and Francisco J. Márquez-Fernández supervised the work and reviewed the paper.

Additional Publications

Other peer-review contributions by the author not included in the thesis:

Probabilistic Modelling of EV Charging Impact on the Sub-transmission Grid

A. Callanan, O. Samuelsson, and F. J. Márquez-Fernández
2024 International Conference on Renewable Energies and Smart Technologies (REST), Prishtina, Kosovo (UNMIK), 2024, pp. 1–5.

Investigating the Impact of Public En-Route and Depot Charging for Electric Heavy-Duty Trucks Using Agent-Based Transport Simulation and Probabilistic Grid Modeling

M. Ingelström, A. Callanan, and F. J. Márquez-Fernández
World Electr. Veh. J. 2026, 17, 172.

Populärvetenskaplig Sammanfattning

Om du bor i Sverige så har du nog märkt hur tyst det har blivit i trafiken. Elbilarna, som för bara några år sedan upplevdes som en högteknologisk framtidsvision, har nu tagit plats i många svenska hushåll. Över en sjättedel av alla personbilar är idag helt elektriska eller laddhybrider. Dessutom utgör dessa bilar mer än hälften av alla nybilsförsäljningar, även i tider av lågkonjunktur som nu i början av 2026. Trenden verkar alltså vara här för att stanna. Men vad betyder detta för elnätet?

Elektrifieringen av vägtransporter innebär en stor omställning. Från att ha varit en försvinnande liten andel för bara 15 år sedan, förväntas nu en majoritet av Sveriges fordonsflotta drivas med el inom en snar framtid. I den här avhandlingen undersöker jag vad detta betyder för Sveriges elnät. Vad innebär det att helt elektrifiera alla personbilar, lastbilar, eller arbetsmaskiner? För att begränsa omfattningen har jag fokuserat på Skåne, en betydande region i sammanhanget. Skåne har runt en miljon invånare och flera betydande trafiksträckor, där flera transportrutter anländer till Sverige från Europa. Dessutom har det under de senaste åren funnits problem med kapacitetsbrist i elnätet i regionen. För att förstå hur dessa nya laster påverkar vårt elsystem behöver vi skilja på några olika begrepp.

Tillräckligt med el, men ont om plats i nätet

I Sverige exporterar vi mer elenergi än vad vi importerar, vilket betyder att vi har ett överskott av energi. Inte heller är eleffekten ett problem i Sverige, eftersom el importeras från andra länder under de tider då det behövs. Tittar vi däremot lokalt i Skåne som region, så kan det se lite annorlunda ut. Här pratar vi om kapacitetsbrist, som beror på att det finns begränsad plats i vissa delar av nätet (ofta refererade till som flaskhalsar) där vi får vår el från resten av Sverige. Även inom Skåne kan det uppstå kapacitetsbrist, om det inte finns plats i ledningar och transformatorer för att överföra all effekt som produceras eller konsumeras. Begränsningen handlar rent fysiskt om värme. När stora mängder ström transporteras genom ledningar och transformatorer stiger temperaturen i dem. För att undvika att utrustningen skadas, eller att ledningar expanderar och hänger för lågt, finns strikta gränser för hur mycket effekt som får överföras. Frågan är alltså om det finns tillräckligt med kapacitet i Skånes elnät för att transportera den el som behövs för att ladda fordonsflottor om de är helt elektrifierade?

Olika fordon ger olika resultat

Det ser väldigt olika ut om man pratar om elektrifierade personbilar, eller om det är tyngre fordon som står i fokus. Personbilarna står för en stor majoritet av den eltillförsel som behövs, eftersom det rör sig om en så stor mängd fordon i denna flotta. Bara i Skåne finns

cirka 645 000 personbilar registrerade, som alla förväntas att vara elektrifierade i framtiden. Däremot behöver varje enskild personbil relativt låg effekt för att laddas, så det finns stor potential att sprida ut laddningen över tid för att undvika höga effektoppar. Många elbilsägare är också öppna för att tillämpa så kallad smart laddning, det vill säga att laddningen styrs om från tider då vi har hög belastning på nätet, till tider då belastningen är låg. För tyngre fordon (som lastbilar och arbetsmaskiner) ser det lite annorlunda ut. Dessa fordonsflottor kräver mindre mängd energi, men det visar sig att den sammanlagrade effekten som krävs är jämförbar med personbilsflottan.

Ett nytt sätt att beräkna kapacitet

Tidigare har elnätsplanering utgått från ett värsta tänkbart scenario, vilket är vad elnätet dimensioneras efter (med god marginal). I praktiken innebär detta att elnätet under en stor del av årets timmar är överdimensionerat för de flöden av el som faktiskt uppstår. I min forskning har jag visat på fördelen med att införa statistik i dessa beräkningar. Om vi känner till sannolikheten för att olika belastningar uppstår, så kan vi också beräkna risken för att något går fel. Detta är grunden till den metodik jag använder mig av i den här avhandlingen, där jag beräknar risken för att olika belastningar i nätet ska uppstå när vi introducerar elbils-laddning.

Slutsats - klarar vi det?

Så vad kan vi då säga om kapaciteten i Skånes elnät, är den tillräcklig för att möta den snabba elektrifiering av fordon som vi ser? Svaret är både ja och nej. Den positiva nyheten är att det överlag verkar gå ganska bra att introducera denna nya förbrukning i Skånes regionnät. Det finns specifika punkter där utbyggnad krävs, men mycket kan lösas genom flexibilitet och smart styrning. En negativ överraskning har varit insikten om hur svårt det är att förutspå den tekniska belastningen i nätet bara genom att titta på trafiksimuleringar. Det har blivit väldigt tydligt i mitt arbete att kunskap om både de laddbehov som uppstår kommer att krävas, men även detaljerad kunskap om hur elnätet ser ut och hur laddningen påverkar och påverkas av övrig förbrukning och produktionsslag. Min slutsats är att en fullskalig elektrifiering av Skånes transporter är möjlig, men den kräver både smartare planering och riktade investeringar i nätet.

Acknowledgement

This PhD journey has been both challenging and rewarding. I am deeply grateful to the people who have supported me along the way, whether by sharing valuable knowledge and perspectives or simply by being there during difficult moments.

I would like to begin by thanking my main supervisor, Professor Olof Samuelsson, who has provided steady guidance and support throughout my PhD. Having had the opportunity to discuss anything from electric power systems to pedagogy and road cycling has been a constant source of inspiration. I would also like to thank my co-supervisor, Dr. Fran Marquez, who has brought enthusiasm, energy, and many ideas. I have greatly appreciated all the feedback on my work, sometimes even arriving at odd times during the day (and night). I am also grateful to both my supervisors for accepting my occasional side quests of a less technical nature and for encouraging me to pursue a PhD in the first place.

This thesis has been financially supported by the Swedish Electromobility Centre, for which I am very grateful. Being part of this community has provided valuable networking and learning opportunities. I would especially like to thank my reference group and the representatives from E.ON, Vattenfall, Scania, Volvo Cars, Volvo CE, and Zeekr. In particular, I would like to thank Dr. Bobbie Frank for many insightful discussions about electric construction machines. I would also like to thank Hampus Möller for his support with grid modelling and his enthusiasm for probabilistic methods.

Beyond my thesis work, I have had the opportunity to meet many inspiring people within the field of electric power systems and electromobility. I would like to thank Professor Thomas Overbye, Dr. Jonathan Snodgrass, and the entire group at Texas A&M University for welcoming me as a visiting researcher. This was a highly valuable experience that broadened my knowledge of power systems research and gave me many memorable experiences. I would also like to thank my mentor in Sweden, Dr. Ambra Sannino, for her guidance in both research and career development.

I have had the pleasure of being a PhD student at the Division of Industrial Electrical Engineering and Automation at Lund University. This has been a supportive environment where I have been able to grow both as a researcher and as a person. I would like to thank Dr. Ulf Jeppsson, who served as head of the division during most of my time at IEA, for his support. I am also grateful to the administrative staff, Carina Lindström and Elena Kuleshova, for their assistance, as well as to Ulrika Westerdahl, Monica Almqvist, and Ingrid Svensson for their support from BME.

During my time at IEA, I have also had the pleasure of forming many friendships. I would like to thank Dr. Martin Lundberg, who started as an unofficial mentor and quickly became my go-to colleague and sidekick. Thank you to Mattias Ingelström for being an excellent collaborator in both research and PhD student representation, and to Leonardo Colombo for teaching me how to make a perfect carbonara. I am also grateful to my colleagues at IEA for making the work environment enjoyable, especially to my office mates over the years: Gabriel, Ghazal, Imran, and Elina. I would also like to thank my colleagues Edwin, Amir, Abdullah, Hamoun, Zhitong, Sebastian, Erik, Huan, Samuel, David, Anton, Max, Meng, Akanksha, and Ferdinand for the many enjoyable lunchtime conversations. Thanks also to my colleagues at BME, Franzi and Simon, for always providing a good time when I ventured outside of IEA.

I have had the opportunity to supervise many students during these years, which has been a valuable part of my development as a researcher. Thank you all for sharing your learning journeys with me. I look forward to seeing many of you in the electric power industry in the future.

Finally, I would like to thank my friends and family for their support. To my parents and my siblings, thank you for always being there and for providing a perspective beyond academia that has helped me stay grounded. To Gareth, thank you for your patience and for sharing this journey with me as we both worked towards becoming doctors. Having you by my side throughout these years has made the journey a lot easier. And to my cats, thank you for your constant companionship during long writing days.

Declaration of the use of Generative AI

In accordance with academic transparency guidelines, the author acknowledges the use of artificial intelligence tools during the preparation of this thesis. The author has used generative AI tools (such as ChatGPT and Google Gemini) to assist with language editing, structural refinement, and the formatting of references. The author has thoroughly reviewed, edited, and validated all AI-assisted text and takes full responsibility for the final content of this thesis. It should be noted that AI tools were used strictly as editorial assistants to improve the clarity, flow, and scannability of the English prose. All underlying data, scientific analysis, simulation results, and core conclusions are the original work of the author.

Chapter 1

Introduction

Global decarbonization efforts are driving major energy transitions, particularly within the transportation and power sectors. Growing concerns over climate change, air quality, and energy security are accelerating a paradigm shift toward electrification, especially in regions with high shares of renewable electricity. In this context, the electrification of road transport has emerged as a key strategy for reducing greenhouse gas emissions [1]. In the European Union, one-fourth of greenhouse gas emissions come from the transport sector, of which road transport accounts for 73% of these emissions [2]. Electrification of the transport sector could therefore significantly decrease greenhouse gas emissions in countries with low carbon intensity in electricity generation.

The environmental benefit of electrification is largely dependent on the carbon intensity of the electricity generation. The global average carbon intensity is at a level of 473 gCO₂/kWh, which can be compared to the EU average of 213 gCO₂/kWh. In Sweden, the electricity generation is exceptionally clean at 36 gCO₂/kWh [3], making Sweden an ideal case for electrification, as seen in Figure 1.1. While the production of electric vehicles (EVs), particularly the manufacturing of lithium-ion batteries, results in higher initial carbon emissions compared to internal combustion engine vehicles, these emissions are typically offset after a certain mileage. This break-even point is achieved more swiftly in regions with low-carbon electricity generation, such as Sweden [4]. By facilitating the integration of electric vehicles into the power grid, this thesis aligns with the United Nations Sustainable Development Goals, particularly Goal 7 (Affordable and Clean Energy) and Goal 13 (Climate Action).

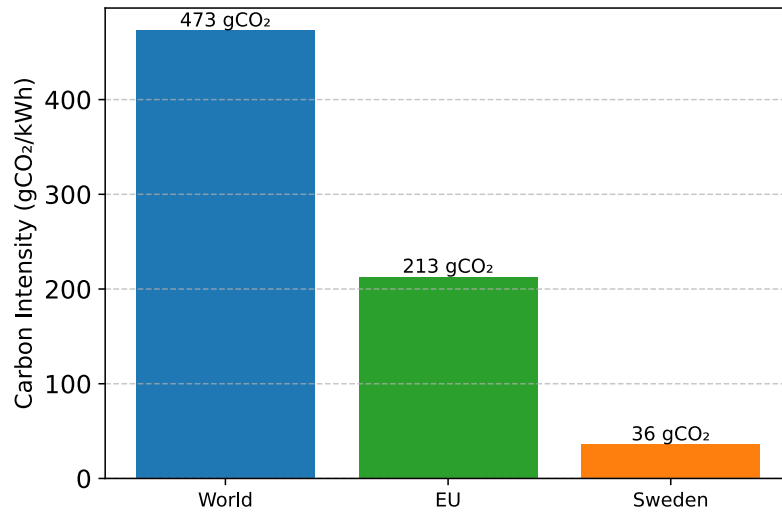


Figure 1.1: Comparison of carbon intensity of electricity generation in Sweden, the EU, and the world [3].

The global adoption of electric vehicles is accelerating, creating new patterns of power and energy demand on electricity grids. Worldwide, 50 % of new cars sold are expected to be electric by 2031 [5]. In Sweden, this adoption rate has already been achieved, and 15 % of the total car fleet consists of battery electric (BEV) and plug-in hybrid electric (PHEV) cars [6]. However, the fast pace of transport electrification contrasts with the traditional time frames for grid expansion. The lead times for grid expansions on the transmission and sub-transmission grids can be up to 15 years [7], which is approximately the time it took to reach a 15% electrification rate of Sweden's transport fleet. This highlights the need to quantify the required energy and power from the electrified vehicle fleet and to investigate whether the grid capacity will be enough to supply the demand.

While the electrification of road transport offers substantial environmental benefits, it also introduces new challenges at the interface between the transportation and power systems. The growing interdependence of these two critical infrastructures requires a deeper understanding of how charging demand from electric vehicles interacts with existing grid capacity, particularly as electrification scales up. Historically, there has been no direct link between the electric power system and the road transport sector. This is drastically changing with the introduction of electric road transport, as new charging loads directly affect the power grid's capacity.

Previous research in this field has primarily focused on interactions at the local grid level, near the charging points of electric vehicles. With large-scale electrification, however, the

aggregated effects are becoming visible at higher voltage levels, where the involvement in the process of planning for the new charging infrastructure is less direct. Furthermore, traditional grid planning applies deterministic methods that rely on worst-case scenarios to dimension the grid. In reality, EV charging is inherently stochastic as it depends on human behavior, driving patterns, and vehicle models. Consequently, there is a need to develop and apply new frameworks to analyze the impact of new loads on the power system. This work is further driven by the upcoming EU regulations that require transmission system operators to conduct probabilistic risk assessments by 2027 [8]. This thesis addresses these challenges by proposing a novel probabilistic framework for the analysis of aggregated EV charging loads on the sub-transmission grid.

1.1 Aim and Objectives

This research aims to explore the coupling between the transportation and power systems in a scenario of full-scale electrification of road transport. Transportation and electric power systems represent two fundamental societal infrastructures that, until recently, have evolved largely in isolation from one another. However, recent trends in transport electrification have forged new dependencies between the two systems, making coordinated planning essential. This thesis aims to bridge these two systems by introducing coupled simulations, focusing on the grid capacity impact due to introduced charging loads, and possible mitigation strategies.

To reach this aim, the following research questions have been defined:

- RQ1:** How can the aggregated energy and power requirements of a fully electrified road transport fleet be modeled?
- RQ2:** How can a simulation framework be developed to assess the impact of aggregated electric vehicle charging loads on sub-transmission grid capacity?
- RQ3:** To what extent can the grid capacity impact of electric vehicle charging be mitigated through temporal flexibility in charging demand?
- RQ4:** How can the developed modeling and simulation framework be applied to a real-world, large-scale case study to evaluate interactions between transportation and power systems under full transport electrification?

1.2 Summary of Contributions

This thesis has contributed to the understanding of transport electrification by developing and applying the following frameworks:

1. Models of aggregated charging demand from large fleets of electric passenger cars, long-haul trucks, and heavy construction equipment.
2. Models of electricity consumption and generation in a full-scale power grid model.
3. A methodological framework to combine modeled charging loads with power system simulations.

The developed models and frameworks have been applied to a case study in the Skåne region in southern Sweden. Skåne lies within the SE₄ bidding zone of the Nordic power system, as illustrated in Figure 1.2. This case study has enabled the quantification of charging demand from electric vehicle fleets and their potential impact on grid capacity in the study area of Skåne.

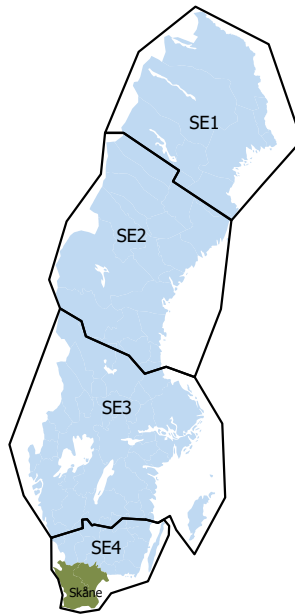


Figure 1.2: Division of Sweden into bidding zones (SE₁–SE₄). The study area considered in this thesis is the Skåne region (marked in green), located within SE₄ in southern Sweden.

The probabilistic models of consumption and generation (connecting to RQ2) and the framework for studying the grid capacity impact of new system loads are outlined in Paper I. This framework is applied in the rest of the papers, where the aggregated charging loads from different electric vehicle fleets are considered. The charging demand models for electric passenger cars are developed and presented in Papers II and III. To support open science and reproducibility, the simulation code used to generate these EV load profiles, as well as the resulting high-resolution datasets for Sweden, have been made publicly available [9]. Probabilistic charging loads of electric long-haul trucks are introduced in Paper IV, and for electric heavy construction equipment in Paper V. RQ1 is explored throughout these papers, which all aim to create probabilistic models for aggregated charging demand. Finally, all developed models are combined in Paper VI, where the combined charging demand and grid impacts are presented. Here, a specific focus has been placed on the analysis of temporal shifts in charging, as related to RQ3. Finally, the application of the framework to the Skåne study area has illustrated its use in real-world examples, related to RQ4.

1.3 Delimitations

Transportation and power systems simulations are two distinct fields with intricate methods, often resulting in computationally and detail-heavy models. Combining the two has required certain simplifications to make the integrated simulations feasible. Furthermore, dealing with future prognoses will naturally involve uncertainty, and assumptions need to be made. The following simplifications, assumptions, and delimitations have been applied in this thesis:

- The vehicle fleets studied are delimited to passenger cars, long-haul trucks, and heavy construction equipment. These fleets are selected based on expected electrification potential in a Swedish setting, where trains and many bus fleets are already electrified. Furthermore, passenger cars represent high total energy demand, long-haul trucks high peak charging power, and heavy equipment high-power, site-concentrated loads.
- The charging demand models are based on present-day driving and charging behavior. This assumption allows for the use of validated statistical data rather than speculative projections.
- The power grid simulations are restricted to capacity simulations under normal operating conditions (N-o), with no contingency analysis (N-i). This simplification is motivated by the focus on steady-state grid capacity impacts and the assumption that electric vehicle charging loads are flexible and can be curtailed or shifted under contingency conditions.

- The probabilistic load flow simulation includes statistically varied consumption and generation within the study area, but treats the rest of the system as static. The grid outside of SE4 is modeled by a slack-bus representation.
- Market dynamics, price signals, or optimization/control strategies are not included, as the analysis focuses on technical grid capacity impacts under various behavioral and temporal charging scenarios.
- The case study location is the region of Skåne in southern Sweden. The data, statistics, and grid loading results presented in this thesis are specific to this region.
- The grid model considered in the case study is a full-scale grid model of the study area, including the transmission (400 kV) and sub-transmission (135 kV) grids. The model reflects the power grid in 2026, without future reinforcements. The model is the Nordic grid model used in grid planning, which has been adapted to include only the grid in the Swedish bidding area SE4.

1.4 Thesis Outline

This thesis is written as a compilation thesis, divided into two main parts. Part I contains a comprehensive summary and synthesis of the research context, methodology, and main findings. Part II includes the appended scientific papers.

The remainder of the first part is organized as follows. Chapter 2 presents the research context, including the present state of electrification trends and policies at the time that this thesis is published. This is followed by an overview of related research in the fields of transportation and electric power grid simulations. Next, Chapter 3 outlines the methodological framework developed and applied in the thesis. Chapter 4 summarizes key results from the appended research papers. Instead of directly repeating the results from the papers, this chapter aims to provide a comprehensive overview of the results and allow for a comparison between vehicle fleets and scenarios. Chapter 5 then discusses and synthesizes the main findings of the thesis. In this chapter, a summary of contributions to industry and society is outlined. Finally, the thesis is concluded in Chapter 6, and recommendations for future research directions are suggested.

Chapter 2

Transport Electrification and Grid Modeling

Electrification has emerged as a key strategy to reduce greenhouse gas emissions in regions with low-carbon electric power systems. This transition means that new electric loads are introduced and need to be integrated into the power system. This chapter presents recent trends in electrification, with special focus on the transportation sector in Sweden. Furthermore, research trends in modeling new loads and their integration into the power system are outlined.

2.1 Electrification Trends and Policies

Electrification in Sweden is driven by decarbonization targets. In the European Union, EU climate policies serve as a measure to implement treaties such as the Paris Agreement. The overarching climate goal in the EU is to reach climate neutrality by 2050. More specifically, the "Fit for 55" target legislation states that net greenhouse gas emissions must be reduced by at least 55% by 2030, compared to 1990 levels [10]. Within this package, several pieces of legislation relate to the transportation sector. Specifically, EU Regulation 2023/851 [11] outlines the CO₂ reduction targets within the transport sector in the EU, stating that by 2035 the average emission of new cars must be reduced by 100%. In practice, this means a ban on the sale of new fossil-fueled vehicles by 2035.¹ Furthermore, the Alternative Fuels Infrastructure Regulation (AFIR) [12] states mandatory deployment targets for electric charging infrastructure along the core transport routes in the EU. The targets include mandatory

¹It should be noted that in December 2025, this target was revised to a 90% reduction. However, the work in this thesis is based on the 100% target in force during the research period.

fast-charging stations (above 150 kW) every 60 km along the core routes. Additionally, the overall fleet-wise targets state that 1.3 kW of public charging infrastructure needs to be installed per battery electric vehicle in all member countries.

As a member country of the EU, Sweden needs to follow the targets set within the union. However, Sweden implemented more ambitious climate targets through the Swedish Climate Law in 2017 [13]. These targets include reaching net-zero greenhouse gas emissions by 2045, which is five years prior to the targets set by the EU. In the transport sector, an aim was adopted to reduce the emissions of domestic road transport by 70% by 2030. A key strategy to reach these targets is through electrification, which includes electrification of the transport sector [14]. Electrification is projected to remain an overarching trend, as reflected in several forecasts of future electricity consumption in Sweden. The Swedish Energy Agency predicts a total electricity demand of 223 - 357 TWh in 2050 [15]. Despite the large spread between the analysed scenarios, there is a large expected growth in electricity demand compared to today's values of 130 - 140 TWh per year. A selection of the scenario analysis results from this report is shown in Figure 2.1. Here, the electricity use per sector in 2050 in the four scenarios applied by the Swedish Energy Agency is compared to today's numbers. The scenarios span a range of potential developments, differing primarily in the extent of industrial electrification (in light blue) and hydrogen production (in yellow). However, throughout the scenarios, the transport sector (in grey) is expected to become electrified to a large extent, reaching a yearly electricity demand of 26-31 TWh. This can be compared to 4 TWh in 2023.

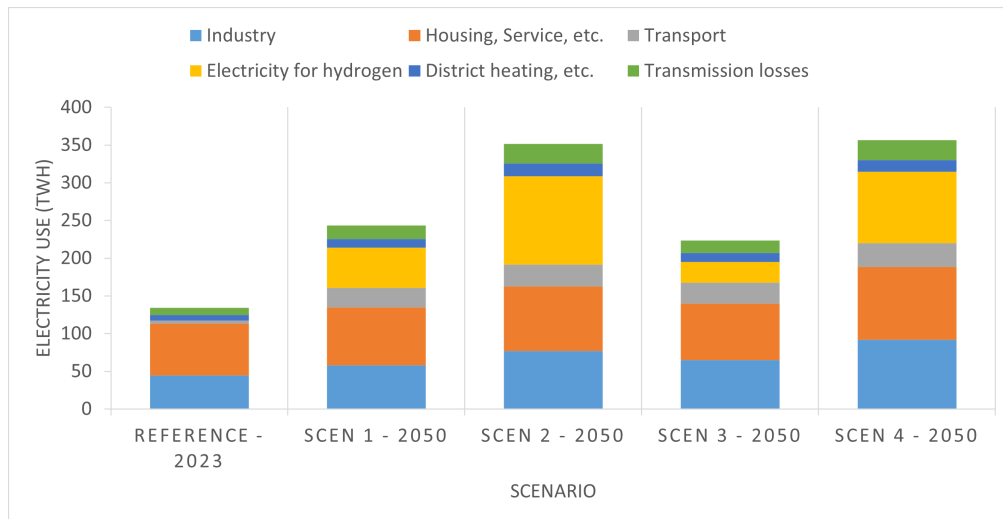


Figure 2.1: Summary of the Swedish Energy Agency scenario prognoses of national electricity consumption in 2050, compared to today's values.

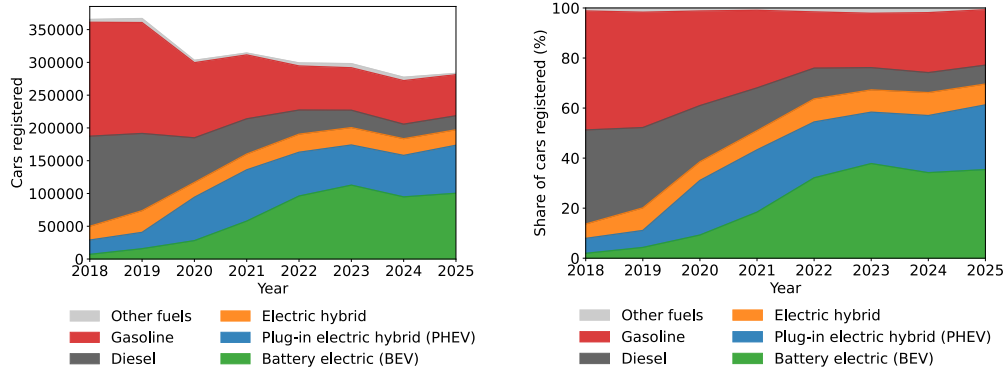
The projected growth of electrification is already demonstrated in the fast adoption of electric vehicles in Sweden. To provide context for this work and illustrate the current transition rate, key statistics (collected from PowerCircle [6]) on the Swedish transport fleet as of January 2026 are presented in Table 2.1. Nationally, approximately 15% of both passenger cars and buses are electrified, and the electrification of the truck fleet has begun to accelerate. The adoption rate for passenger cars remains high, with 68% of all new car sales consisting of electric or hybrid vehicles.

Table 2.1: Transportation electrification in Sweden, January 2026. Statistics collected from PowerCircle [6].

Category	Values
Fully electric cars	414 427
Plug-in hybrid electric cars	341 648
Light-duty trucks	36 175
Heavy-duty trucks	1 634
Share of car fleet	15%
Share of bus fleet	17%
Share of newly registered cars	68%

The transition to electrified transport is progressing unevenly across vehicle segments. Passenger car sales in Sweden have generally declined since the peak in 2019 (Figure 2.2a), but the combined share of electric and plug-in hybrid cars has stabilized between 50 – 60% of new registrations (Figure 2.2b) [16]. This trend is also evident in commercial fleets where new registrations of light-duty trucks are seeing increased electrification, with approximately 22% being Battery Electric Vehicles in 2024 [17].

In contrast, the heavy-duty truck segment has only recently begun its transition. In 2024, the share of electric heavy-duty trucks (above 16 tons) was around 6% [18]. Despite the low current share in sales, projections for this show predictions in the range of 93-95% electrification by 2040-2045 [6, 19]. Finally, the heavy equipment fleet in Sweden has seen less progress in decarbonization compared to cars and trucks. In 2024, it accounted for approximately 6% of national greenhouse gas emissions, with construction equipment representing a large share [20]. Emissions are primarily from fossil-fuel combustion, making electrification a relevant mitigation measure. Although no heavy equipment is fully electrified in Sweden today, electric machines are becoming commercially available [21].



(a) Passenger cars registered per year in Sweden during 2018-2025. (b) Fuel type share per year in newly registered passenger cars.

Figure 2.2: Comparison of absolute and percentage of new passenger car registrations by fuel type.

2.2 Charging Demand Modeling

To understand how new loads impact the power system, these loads need to be modeled. Early studies on charging demand relied heavily on logged empirical charging data to derive initial load profiles. There are several examples of openly available datasets collected when electric vehicles were new on the market, such as the charging data collected in the Electric Nation [22] and My Electric Avenue [23] projects in the UK in the mid-2010s. These data collections have served as an important foundation for understanding charging behavior and developing initial charging demand models. Following the stochastic nature of EV charging, probabilistic models were adopted for charging demand early on. For example, [24] used the data collected in the My Electric Avenue project to create Gaussian mixture models of EV charging demand. Similarly, [25] analyzes collected charging data to fit parameterized probability distributions for probabilistic load flow simulations. Despite laying the groundwork for many charging demand models, there are few updated and openly available datasets containing logged charging data. An exception to this is, to some extent, the availability of aggregated public charging data collected in Germany in the late 2010s, where a few examples of aggregated datasets are available [26, 27].

Due to the limitations in data accessibility and geographic relevance, the research community transitioned toward synthetic load profile generation using transport data as the primary input. In many cases, the models are based on transport data from non-electric vehicles, coupled with assumptions on charging behavior [28, 29]. Similar methods have been applied to estimate the charging demand of electric trucks, although these studies are not as numerous as those for passenger cars. Here, the models are often based on fleet oper-

ations [30, 31], or traffic flow on specific roads [32]. For other types of heavy vehicles, such as construction equipment, studies on their power or energy demand are limited, presenting a clear gap in the literature. For any vehicle fleet, simulation models are critical for examining the required charging demand. Agent-based simulations are frequently used to estimate traffic flows and resulting charging demand, with examples analyzing electric car fleets [33] and focusing on the heavy transport sector, including long-haul trucks in the Swedish context [34]. Other common simulation methodologies include spatial Markov chain models [35], trip-chain models used specifically for simulating battery electric long-haul routes [36], and methods based on graph theory [37].

The literature that uses these demand models to assess grid impacts typically distinguishes between two key scenarios. The first, 'unmanaged' or 'uncoordinated' charging, assumes that charging begins immediately upon the vehicle's arrival, often creating a 'worst-case' load that coincides with existing residential peaks [38]. The second is 'managed' or 'smart' charging, which models temporal shifts in charging to limit the grid impacts, or to gain economic savings for the EV owner. This approach is widely explored in the literature, with many studies reviewing the strategies and potential of smart charging [39]. A recent, highly relevant empirical study analyzing 334 EVs in Sweden found that vehicles are often parked four times longer than necessary for charging [40]. This finding confirms a large potential for temporal shifts in EV charging, which will most likely affect how EV charging impacts the grid capacity.

It is important to note that a significant portion of the literature on EV charging focuses exclusively on the development of charging profiles, often presenting the aggregated load as the final result. While crucial for quantifying the scale of the new demand (as in RQ1 of this thesis), these studies do not assess the actual technical impact on power system assets. To understand the impact on grid capacity, such as the risk of thermal overloads, these demand models must be integrated as inputs into power system simulations. The following section reviews the literature on the methodologies used for performing such grid impact assessments.

2.3 Grid Capacity Impact Assessment

Grid capacity is a measure of the maximum power that an electric power system can deliver, and can be defined regarding load serving or generation acceptance [41]. Several factors affect grid capacity, as summarized in Table 2.2. While all these factors are essential for the secure and reliable operation of the power system, they serve different functions. Stability and protection limits are primarily concerned with the grid's dynamic response to sudden events or faults. Generation availability defines the overall energy supply, and voltage limits ensure power quality. However, the focus of this thesis concerns the steady-state impact of

Table 2.2: Key Limiting Factors for Grid Capacity

Limiting Factor	Description
Generation availability	The available power from system generators will decide how much load can be served.
Thermal limits	Electrical components like power lines and transformers have temperature limits they must not exceed to avoid reaching critical conditions.
Voltage limits	The voltage needs to stay within the acceptable voltage range to ensure the quality and reliability of power supply.
Stability limits	Limits define the maximum power transfer before the system becomes unstable.
Protection limits	In the event of a fault or contingency, the system's protection relays must operate correctly to isolate the faulted section without causing cascading failures.

aggregated EV charging loads on the existing infrastructure's ability to meet demand under normal operating conditions. The introduction of EV charging loads directly leads to an increase in power flow through the power lines and transformers. Although individual EV chargers have relatively low power ratings, the coincidence of many simultaneous charging events generates significant aggregate loads on the system [42]. In this context, the most critical metric for assessing grid stress is the thermal capacity of the physical assets, such as the power lines and transformers. For power lines, the current capacity is limited by line sagging, as the wires expand with higher temperature. For transformers, the rated power is limited by the heat losses generated by power transfer, to avoid risks of degradation of their insulation and causing premature failure [43]. In this context, traditional grid planning practices must also be considered. Thermal limits are typically assessed under N-1 contingencies, ensuring secure operation following the loss of a single system component [44]. In contrast, this thesis restricts the analysis to normal operating conditions (N-0). This choice is motivated by the inherent temporal flexibility of electric vehicle charging loads, which can be curtailed or shifted in response to system disturbances. This assumption is supported by empirical studies of real-world EV usage patterns, which show that vehicles are typically parked for significantly longer durations than required for charging, indicating substantial potential for temporal flexibility in charging behavior [40].

To understand how new connections will affect the loading of power lines and transformers, simulations must be performed. The most common approach in traditional grid planning is to perform load flow simulations of a deterministic worst-case scenario [7]. This is also

a common approach in early literature assessing the grid impact of electric vehicles [45]. A more detailed deterministic approach is the use of quasi-static time series simulations of hourly resolution, where temporal variations are captured on the selected days of study [46]. Although power flow simulations are the most common when examining the EV impact on flows and voltages in electric power systems, other alternatives exist, such as optimal power flow [47].

The primary limitation of deterministic methods is their failure to capture the uncertainty and stochasticity of modern power systems. The growing integration of variable generation and new, stochastic loads, like electric vehicle fleets, requires a transition from "worst-case" analysis to risk-based assessment. The most common technique for this is probabilistic load flow simulations, often implemented by the numerical Monte Carlo method [48]. In contrast to the use of fixed inputs in the deterministic methods, probabilistic simulations model variables, such as base load, generation, and EV charging demand, as probability distributions. The resulting outputs, such as loading and voltages, are also given as probability distributions. A conceptual comparison of deterministic and probabilistic approaches is shown in Figure 2.3. In a deterministic simulation, only a single operating point is evaluated, typically corresponding to a worst-case scenario (a loading level of 110% in the example shown in Figure 2.3a). In contrast, a probabilistic simulation considers the full range of possible outcomes and their associated probabilities. In the example in Figure 2.3b, the maximum loading is the same as in Figure 2.3a (110%), but the probabilistic approach also quantifies the likelihood of exceeding operational limits, with a probability of 1.3% for loadings above 100%.

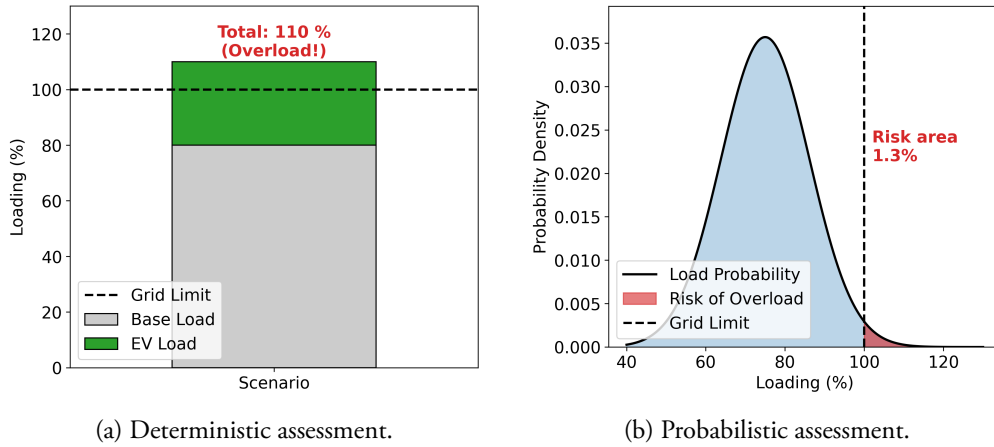


Figure 2.3: Conceptual comparison of grid capacity assessment methods. (a) Deterministic methods rely on worst-case scenarios, leading to binary outcomes. (b) Probabilistic methods quantify the risk (red area) of exceeding limits.

While frameworks for probabilistic load flow simulations to assess EV grid impacts were developed at an early stage [38], recent research has focused on improving the realism and accuracy of the simulation inputs. In addition to the development of precise probability distributions for individual EV loads (as discussed in Section 2.2), a primary challenge is the modeling of co-dependency between different stochastic variables. To address this, copulas have emerged as a common and effective method to integrate these correlated variables into a probabilistic load flow simulation, as outlined in [49]. A broader review of the various correlation factors considered in probabilistic simulations, particularly between EVs and other system loads, is provided in [50].

2.4 Integration of Transport and Power System Models

The interface between electric vehicles and the power grid is through the chargers. Most chargers for passenger cars have low enough power to be connected to the residential grid, especially in the case of home chargers. Recent studies in Sweden suggest that around 70% of all passenger car charging occurs at the home of the car owner [40]. The majority of public chargers in Sweden also have relatively low power, as seen in Figure 2.4 [6]. Due to the typical connection point at low voltage levels, a large body of research has focused on the impact of EV charging on residential and radial low-voltage grids.

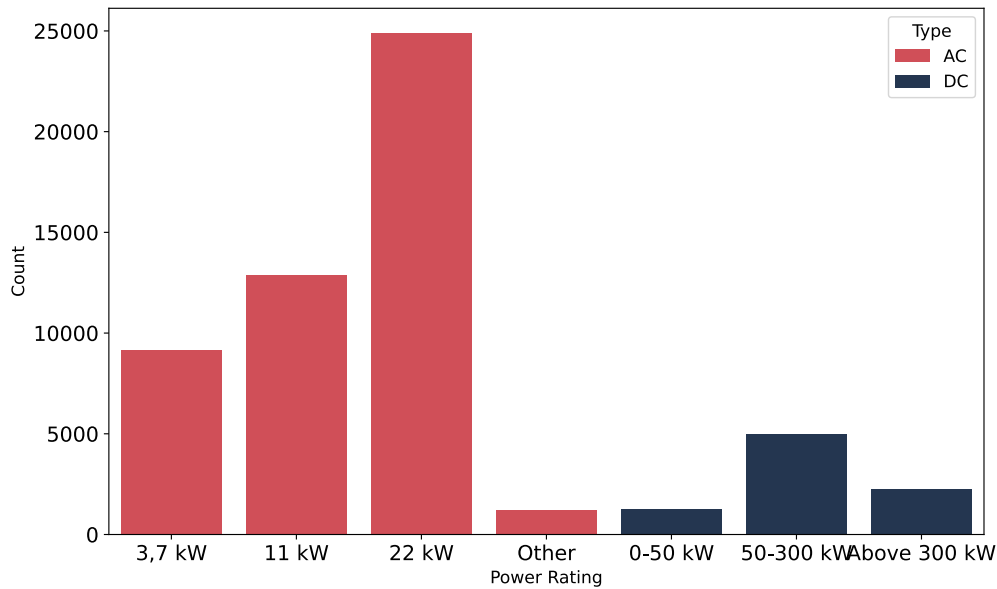


Figure 2.4: Registered public chargers in Sweden in 2025, divided by power level.

The analysis of grid impacts from the installation of EV charging loads requires an integration of the EV loads into the grid model analyzed. For residential network simulations, the EV charging loads can be added directly to the already existing household loads [28]. The process of mapping EV charging loads to higher aggregation levels can be as simplistic as randomly allocating generated EV loads to connection points in a grid model [29]. However, transportation networks and electric power infrastructures each possess distinct geographic distributions. This makes geographically realistic models, including the interconnection locations, essential for accurate and integrated transport and power system simulations. A more accurate integration strategy is to use GIS mapping of modeled EV loads and the geographic location of connection points [51]. To achieve this, geographical zones can be established around each feeding substation, and all modeled loads within a zone will be combined, as described in [52].

If realistic interconnection points are to be simulated, realistic grid models are needed. However, access to real-life grid topologies, particularly at the sub-transmission and transmission levels, is often restricted due to national security and confidentiality concerns. As previously noted, a significant portion of research focuses on low-voltage grids, where detailed, real-life residential grid models are more readily available for analysis [46]. While valuable, these studies cannot capture the aggregated, large-scale effects on the higher-voltage system. Few studies exist that integrate aggregated EV charging loads to real-life grid models at higher voltage levels. A possible solution to the problem of confidentiality has been the recent development of synthetic grid models, which keep the grid model statistically accurate with regard to the grid-specific behavior [53]. Unfortunately, no synthetic grid model is available for the Swedish sub-transmission grid. Studies that do attempt to analyze impacts at the sub-transmission or transmission levels are often forced to make significant methodological compromises. These studies frequently rely on deterministic modeling [29, 47, 51], use general benchmark models with no real-world geographic applicability [25], or employ simplistic, non-spatial load allocation [29].

Consequently, a significant research gap exists. There is a lack of frameworks that simultaneously integrate geographically explicit charging demand (across diverse fleet types) with realistic sub-transmission grid models using probabilistic simulation. This thesis is dedicated to filling this gap.

Chapter 3

Simulation Framework

This chapter presents the methodological framework developed in this thesis to assess the grid impact of transport electrification. An overview of the simulation framework is given in Figure 3.1. The framework consists of two main parts: charging demand modeling (presented in detail in Section 3.1) and grid impact assessment (in Section 3.2). The framework is implemented using a coupled simulation approach. Python or MatSIM is used to generate the charging profiles, which are then introduced to the steady-state grid simulations in DIgSILENT PowerFactory [54] using an automated Python/PowerFactory coupling.

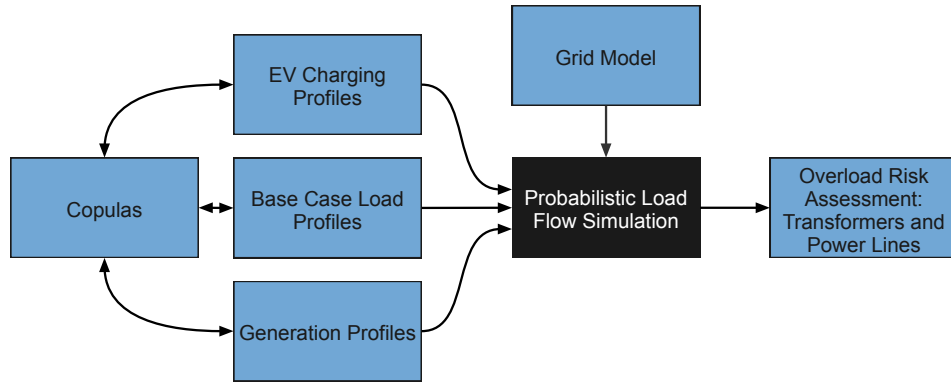


Figure 3.1: Overview of simulation framework.

3.1 Charging Demand Models

The charging demand models developed and applied in this thesis are based on the assumption of 100% vehicle electrification. Three vehicle fleets are studied: passenger cars, long-haul trucks, and heavy construction equipment. These fleets differ in the extent to which electrification has already been achieved. Consequently, there is a large difference in the availability of datasets describing electric vehicles. For passenger cars, which have already been electrified to a large extent in Sweden, EV charging datasets are available. For long-haul trucks and heavy equipment, however, limited data and knowledge on the charging patterns are available. For this reason, the models estimating the charging demand of the different fleets differ, reflecting the underlying datasets. Figure 3.2 presents an overview of the charging demand models and the scenarios defined. The fleets were modeled independently from one another, and the resulting charging demand has been analyzed both individually (Papers II and III for the car fleet, Paper IV for the long-haul truck fleet, and Paper V for the heavy equipment fleet) and for the combined fleets (Paper VI). The remainder of this section will provide a detailed description of the developed charging demand models.

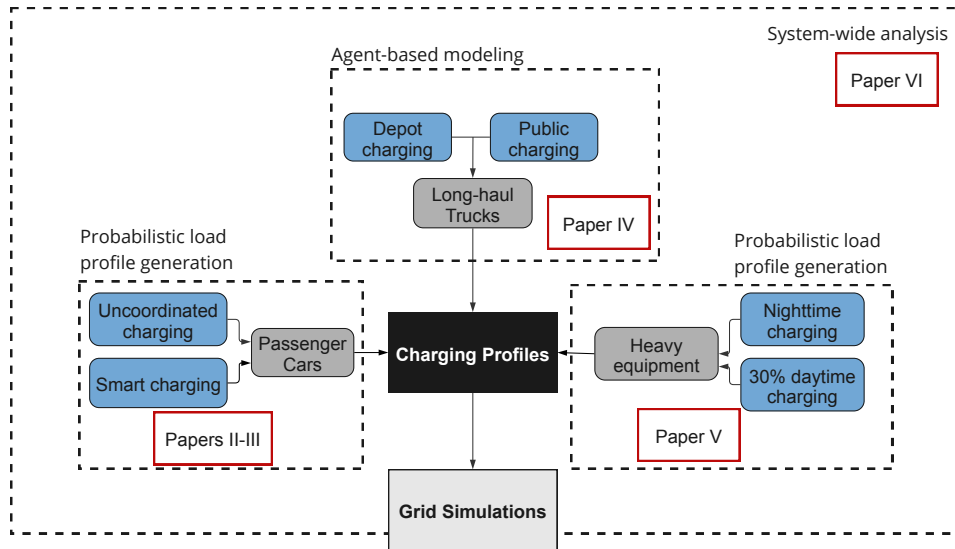


Figure 3.2: Overview of charging demand models, scenarios, and how this relates to the appended papers.

Passenger Cars

The car fleet in Sweden has already reached an electrification level of 15% in 2025, including both fully and hybrid electric passenger cars [6]. Consequently, there is a high level of maturity and data availability regarding travel, charging, and vehicle characteristics, which have been used when creating the passenger car charging demand model. The model, which is built and run via Python, is presented and applied in Papers II and III. An overview of the model is shown in Figure 3.3 and described in more detail in Algorithm 1. The source code and the resulting high-resolution temporal and spatial charging profiles for the Skåne region have been published open-source at [9]. This allows other researchers to reproduce the studies and to utilize the modeled EV loads for further power system simulations or regional planning.

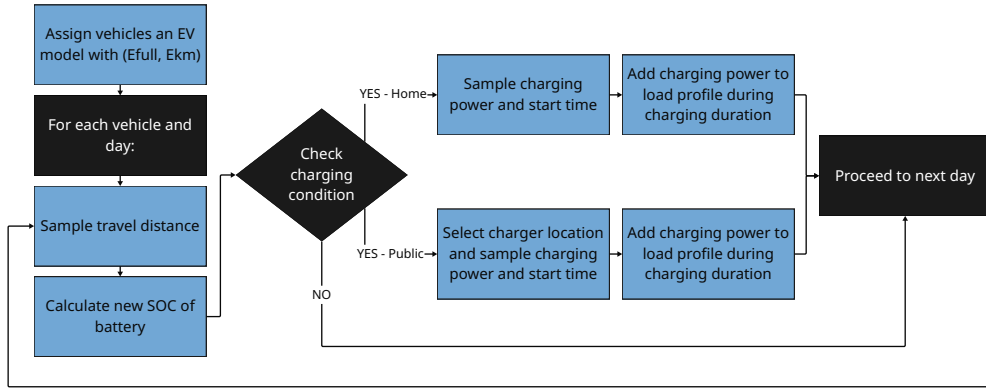


Figure 3.3: Overview of passenger car fleet charging demand model.

The car charging model aimed to combine as updated and realistic data sources as possible to build a data-based model representing an aggregated fleet of passenger cars at the sub-transmission grid level. A summary of the collected data and statistics used in the car fleet charging demand model is shown in Table 3.1. The statistics and data sets were collected in 2023 and 2024 when the model was built. Despite applying a probabilistic model of the car charging demand, some parameters were modeled statically due to a lack of representative datasets. To assess the influence of these static assumptions, a sensitivity analysis was performed, the results of which are presented in Paper II and discussed in Chapter 4.1.

Algorithm 1: Probabilistic passenger car charging demand model

Input: Simulation period D , car fleet C , EV model parameters (battery size E_{full} , energy consumption E_{km}), travel distance $\mathcal{N}(\mu_v, \sigma_v)$, charging probability p_{charge} , charging power ($P_{\text{home}}, P_{\text{public}}$), start time ($T_{\text{home}}, T_{\text{public}}$), public charger location p_i , public charging duration T_{duration} , and home/public charging shares.

Output: Aggregated hourly charging load profiles for each primary substation.

```
1 Assign each vehicle  $v \in C$  an EV model with  $(E_{\text{full}}, E_{\text{km}})$ ;
2 Initialize total load profile  $L(t) \leftarrow 0$ ;
3 foreach vehicle  $v$  do
4   Initialize battery state  $E_{\text{batt}}$ ;
5   Initialize individual load profile  $l_v(t) \leftarrow 0$ ;
6   foreach day  $i \in D$  do
7     Sample travel distance  $d_i \sim \mathcal{N}(\mu_v, \sigma_v)$ ;
8     Update battery energy:  $E_{\text{batt}} = E_{\text{batt}} - d_i \cdot E_{\text{km}}$ ;
9     if random draw  $r < p_{\text{charge}}(\text{SOC})$  then
10       Select charging type: home or public;
11       if home then
12         Sample charging power  $P_{\text{home}}$  and start time  $t_{\text{start}} \in T_{\text{home}}$ ;
13         Determine duration  $t_{\text{home}} = (E_{\text{full}} - E_{\text{batt}})/P_{\text{home}}$ ;
14         Add  $P_{\text{home}}$  to  $l_v(t)$  during  $t_{\text{home}}$ ;
15         Set  $E_{\text{batt}} = E_{\text{full}}$ ;
16       else if public then
17         Select location based on  $p_i$  and sample  $(P_{\text{public}}, t_{\text{public}})$ ;
18         Add  $P_{\text{public}}$  to  $l_v(t)$  during  $t_{\text{public}}$ ;
19         Update  $E_{\text{batt}} = \min(E_{\text{full}}, E_{\text{batt}} + P_{\text{public}} \cdot t_{\text{public}})$ ;
20   Add  $l_v(t)$  to substation-level profile  $L(t)$ ;
21 return  $L(t)$ 
```

Table 3.1: Model parameters, modeling approaches, and data sources used in the car charging demand model.

Statistic / Parameter	Unit	Modeling approach	Data source
Car fleet size (C)	#	Static per geographic area	Statistics Sweden [55]
Electric car models	–	Random selection	Power Circle [6]
Battery size (E_{full})	kWh	Static per car model	EV Database [56]
Energy consumption (E_{km})	kWh/km	Static per car model	EPA [57]
Daily travel distance ($\mathcal{N}(\mu_v, \sigma_v)$)	km	Normal distribution	Transport Analysis [58]
Home charging power (P_{home})	kW	Random selection	–
Home charging start SOC ($\text{SOC}_{\text{start}}$)	%	Scenario based	–
Home charging end SOC (SOC_{end})	%	Static assumption	–

In addition to the public data sources, three different datasets of logged charging sessions have been analyzed, as outlined in Table 3.2. The ”Uncoordinated AC charging” dataset is publicly available, and includes charging sessions logged in the UK project Electric Nation in 2018 [59]. The dataset used is the subset in the experiment where no temporal shifts were applied to the charging. Consequently, this dataset represents a baseline case with completely uncoordinated charging. In contrast, the ”Smart AC charging” dataset was provided by a car manufacturer and includes logged charging sessions from electric cars with installed smart charging technology. All cars in the dataset are located in Sweden, and the data was collected during 2023. Exactly how the car owners employed the smart charging is not known and likely varies between the users. This dataset represents a mixed EV fleet where a share of the car owners apply smart charging. It should be noted that the ”Smart charging” dataset does not intend to represent optimal charging behavior. Rather, the choice of including two different datasets, collected at different times, in different countries, and with varying car fleets, enables a general analysis of how the charging behavior

Table 3.2: Overview of logged charging session datasets and model parameters derived.

Dataset	Description	Statistics collected
Uncoordinated AC charging	Contains 58,426 logged charging sessions collected in the UK Electric Nation project [59] during 2018. Represents uncontrolled home AC charging behavior, collected before smart charging technology was available.	Home charging start time distribution T_{home}
Smart AC charging	Contains 50,695 logged charging sessions collected in Sweden during 2023. All cars in the EV fleet are equipped with smart charging technology, which may be used by the EV owner.	Home charging start time distribution T_{home}
Public DC charging	Contains 117,134 logged public charging sessions collected in Sweden in 2024.	Distributions of public charging power P_{public} , start time T_{public} , and session duration T_{duration} .

may impact the results of the simulations. Finally, the "Public DC charging" dataset is provided by a Swedish charging point operator and includes all charging sessions logged at their chargers during a full month in 2024. The analyzed datasets were used to calculate probability distributions of the starting time of charging sessions for home and public charging, respectively. Additionally, probability distributions of the duration and charging power of public charging sessions were derived from the public charging dataset.

The final input parameter considered is the charging probability distribution, denoted by p_{charge} . This parameter models the car owner's decision to charge their car, based on its state of charge (SOC). Table 3.3 outlines the three charging behavior scenarios explored in Paper II, where only the home charging part of the model was applied. In the rest of the simulations (Papers III and VI), the "Random charging" scenario was considered, and the model was expanded to also include public charging sessions.

Table 3.3: Home charging behavior in the three modeled scenarios.

Scenario	Charging behavior
Charging at 80%	The vehicle initiates charging when the SOC drops below 80%.
Random charging	The vehicle initiates charging when SOC is below 30%, or with a 50% probability when SOC is below 80%.
Charging at 30%	The vehicle initiates charging when SOC falls below 30%.

Long-haul Trucks

This section introduces the modeling of the long-haul truck fleet, which is the central focus of Paper IV. This research was conducted in collaboration with Mattias Ingelström, who developed and executed the underlying transport modeling using the agent-based simulation framework MATSim [60]. The choice of an agent-based simulation framework to model the charging demand of long-haul trucks is due to the lack of available charging data sets for these vehicles, as they are still only electrified to a small extent. Instead, detailed travel data of the current fleet of trucks has been used as a basis for the transport simulation, in which all trucks are assumed to be electric. The detailed mechanics of this transport simulation are presented in Paper IV and Ingelström et al.'s related publications [61, 34]. The resulting charging demand profiles have been published as an open-access dataset in [62].

Building upon this work, the core contribution of this thesis involved post-processing the transport simulation outputs to generate the aggregated load profiles required for the probabilistic load flow analysis. Figure 3.4 presents an overview of the integrated framework, highlighting that the specific contributions of this thesis are focused on the power system modeling shown on the right-hand side of the flowchart. The charging demand profiles

from the MatSIM simulation are in the format of consecutive daily profiles with hourly resolution. The post-processing included allocating each charging station to the geographically closest primary substation using GIS techniques. All charging loads allocated to a substation were then aggregated to generate the resulting aggregated load profile. Stochastic variations between the days are present due to the random selection of the starting SOC of the simulated trucks, as well as a stochastic variation of the number of trucks in the fleet.

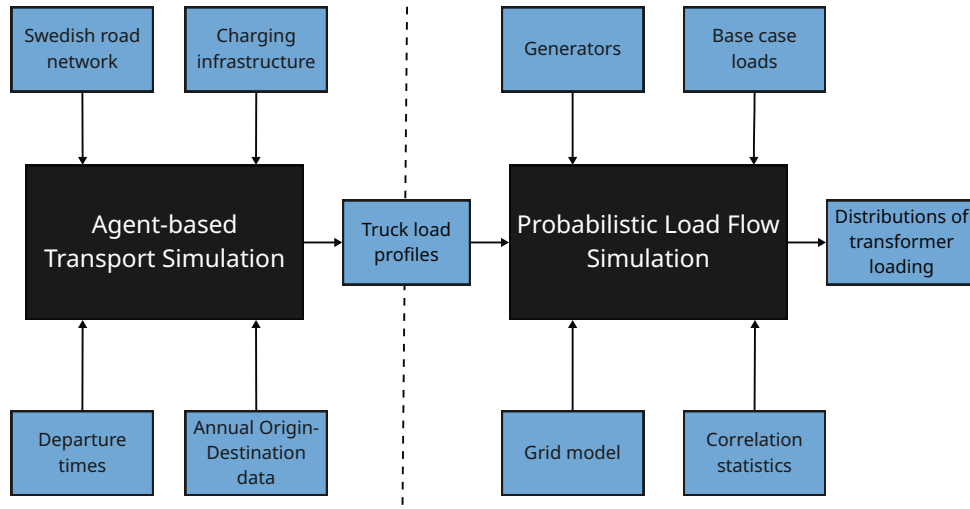


Figure 3.4: Overview of simulation framework for coupled agent-based long-haul truck simulations with the probabilistic framework developed in this thesis.

The truck transport simulation in Paper IV assumes a 100% electrification of the long-haul truck fleet, including all trucks in Sweden that perform trips longer than 300 km. Public fast-charging stations are simulated at pilot locations defined by the “Regional Electrification Pilots” at the Swedish Energy Agency [63]. Since the power grid analysis is limited to the region of Skåne, only the resulting charging events within this region were collected. The vehicle characteristics of the truck fleet are presented in Table 3.4.

Table 3.4: Vehicle characteristics of the trucks in the long-haul truck simulation.

Weight class [tonnes]	Battery capacity [kWh]	Average range [km]	$\pm \sigma$ [km]	Population share [%]
3.5-16	180	280	4	<1
16-24	300	340	30	6
24-40	400	330	40	36
40-60	500	300	10	58

The simulation was expanded in Paper VI to include overnight charging events. The details of the expanded simulation can be found in [61]. Figure 3.5 presents the geographical distribution of the modeled infrastructure, showing both the public fast-charging stations from Paper IV and the overnight charging locations introduced in Paper VI.

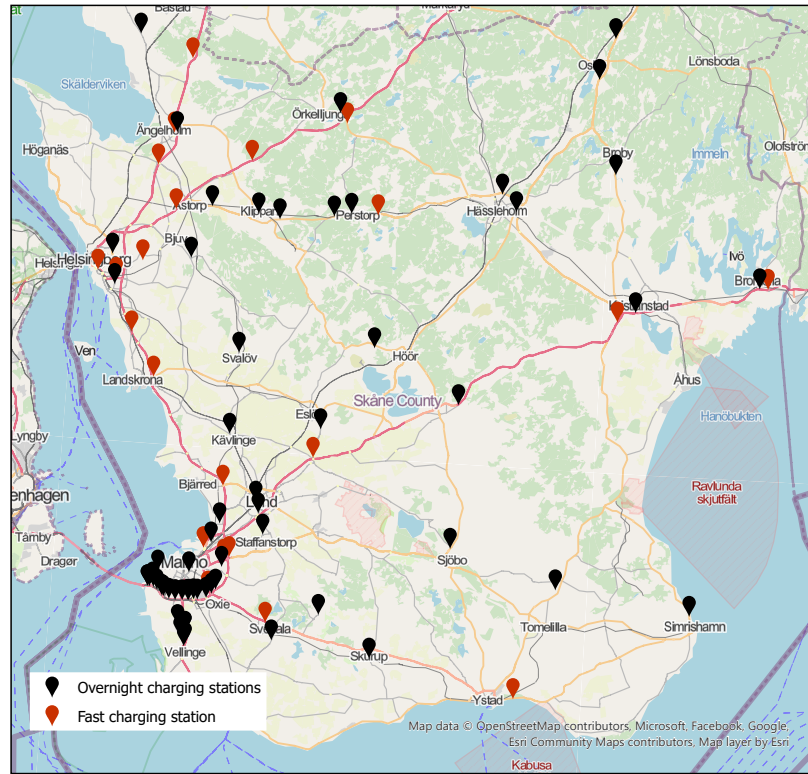


Figure 3.5: Map of Skåne showing the fast charging (in red) and overnight (in black) charging stations in the long-haul truck simulation.

Heavy Equipment

The heavy equipment fleet is not yet electrified to any significant extent, making it difficult to directly apply modeling approaches based on charging data. In addition, non-road heavy machinery typically operates at fixed project sites, meaning that conventional traffic-based data is not available. Instead, an algorithm has been developed in Python to generate aggregated charging load profiles for heavy equipment based on operational and fleet data. The model and selected results are presented in Paper V, and some key points are repeated here. The charging demand model is based on a dataset containing operational data of approximately 14 000 heavy equipment machines sold in Sweden during the years 2013 -

2023. The dataset contains the delivery location, market share, energy consumption per hour, and the average daily operational hours for each machine. A total of 65 machine models are present in the dataset, which can be divided into 8 more general sub-categories, as listed in Table 3.5. This table also presents statistics on the operational hours and energy consumption for the general machine categories.

Table 3.5: Statistics of daily operational hours and energy consumption for different heavy equipment categories in the studied dataset.

Machine Type	Count	Op hours [h]: Average	Op hours [h]: Standard Dev	Energy cons [kWh/h]: Average	Energy cons [kWh/h]: Standard Dev
Articulated Haulers	332	7.58	3.59	82.91	16.73
Compact Excavators	1608	2.12	1.19	20.88	11.74
Compact Wheel Loaders	1370	2.54	2.16	15.94	2.99
Compaction Machines	160	1.33	1.11	23.49	8.73
GPE Crawler Excavators	2389	5.78	2.35	43.22	22.57
GPE Wheel Excavators	2330	5.46	1.98	62.38	23.84
GPE Wheel Loaders	5832	6.65	3.98	42.02	19.52
Paving Machines	42	5.07	2.71	62.92	6.87

The charging demand model is built based on the available operational and vehicle data presented above in Table 3.5. However, the model is more specific, considering each of the 65 machine models individually. The model-specific statistics serve as input probability distributions to the developed charging demand profile model, which is outlined in Algorithm 2. The initial steps of the algorithm, estimating the equipment fleet size and its geographical distribution, are based on the studied dataset. It is assumed that machines operate near their delivery locations; all machines sold and delivered within the study area are considered to be in operation there. More specifically, each machine is assumed to operate within the same municipality in which it was delivered. However, its exact operating location, and consequently the associated primary substation transformer to which it is aggregated, is assigned randomly.

The charging behavior of electric heavy construction equipment is a major source of uncertainty, considering the very low degree of electrification of today's heavy equipment fleet. For this reason, three charging scenarios based on present-day operations have been introduced to capture the possible variations based on any assumptions made about charging behavior, as outlined in Table 3.6. For the dataset considered, most construction work takes place between 06 and 17 on workdays, with two daytime breaks. The first scenario, "Night charging," simply assumes that the entire energy requirement will be charged evenly outside of these operational hours. To study the impact of faster daytime charging, two scenarios were introduced where daytime charging is utilized during the breaks. The "Half Night charging" assumes that half of the energy requirement is provided through nighttime charging, and the rest during the daytime breaks. Similarly, the "Third Night charging" scenario assumes that only one-third of the energy is charged at night.

Algorithm 2: Generation of Aggregated Heavy Equipment Charging Load Profile

Input: Simulation period D , heavy equipment models M , operation hour distributions H_m , energy consumption C_m , charging scenarios $s \in \{\text{Night, Halfnight, Thirdnight}\}$

Output: Aggregated charging load profiles $L(t)$ of length $D \cdot 24$ hours

```
1 Estimate total heavy equipment fleet size in the study area;
2 Select geographical distribution of the heavy equipment fleet;
3 Initialize substation load profile  $L(t) \leftarrow 0$ ;
4 foreach machine  $m \in M$  do
5     Initialize machine load profile  $l(t) \leftarrow 0$ ;
6     foreach day  $d \in D$  do
7         Draw operational hours  $h_m$  from distribution  $H_m$ ;
8         Calculate energy used  $E_m = h_m \cdot C_m$ ;
9         Update machine charging profile  $l(t)$  according to charging scenario  $s$ ;
10        Update total profile:  $L(t) \leftarrow L(t) + l(t)$ ;
11 return  $L(t)$ ;
```

Table 3.6: Temporal charging distribution in the three charging scenarios defined.

Scenario	Nighttime (17 - 06 $\pm$ 1h)	Break 1: 30 mins (09 - 10 $\pm$ 1h)	Break 2: 30 mins (14 - 15 $\pm$ 1h)
Night Charging	100 %	None	None
HalfNight Charging	50 %	25 %	25 %
ThirdNight Charging	33 %	33 %	33 %

3.2 Grid Simulations

The EV charging demand models described above are used as inputs to a probabilistic load flow simulation framework to assess the impact of these new loads on power grid capacity. This section presents the developed simulation framework. First, an overview of the grid model is provided, including key characteristics. Next, the models of basecase consumption and generation are described. Finally, the methodology for incorporating correlations between stochastic variables is outlined. The framework was developed within the scope of Paper I and applied in Papers II-VI.

The simulation framework is based on a Monte Carlo simulation of load flow calculations, as implemented in the DIGSILENT PowerFactory simulation software [54]. A Monte Carlo

simulation numerically calculates the expected value $E(X)$ of a function $f(x)$ depending on a variable X , as in Equation 3.1 [64].

$$E[f(X)] = \int f(X) dP \approx \frac{1}{N} \sum_{n=1}^N f(X_n) \quad (3.1)$$

A probabilistic load flow simulation uses the Monte Carlo technique to estimate the probability distributions of possible load flow calculation results. Table 3.7 outlines the parameters and equations in the probabilistic load flow formulation.

Table 3.7: Probabilistic Load Flow simulation parameters.

Variables X	Input parameters: Loads, generators
Function $f(x)$	Power flow equations
Expected value $E(x)$	Output parameters: Voltages, angles, power flows, loading

Grid Model

The grid model used in this thesis covers the transmission (400 kV) and sub-transmission (135 kV) grid within the Swedish bidding zone SE4, including primary substations (135/22 or 135/11 kV). This model is a reduced version of the full Nordic synchronous area model, where the parts of the system located outside SE4 are represented by Thévenin equivalents at the model boundaries. The specific study area is the region of Skåne, a sub-area of SE4. A geographic overview of the grid model is shown in Figure 3.6. While the model boundary uses a slack-bus representation, the inclusion of the wider SE4 grid creates an electrical buffer zone between the study area (Skåne) and the model boundary. This buffer effectively damps the influence of the slack bus on the simulation results within Skåne. The grid is meshed at all voltage levels. Throughout the simulations, parameters are stochastically varied within Skåne, while the rest of the model (the buffer zone) remains static.

The grid model cannot be shared openly due to confidentiality issues. However, some key numbers of the grid model within the study area of Skåne are presented in Tables 3.8 and 3.9. At the 135 kV level, there are 167 busbars in the study area, divided between 86 primary substations. The new system loads have been introduced at these substations, at the low-voltage side of the primary substation transformer, to investigate their impact on the transformer and power line capacities. The simulation outputs include power flow and loading data for all power lines and transformers in the study area, comprising 345 individual result elements. The analysis mainly targets the 86 primary substation transformers nearest to the installed loads, since this is where the impact of the new loads is highest.



Figure 3.6: Map showing the sub-transmission grid in the study area, where brown lines represent transmission lines (400 kV), blue lines represent sub-transmission lines (135 kV), and red lines represent 50 kV lines. The black line indicates the approximate border of the Skåne region. Image from E.ON Sweden.

Table 3.8: Key numbers for busbars, power lines, and 3-winding transformers in the grid model.

Element/ Voltage level		400 kV	135 kV	55 kV
Busbar	Nbr of elements	5	167	20
Power lines	Nbr of elements	28	198	0
	Median length (km)	33.8	4.8	-
3-winding transformers	Nbr of elements	0	33	0
	Median rated power (MVA)	-	40/40/25	-

The stochastically varied elements are generators and loads in the study area, as summarized in Table 3.10. The study area has only wind power and CHP plants at present. In total, 212 elements in the original model (before any EV charging is introduced) are varied stochastically.

Table 3.9: Key numbers for 2-winding transformers in the grid model.

Voltage (kV)	400/135	135/55	135/22	135/11	22/11
Nbr of elements	4	4	43	64	4
Median rating (MVA)	750	81.5	40	40	10

Table 3.10: Key numbers for generators and loads in the grid model.

Type	CHP generator	Wind power generator	Load
Nbr of elements	11	51	150
Median rating (MW)	56.3	7.7	14.2

Consumption and Generation

Before new loads could be introduced to the system, a method for modeling existing consumption and generation in the study area was required. At the beginning of this thesis work, no historical data on aggregated loads or generation were available for the study area. For this reason, synthetic models were developed describing the probability distributions of aggregated loads, wind power plants, and combined heat and power (CHP) plants. This model development is the core of Paper I, and the methodology is outlined in Figure 3.7. The data analysis was based on the data sources listed in Table 3.11, and the grid model described above. The aim was to develop a method to populate a static grid model, containing the typical worst-case scenario, with probabilistic input data. Later in the project, historical time series data became available for the modeled loads and generators. This enabled a validation process where the synthetically generated data sets could be compared with the historical ones provided by the DSO.

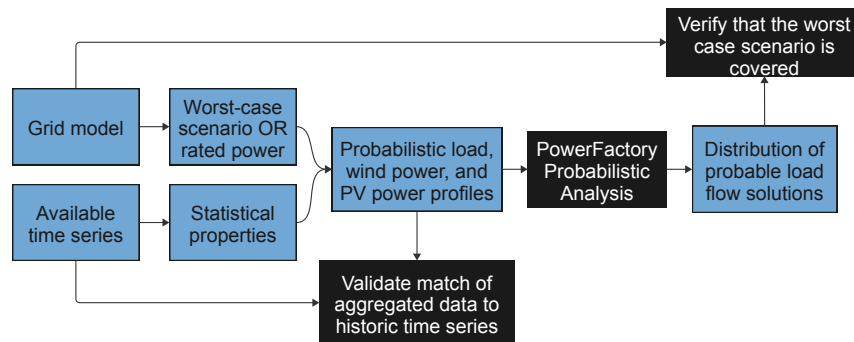


Figure 3.7: Methodology for generation of synthetic probability distributions.

Table 3.11: Overview of data sets used for statistical analysis of consumption and generation.

Dataset	Voltage Level	Content	Time span	Time Resolution	Availability
SE4 Load	400 kV	Mixed consumption	2011-2021	1 hour	Open-source
Sub-Transmission Load 1	50 kV	Mixed consumption	2020-2021	1 hour	DSO
Sub-Transmission Load 2	50 kV	Mixed consumption	2020-2021	1 hour	DSO
Residential Load	Lower	126 Households	2020-2021	1 hour	DSO
SE4 Wind Power	400 kV	Total generation	2017-2021	1 hour	Open-source
Wind Power Farm	Lower	23.7 MW park	2017-2021	1 hour	DSO
SE4 CHP	400 kV	Total generation	2017-2021	1 hour	Open-source

The goodness of fit of the studied probability distributions was measured using a Kolmogorov-Smirnov (KS) test [64]. The null hypothesis (that the data follows the distribution) is accepted if the p-value exceeds the significance level $\alpha = 0.05$.

The wind power generation analysis concluded that a Weibull distribution is the best fit for the data set examined, with a p-value of 0.143. The distribution is seen in Equation 3.2, where $k = 0.85$ and the scale parameter is dependent on the rated power P_{rated} as $\lambda = 0.22 \cdot P_{rated}$.

$$f(x) = \frac{k}{\lambda} \cdot \left(\frac{x}{\lambda}\right)^{k-1} \cdot \exp\left(-\left(x/\lambda\right)^k\right) \quad (3.2)$$

For CHP plants, no confident fit was found. For this reason, a simplified model was applied, assuming a uniform probability distribution as defined in Equation 3.3. Here, equal probability is assumed between 0 and the maximum power P_{max} .

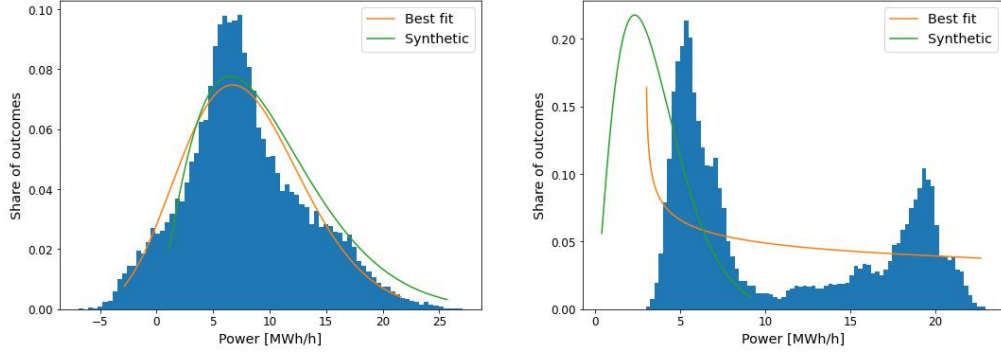
$$f(x) = \begin{cases} \frac{1}{P_{max}-0}, & \text{if } 0 \leq x \leq P_{max}, \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

The consumption data analysis led to a best fit of the beta distribution, as defined by Equation 3.4. Here, the optimal parameters were found to be $a = 2.38$ and $b = 11.9$. Furthermore, the distribution should be scaled based on the maximum load P_{max} .

$$f(x) = \frac{\Gamma(a+b)x^{a-1}(1-x)^{b-1}}{\Gamma(a)\Gamma(b)} \quad (3.4)$$

The synthetic consumption model was validated against 10-year historical time series of the aggregated loads modeled in the study area. The validation revealed that the synthetic profiles were a relatively good match for aggregated loads with high shares of household loads, as is shown in an example substation in Figure 3.8a. However, for mixed and industrial loads, the fit was poor, as can be seen in the example shown in Figure 3.8b. The analysis

concluded that more detailed modeling needs to be applied to accurately model synthetic consumption probability distributions.



(a) Visual validation example of aggregated household loads.

(b) Visual validation example of mixed household and industrial load.

Figure 3.8: Validation examples of synthetic consumption models compared to historical data.

For the reasons stated above, the consumption loads in the system have been modeled using the bootstrapping method. This approach involves drawing random samples with replacement directly from the historical time series [65]. By using bootstrapping, the non-standard distribution shapes are preserved without assuming a specific parametric shape. Consequently, while wind and CHP generation retained the synthetic probability distributions (Weibull and Uniform) described above, all consumption loads in the final grid capacity analysis were modeled using the bootstrapping method.

To summarize, all stochastic input data to the probabilistic load flow analysis are shown in Table 3.12. This includes the base case models for consumption and generation discussed in this section, as well as the EV charging demand models presented in Section 3.1.

Table 3.12: Summary of modeling strategies for all stochastic elements in the probabilistic load flow analysis.

Grid Element	Modeling Method	Key Input Data	Reference
Base Consumption	Bootstrapping (Time Series)	Historical hourly load data	Paper I
Wind Generation	Weibull Distribution	Historical generation data	Paper I
CHP Generation	Uniform Distribution	Rated power	Paper I
EV Charging (Cars)	Probabilistic Model	Travel, charging, and EV fleet data	Paper II, III
EV Charging (Trucks)	Agent-Based (MatSIM)	Regional freight flows, Pilot stations	Paper IV
Heavy Equipment	Probabilistic Model	Fleet sales, operational data	Paper V

Modeling Co-dependencies

The stochastic variables listed in Table 3.12 are not independent. To capture their relationships, co-dependencies are modeled using Gaussian copulas. A Gaussian copula C is defined by Sklar's theorem, stating that the random variables X and Y are joined by the copula C if their continuous distributions F_X and F_Y can be expressed as in Equation 3.5 [66].

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)). \quad (3.5)$$

The simulation procedure for drawing co-dependent random samples follows the Gaussian Copula implementation in DIgSILENT PowerFactory [67]. The procedure is defined as follows, where X_1, X_2 are the coupled random variables, and $Y = (Y_1, Y_2, \dots, Y_d)$ is the multidimensional distribution. This is done for each pair of random variables X_1, X_2 .

1. Generate random samples of the multidimensional distribution $Y = (Y_1, Y_2, \dots, Y_d)$
2. Transform the vector Y to a coupled uniform distribution, $U_i = F_{Y_i}(Y_i)$
3. Transform the vector U back to the desired distribution, $X_i = F_{X_i}^{-1}(U_i)$

A copula can be implemented with equal or varying correlation between the elements. The implementation strategies to model co-dependencies for the different stochastic elements are presented in Table 3.13.

Table 3.13: Copula implementation strategy per element category in probabilistic load flow simulation.

Element	Correlation
Loads (Base Consumption)	Based on historical time series
Loads (EV Charging)	Based on generated time series
Generators (Wind)	Equal: 0.7
Generators (CHP)	Equal: 0.2

This thesis has assumed equal correlations between generator elements, per generator type. This is based on the assumption that there is a correlation between different wind power parks, since they are not too spread out geographically within Skåne. Similarly, different CHP plants are assumed to be correlated since they respond to similar price signals. A time series analysis was performed on the historical wind and CHP generation data sets in Table 3.11. No significant cross-correlation was found between wind power plants and CHP plants, as the former depends on wind speed and the latter on price signals. Supported by

this analysis, the generators are not assumed to be correlated to consumption loads in the system, assuming independent drivers for local wind generation and aggregate consumption patterns.

All consumption loads modeled are assumed to be mutually dependent, including both basecase and EV charging loads. However, the modeled degree of correlation varies depending on the characteristics of each load. For instance, aggregated consumption areas dominated by household demand tend to exhibit strong correlations with other similar areas, while they are likely less correlated with areas where industrial consumption dominates. These relationships are represented using copulas, where pairwise correlations are derived from the time-series characteristics of the individual loads. The basecase loads are modeled using annual time series, which also serve as the basis for calculating correlations. For EV charging loads, the generated synthetic time series are used to estimate their correlations with other loads.

Chapter 4

Estimated Charging Demand and Grid Impact

This chapter presents the main findings from the appended papers, structured to address the research questions defined in the Introduction. The results are obtained from the probabilistic modeling framework described in Chapter 3, applied to the transmission and sub-transmission grid of Skåne in southern Sweden. Throughout this chapter, the results highlight the stochastic nature of the system, presenting findings not as single deterministic values but as overall statistics or probability distributions. The first section explores the results related to RQ1, namely the estimated charging requirements of the electrified vehicle fleets. The second section deals with the impact of the charging loads on the grid capacity, related to RQ2 and RQ3, using the developed probabilistic simulation framework. The last research question, RQ4, on how to apply the methodology to a realistic case study, is explored throughout the chapter.

4.1 Aggregated Energy and Power Requirements

This section summarizes the results connected to RQ1: What are the aggregated energy and power requirements for a fully electrified road transport fleet? The results presented here are collected from Papers II, III, IV, V, and VI.

The total energy demand derived from the simulations highlights the distinct scale of the different transport fleets. As illustrated in Figure 4.1, the passenger car fleet accounts for the largest share of total energy requirements. The fleets differ in simulation scope, as passenger cars are modeled over a full year and commercial heavy vehicles are simulated

on workdays only. Furthermore, the truck simulation considers only long-haul trucks, excluding regional distribution vehicles. However, the magnitude of the difference confirms that passenger vehicles will drive the bulk of the total energy consumption in the study area. This is further supported by national statistics on greenhouse gas emissions from domestic transport, where heavy and light trucks together account for approximately 34% of emissions. In contrast, passenger cars account for over 60% [68]. Since CO₂ emissions are directly proportional to fuel consumption, this ratio serves as an estimate of the current fleet's energy demand.

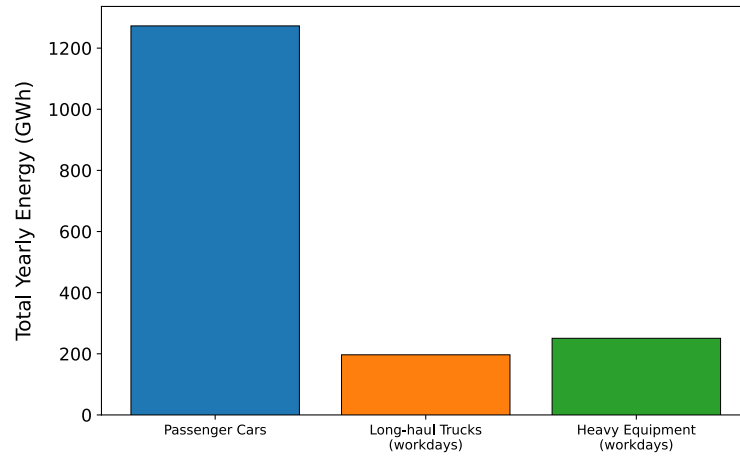


Figure 4.1: Yearly energy demand of simulated vehicle fleets.

In the context of grid capacity constraints, the total energy volume is less critical than the instantaneous power demand. A sector with lower total energy demand may still cause significant grid stress if its charging is highly concentrated in time or location. Therefore, the remainder of this section focuses on the aggregated power profiles and peak demand characteristics of the simulated fleets. Figure 4.2 shows the average and maximum peak power demand per substation in the simulated datasets. Here, the average peak load refers to the mean of the peak values calculated across all 86 primary substations, whereas the maximum peak load corresponds to the single highest peak observed in the worst-case substation. It is clear that although the passenger car fleet requires the bulk of the energy consumption, the fleets are comparable when it comes to power demand. The scenarios defined have an impact on the resulting peak power, which is especially seen in the heavy equipment fleet. To better understand the power demand of the different vehicle fleets, the following sections will present detailed analyses of the individual fleets.

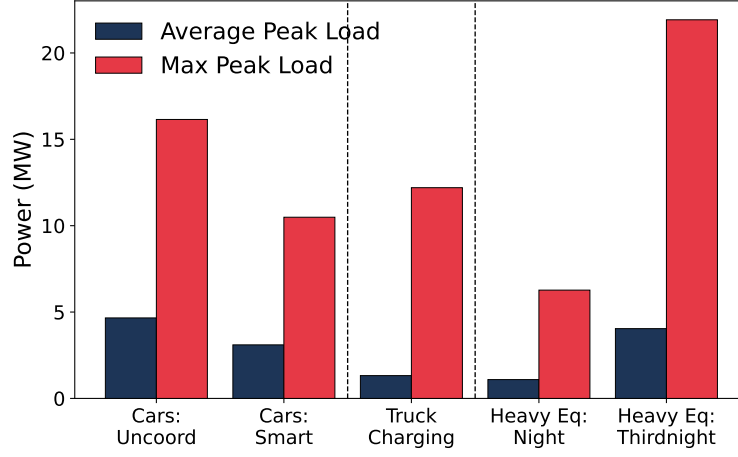


Figure 4.2: Comparison of average and peak loads for the simulated vehicle fleets.

Passenger Cars

The passenger car fleet has been simulated and analyzed in Papers II and III. This section summarizes some of the key findings from these papers. First, the impact of the charging start time on the aggregated power demand is analyzed based on the comparative study in Paper III. This comparison contrasts the "Uncoordinated" scenario (representing immediate charging upon arrival) with the "Smart" scenario (representing temporally shifted charging sessions). Figure 4.3 presents the typical daily load profile per primary substation. The curves shown are derived by calculating the median load curve for each substation (temporal aggregation) and then averaging these across all 86 substations (spatial aggregation). In the "Uncoordinated" scenario, there is a significant peak in the evening, whereas in the "Smart" scenario, the demand is more evenly distributed over time. This indicates that the peak charging demands are higher if charging happens with a higher simultaneity factor, which is also well supported by literature in the field [28, 33].

An overview of the power demand is shown in Figure 4.4, where the average and peak power are plotted for the "Uncoordinated" and "Smart" scenarios on the x- and y-axes, respectively. The unity line is included in the plots to visually indicate how the resulting power demand differs between the scenarios. Since the driving distances and energy consumption are identical in both cases, the energy demand and thus the average power remain the same in both scenarios, as shown in Figure 4.4a. The maximum power is influenced by the selection of the charging scenario, as this impacts the simultaneity factor of the charging sessions. This is clearly seen in Figure 4.4b, where all points fall below the unity line. This indicates that for every substation modeled, the peak power demand is higher in the "Uncoordinated" scenario than in the "Smart" scenario. On average, the peak power per substation increases

by 32% in the uncoordinated scenario compared to the smart charging case. In the most extreme individual substation, this increase reaches 38%.

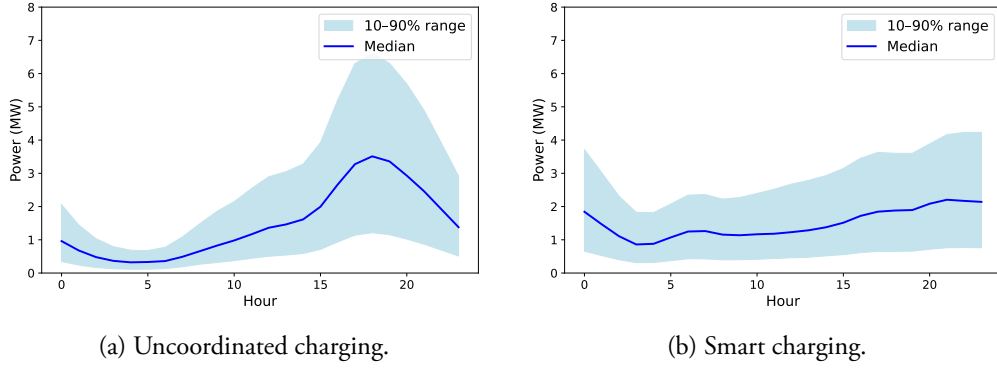


Figure 4.3: Ensemble daily load profile for an average substation for the "Uncoordinated" (left) and "Smart" (right) charging scenarios. The median profile is shown in a dark blue line, the 10-90% range is indicated by the light blue area.

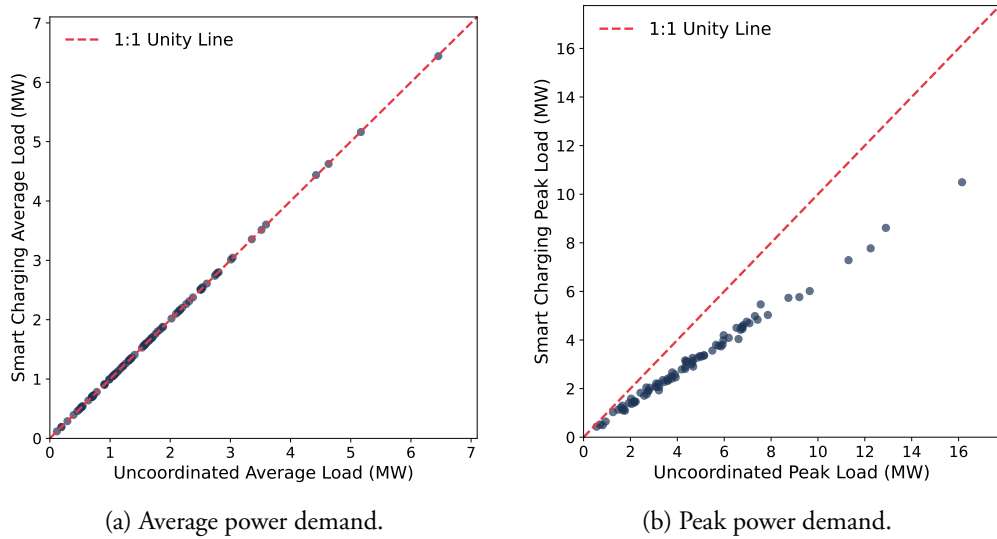


Figure 4.4: Comparison of the power demand of aggregated car charging loads at primary substations under Uncoordinated (x-axis) and Smart (y-axis) charging scenarios. The left panel (a) shows the average power demand, while the right panel (b) shows the peak power demand. Each data point represents one primary substation. The unity line ($y = x$) is included for reference.

To understand the co-dependencies of the aggregated charging loads at different primary substations, a correlation analysis was run. The average and standard deviation of the calculated in-group (between elements of the same kind) and cross-group (between different types of elements) correlations are presented in Table 4.1. From the correlation analysis, it is evident that uncoordinated charging gives rise to significantly higher correlations than the more spread-out charging loads represented by the smart charging scenario. This is expected, since the two scenarios are selected to represent the different levels of simultaneity of the modeled charging sessions. The basecase loads, which to a large extent represent household loads, are generally more correlated with the uncoordinated charging loads. This is due to the typical charging curve of the uncoordinated charging scenario, as presented in Figure 4.3a, which peaks in the evening, just as typical household loads. The similarities between the load curve in the smart charging scenario, as shown in Figure 4.3b, and a typical household load are less evident. These groups also show lower cross-group correlations on average.

Table 4.1: Average and standard deviation of in-group and cross-group correlations.

	Uncoordinated charging	Smart charging	Basecase loads
Uncoordinated charging	0.960 ± 0.030	-	0.150 ± 0.142
Smart charging	-	0.809 ± 0.114	0.018 ± 0.095
Basecase loads	0.150 ± 0.142	0.018 ± 0.095	0.421 ± 0.353

Finally, to assess the robustness of these results, the impact of the static simulation parameters was explored. Variations were introduced in the energy consumption E_{km} , battery size E_{full} , and charging power P_{home} . Paper II presents the impact of a doubling of these parameters, together with an exploration of the different charging scenarios. The main conclusion drawn from this analysis is that the magnitude of the peak charging power is strongly influenced by how synchronized the charging events are across vehicles.

Long-haul Trucks

Two agent-based simulations of long-haul trucks have been performed outside the scope of this thesis [34], and the results have been used as inputs to the probabilistic load flow simulation. This section presents an overview of key results from these simulations. The first simulation is outlined in Paper IV, where the fast public charging of a fully electrified long-haul truck fleet is simulated. In this simulation, fast public charging stations are placed at 18 out of the 86 simulated primary substations. Figure 4.5 presents the aggregated average and peak charging loads, simulated at each substation transformer. The peak loads range from 1.0 - 12.2 MW, and the average load from 0.2 - 3.5 MW.

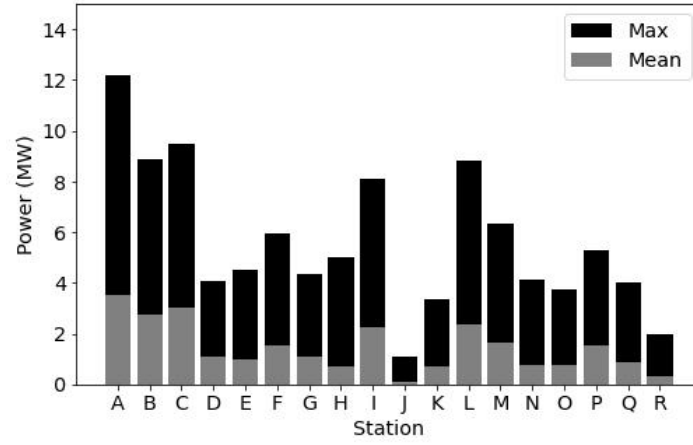


Figure 4.5: Average and maximum charging power per simulated primary substation. Image from Paper IV. © 2025 IEEE

The daily variations can be seen by studying the ensemble daily load profile in Figure 4.6. This profile represents the typical load per primary substation, derived by calculating the median load curve for each station (temporal aggregation) and then averaging these across the 18 substations where fast chargers are located (spatial aggregation). Most of the public charging for long-haul trucks occurs spread out during the day, specifically between 07:00 and 17:00. This coincides with typical rest periods and operating hours for the drivers. The wide 10-90% range indicates that there are large variations between substations, which was also seen in Figure 4.5.

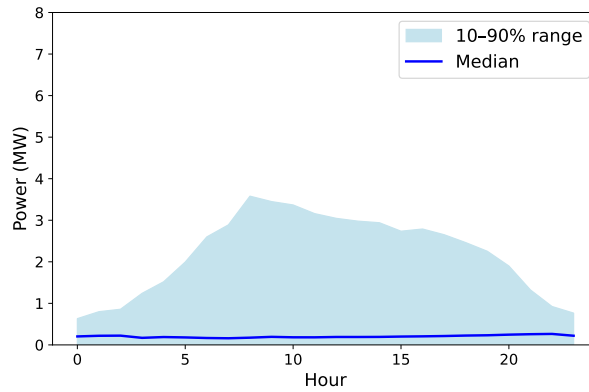


Figure 4.6: Ensemble daily load profile for an average substation with aggregated long-haul truck fast charging loads. The median profile is shown in a dark blue line, the 10-90% range is indicated by the light blue area.

A full simulation of both fast and overnight charging sessions for long-haul trucks is the basis for the truck charging profiles in Paper VI. These charging profiles are a combination of the fast charging profiles from Paper IV with an estimation of overnight depot charging developed in [34]. This expanded simulation includes aggregated fast en-route (at the 18 substations discussed above) and depot charging stations (which are added at 25 substations). The average and peak powers per substation transformer in this simulation are presented in Figure 4.7. The x-axis is sorted to first show the 18 fast charging stations (A–R) identified in the previous section, followed by the additional depot-only locations. Comparing this plot to the fast-charging-only scenario in Figure 4.5, it is evident that the peak power demand is to a high extent driven by the fast en-route charging. However, it is worth noting that some of the new substations show a relatively high average power, which reflects the presence of large logistics depots.

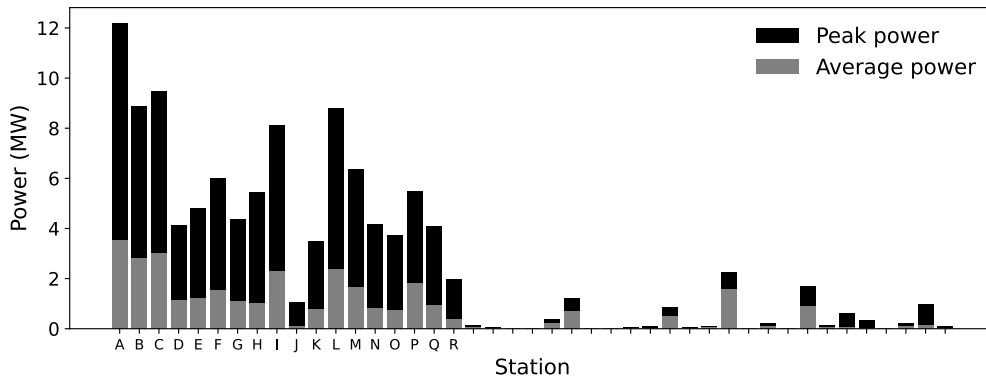


Figure 4.7: Average and maximum charging power for the 43 simulated primary substations (Paper VI). The first 18 stations (A–R) correspond to the fast-charging locations from Paper IV. The remaining bars represent substations hosting only overnight depot charging.

The long-haul truck charging loads show a relatively low in-group correlation compared to the other vehicle fleets, as shown in Table 4.2. The average in-group correlation is 0.029, but with a rather large standard deviation of 0.240. Generally, the public fast charging stations are correlated to other fast charging stations, but not to the depot charging stations, and vice versa.

Table 4.2: Average and standard deviation of in-group and cross-group correlations for the long-haul truck fleet.

	Truck charging	Basecase loads
Truck charging	0.029 ± 0.240	0.059 ± 0.165
Basecase loads	0.059 ± 0.165	0.421 ± 0.353

Heavy Construction Equipment

The third vehicle sector considered in this thesis is heavy construction equipment, which is the focus of Paper V. This section summarizes the key findings regarding the aggregated charging demand of a fully electric fleet of heavy construction equipment.

Two charging scenarios were selected to represent the operational extremes. The first scenario, "Night Charging", assumes that all required energy is charged slowly overnight. This is contrasted by the second scenario, "Thirdnight Charging", which assumes that the majority of energy (approximately two-thirds) is supplied via high-power charging during daytime breaks, with the remainder charged overnight. The resulting daily load profiles are illustrated in Figure 4.8. These profiles represent the typical load per primary substation, derived by calculating the median load curve for each station and averaging these across all locations. When night charging is applied, the charging power is spread out during the nighttime hours when the machines are not operating. In the case of daytime charging, however, high peaks are visible during the breakfast and lunch breaks of daily operations.

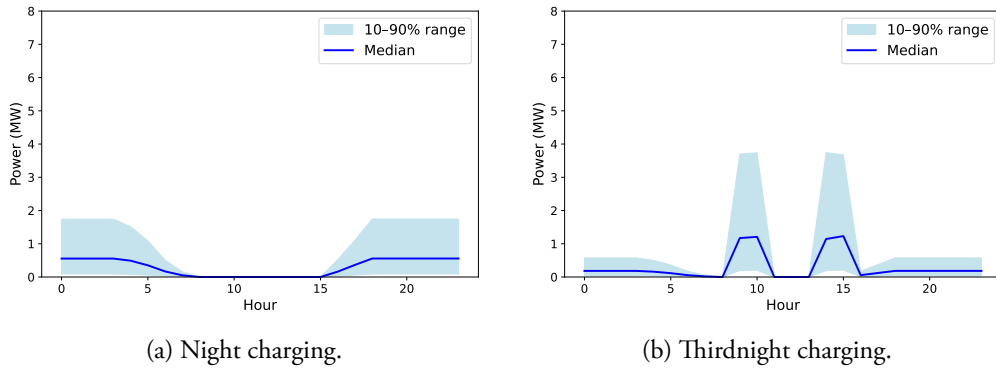


Figure 4.8: Ensemble daily load profile for an average substation under the "Night" (left) and "Thirdnight" (right) charging scenarios. The median profile is shown as a dark blue line, while the light blue area indicates the 10-90% probability range.

The total energy demand is not dependent on the charging strategy, which is why the average power per primary substation is not affected by the choice of scenario. This can be seen in Figure 4.9a, where the average power per substation follows the unity line. However, the charging scenario highly affects the peak power, as seen in Figure 4.9b. Here, the resulting peak power is visibly higher in the "Thirdnight charging" scenario than in the "Night charging" scenario in all the modeled substations. The peak load ranges from 0 - 5.7 MW in the case of night charging, and from 0 - 22.4 MW in the case of fast daytime charging. On average, shifting from the slow night charging strategy to the fast daytime strategy increases the peak power per substation by 277%. This highlights that for heavy

construction equipment, the temporal distribution of charging is very critical to determine the height of the peak power demand.

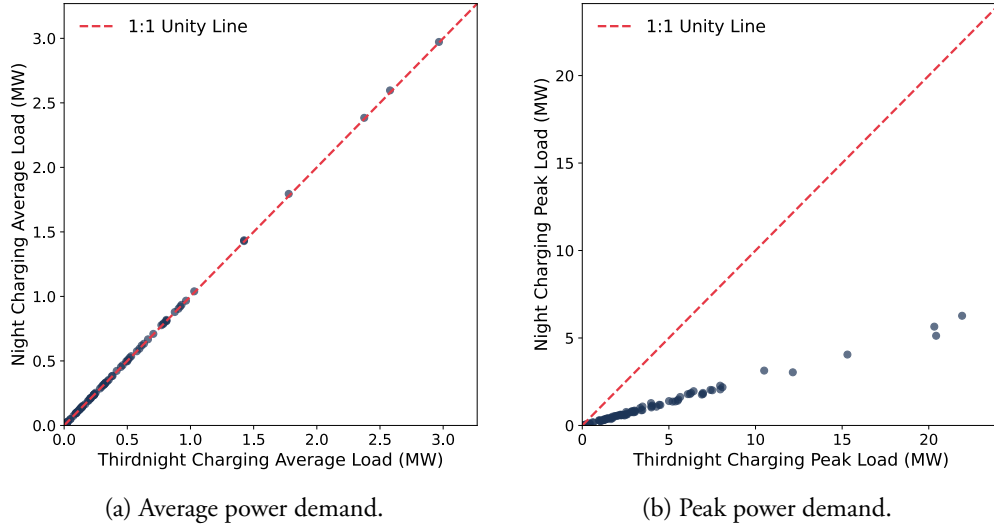


Figure 4.9: Comparison of aggregated power demand at primary substations under Thirdnight (x-axis) and Night (y-axis) charging scenarios. The left panel (a) shows the average power demand, while the right panel (b) shows the peak power demand. Each data point represents one primary substation. The unity line ($y = x$) is included for reference.

The temporal dependencies of the heavy equipment loads were examined through a correlation analysis, summarized in Table 4.3. In-group correlations are notably high, reflecting the modeling assumption of similar operating hours across the fleet. For night charging, the average correlation between aggregated heavy equipment loads is 0.905. The correlation is slightly lower between daytime loads, at 0.711 on average, following the random spread of break times. When compared to other aggregated loads in the system, the nighttime charging loads have a slight negative correlation on average. This is due to most household and industry loads being higher during the day than at night. In the mixed charging scenario, the correlation is instead slightly positive, following the high power at daytime.

Table 4.3: Average and standard deviation of in-group and cross-group correlations.

	Night charging	Thirdnight charging	Basecase loads
Night charging	0.905 ± 0.065	-	-0.177 ± 0.195
Thirdnight charging	-	0.711 ± 0.111	0.056 ± 0.075
Basecase loads	-0.177 ± 0.195	0.056 ± 0.075	0.421 ± 0.353

Combined Fleets

The vehicle fleets modeled in Papers II - V are combined in Paper VI, where the total charging demand is estimated. This section summarizes the key findings on the estimated charging demand of the combined vehicle fleet, applying the same scenarios as for the individual fleets.

First, the impact of the choice of scenarios on the total power demand was examined. This is reflected in Figure 4.10, showing box plots of the peak powers modeled in the 86 substations considered. The figure compares the four possible combinations of car and heavy equipment charging scenarios, with the long-haul truck demand included as a constant baseline. As expected from the individual fleet analysis, the lowest peak powers are reached when combining the "Smart charging" car scenario with the "Night charging" heavy equipment scenario. The other extreme is reached when combining the "Uncoordinated charging" with the "Thirdnight charging" scenario.

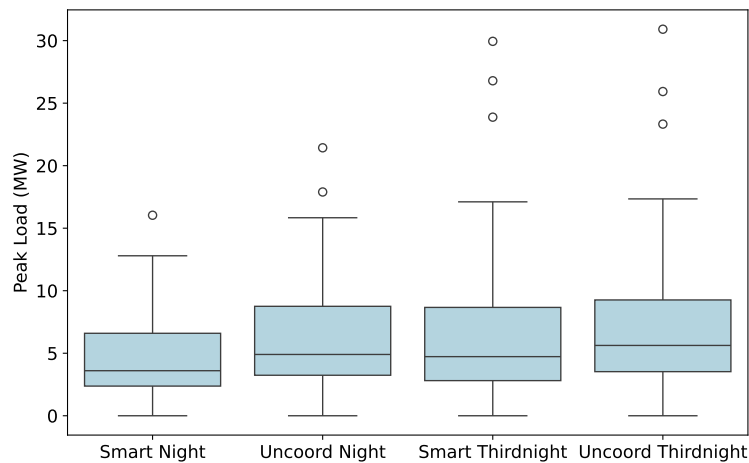


Figure 4.10: Box plot diagrams comparing the peak power in the different vehicle fleet combinations. The long-haul truck fleet is included in all combinations.

A more detailed analysis of the modeled peak power in the two combined scenarios mentioned above is shown in Figure 4.11. Here, the lowest peak power case ("Smart" and "Night" charging scenarios) is shown on the y-axis, and the highest peak power case ("Uncoordinated" and "Thirdnight" scenarios combined) is shown on the x-axis. In all modeled substations, the aggregated peak power demand is higher in the worst-case combination than in the best-case combination, as seen from all the dots being below the unity line. On average, the shift from the best-case to the worst-case scenario represents a 33% increase in peak power demand. This is comparable to the impact in the car fleet alone (32%) and much lower than the impact in the heavy equipment fleet alone (277%). This indicates

that the long-haul truck fleet, which remains constant in both scenarios, constitutes a large share of the total peak power demand. This dampens the relative impact of the other sectors. Additionally, it suggests a degree of temporal smoothing, as the peak demands of the varying sectors do not always coincide.

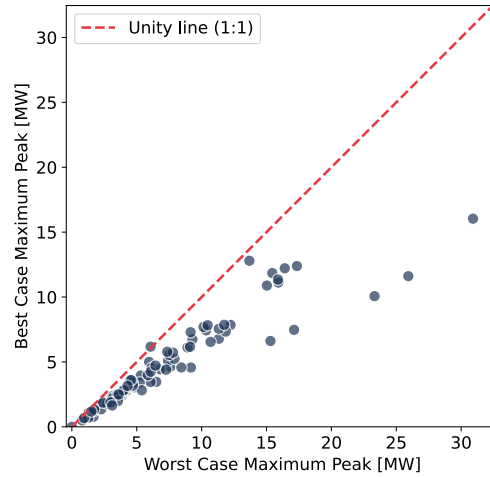


Figure 4.11: Comparison of aggregated peak power demand per primary substation. The y-axis shows the combination of "Uncoordinated" car charging, long-haul truck charging, and "Thirdnight" heavy equipment charging. In contrast, the x-axis shows the combination of "Smart" car charging, long-haul truck charging, and "Night" heavy equipment charging. The unity line is included for reference.

Lastly, the co-dependencies of all the modeled fleets have been investigated to serve as input to the probabilistic load flow simulation. These are summarized in Table 4.4. Notably, the car fleets and night charging heavy equipment fleets are positively correlated. This is expected, as both sectors prioritize charging during the evening and night. In contrast, the Thirdnight charging scenario, where most of the charging happens during the day, has a slight negative correlation with the aggregated car charging loads. The long-haul truck fleet shows negligible correlation with other fleets. This is due to the fast en-route charging events being driven solely by the specific routes and schedules of the individual simulated trucks. This contrasts the synchronized daily rhythms of work-home commuting (in the car sector) or standard operating hours (in the heavy equipment sector).

Table 4.4: Average and standard deviation of in-group and cross-group correlations.

	Cars (Smart)	Cars (Uncoordinated)	Trucks	HE (Night)	HE (Thirdnight)
Cars (Smart)	0.809 ± 0.114	-	0.032 ± 0.298	0.411 ± 0.157	-0.083 ± 0.058
Cars (Uncoordinated)	-	0.960 ± 0.030	0.089 ± 0.173	0.208 ± 0.075	-0.007 ± 0.025
Trucks	0.032 ± 0.298	0.089 ± 0.173	0.029 ± 0.240	-0.092 ± 0.373	0.050 ± 0.109
HE (Night)	0.411 ± 0.157	0.208 ± 0.075	-0.092 ± 0.373	0.905 ± 0.065	-
HE (Thirdnight)	-0.083 ± 0.058	-0.007 ± 0.025	0.050 ± 0.109	-	0.711 ± 0.075

4.2 Grid Capacity Impact at Sub-Transmission Level

The previous section has presented the estimated charging demand from the modeled vehicle fleets. In this section, the resulting impact of the EV fleets on sub-transmission capacity (RQ2) and the potential for temporal load-shifting strategies to mitigate potential overloads (RQ3) are investigated. The analysis is based on the full-scale case study developed in Paper VI, where the probabilistic charging demand models for all three vehicle fleets are integrated into a single simulation framework. In line with the scope of this thesis, grid capacity is defined as the thermal loading limits of lines and transformers. To establish a baseline, the loading of all primary substation transformers and power lines is first evaluated under a reference scenario without additional EV charging. This provides a benchmark against which the impact of the electrified fleets can be compared. Before analyzing the full impact of the combined fleets, it is important to characterize the distinct effects of the different sectors on transformer loading. The following sections therefore summarize key results regarding the impact of fully electrified passenger car, long-haul truck, and heavy equipment fleets. Comprehensive analyses of these individual sectors can be found in Papers II, IV, and V, respectively.

Passenger Cars

The transformer loading impact of the passenger car fleet, which contributes the largest energy demand, is studied in Papers II and III. A key challenge in the passenger car fleet is the evening home charging peak, which coincides with the evening peak of other residential loads. The mitigation of this peak through smart charging was the primary focus of Paper III, which compared the impact of aggregated charging in two scenarios: "Uncoordinated charging" and "Smart charging". These scenarios are described in detail in Chapter 3.1. The median relative increase of transformer loading for the two scenarios is shown in Table 4.5. This metric is derived by calculating the relative increase for each transformer and then calculating the median across the full set. Generally, the average transformer loading increases by 11-12% and the maximum transformer loading by 9-13% following the introduction of the aggregated charging loads.

Table 4.5: Median relative increase of substation transformer loading following the introduction of passenger car charging loads.

Scenario	Average loading	Peak loading
Uncoordinated charging	+12 %	+13 %
Smart charging	+11 %	+9 %

The results indicate that temporal charging shifts have a negligible impact on the average transformer loading. As seen in Figure 4.12a, the mean loading remains nearly constant across scenarios, reflecting that the total energy demand is identical regardless of the timing of the charging sessions. In contrast, the maximum transformer loading is sensitive to temporal shifts (Figure 4.12b), though the background load dampens this sensitivity. Crucially, the benefit of smart charging is less pronounced at the transformer level than at the EV fleet level. While smart charging reduces the aggregated EV power peak by approximately 32% on average, it reduces the maximum transformer loading by only about 6% on average. This indicates a damping effect, where the background load profiles dilute the impact of the charging load. Flattening the charging load curve effectively reduces the peak charging demand, but this is only one of the range of factors that affect the total transformer loading.

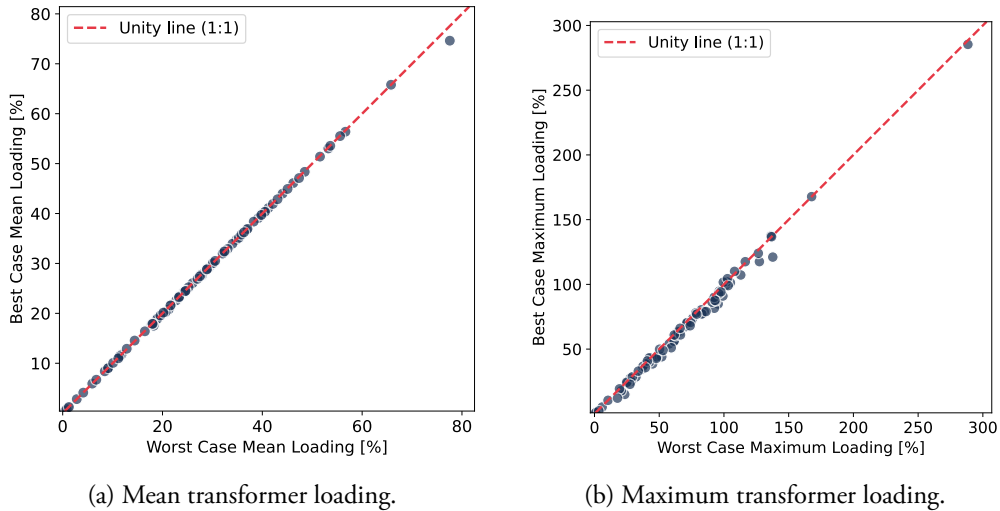


Figure 4.12: Comparison of transformer loading for the uncoordinated charging scenario (x-axis) and the smart charging scenario (y-axis). (a) shows the mean transformer loading, while (b) shows the maximum loading. Each data point represents one primary substation. The unity line ($y = x$) is included for reference.

The consequences of the increased transformer loading after introducing car charging loads can be seen in the calculated risks of overload, presented in Figure 4.13. In total, 17 sub-

station transformers sometimes experience overloads in the passenger car fleet simulation. Out of these, 6 transformers did not have any risk of overload before the charging loads were introduced. The most extreme impact is seen in substation 20, where the risk of overload increases from 0% to 9.35% in the highest loading case. In this substation, the impact of temporal shifts in charging can be seen clearly.

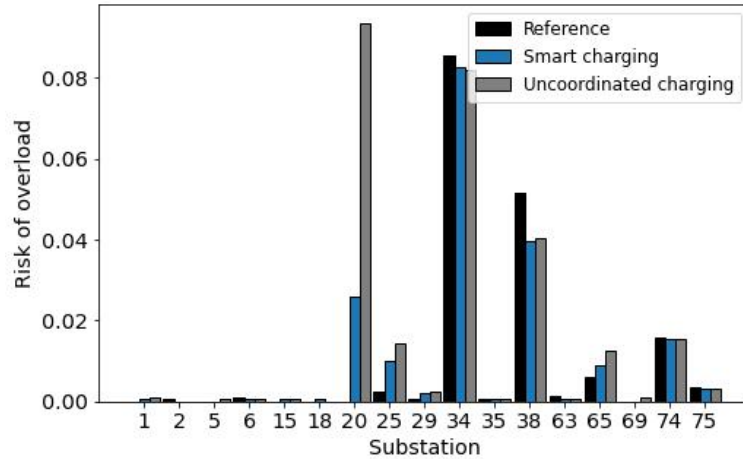


Figure 4.13: Risk of overload in the passenger car simulation, in substations where this is nonzero. The reference case is in black, the smart charging case in blue, and the uncoordinated scenario in grey.

While smart charging shows a "damped" benefit for peak magnitude, it is highly effective at reducing the duration of grid stress. As shown in Table 4.6, Uncoordinated charging increases the total system overload hours by 59% (from 1480 to 2352 hours). Smart charging limits this increase to just 13% (to 1669 hours). This demonstrates that while smart charging cannot eliminate all of the high peak loadings, it successfully avoids a majority of the additional stress duration caused by EV integration.

Table 4.6: Total hours of overloaded transformers per scenario in the passenger car simulation.

Scenario	Hours of overload	Relative increase
Reference case	1480	-
Uncoordinated charging	2352	+59 %
Smart charging	1669	+13 %

Interestingly, the risk of overload is reduced in substations with high levels of distributed generation after adding the EV charging loads. This can, for example, be seen for substa-

tions 34 and 38 in Figure 4.13, where the risk of overload is lower in the cases with added EV charging loads than in the reference scenario. This indicates that a strategic introduction of EV charging loads can mitigate the high loading levels caused by distributed generation. These results are seen throughout the simulations, for each vehicle fleet as well as for the combined fleet simulations.

Long-haul Trucks

The grid impact of the electrified long-haul truck fleet, analyzed in Paper IV, presents a distinct contrast to the passenger car fleet. While cars create a distributed load across the entire grid, fast charging for heavy trucks generates spatially concentrated, high-power loads at specific locations where chargers are located. Consequently, the simulation in Paper IV focused on the specific subset of 18 substations in Skåne where these simulated fast chargers are located.

Fast en-route charging for long-haul trucks substantially raises the peak loading at the substations where it is implemented. This impact is quantified in Table 4.7, which presents the median relative increase in transformer loading. As with the passenger car analysis, this metric is derived by calculating the relative increase for each substation first and then determining the median across all relevant locations. At these substations, the truck charging loads result in a median relative increase of maximum transformer loading of 31.2%. This indicates that even though the overall energy demand is low, the high power levels of the fast charging stations still cause a substantial increase in stress on the transformers. Compared to the passenger car fleet, however, this stress is concentrated in fewer substations, namely those where fast charging stations are present.

Table 4.7: Median relative increase of substation transformer loading following the introduction of passenger car charging loads.

Scenario	Average loading	Peak loading
Long-haul trucks (fast charging)	+8.2 %	+31.2 %

Long-haul fast truck charging is characterized by high power intensity but relatively lower total energy volume compared to the car fleet. The charging has a substantial effect on the maximum transformer loading shown in Figure 4.14b. The effect on average loading is, however, relatively small in many substations, as seen in Figure 4.14a. There are exceptions to this, such as substation A, which sees a doubling of average transformer loading due to the introduced truck charging loads. This again shows that the transformer loading is highly dependent on local conditions, as well as the size of the aggregated charging loads introduced. Just as in the passenger car simulation, there are occurrences where the

introduced charging loads lower the transformer loading due to high levels of distributed generation installed there (substations H and R).

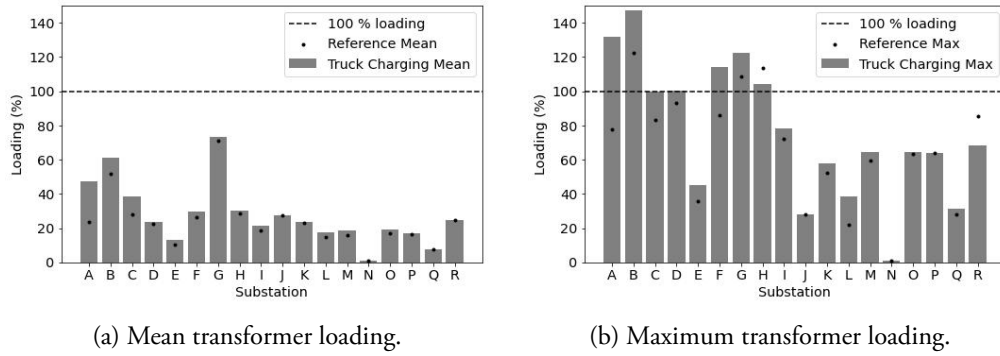


Figure 4.14: Mean (left) and maximum (right) transformer loading at the modeled substations in the long-haul truck fleet simulation. The 100% loading level is marked with a dotted line, the loading in the truck charging scenario in gray bars, and the reference loading with black dots. Images from Paper IV © 2025 IEEE.

The resulting stress on the transformers is quantified by the risk of overloads, presented in Figure 4.15. The risk was increased in 6 substations, and slightly decreased in one. The largest risk of overload was found at substation B, where the risk of 3.4% corresponds to around 300 hours per year.

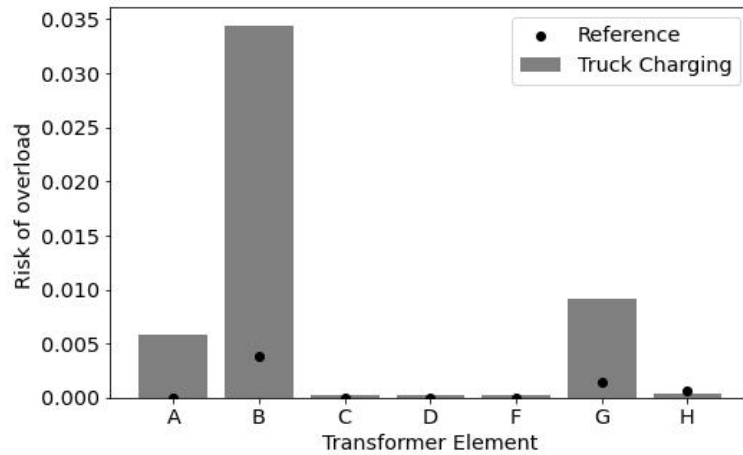


Figure 4.15: Risk of overload in the long-haul truck simulation, in substations where this is nonzero. Image from Paper IV © 2025 IEEE.

Heavy Construction Equipment

The heavy construction equipment fleet is, like the passenger car fleet, spread out across a large part of the study area. This vehicle sector is analyzed in Paper V, and some key findings are presented here.

As seen in Table 4.8, the heavy equipment charging leads to a minimal increase in the median average transformer loading (+2.2% to +2.4%). This is expected given the sector's relatively low total energy demand compared to passenger cars. However, the maximum loading is highly sensitive to the charging strategy. The median relative increase in peak loading (calculated individually per substation and then aggregated across all locations) jumps from 5.2% in the "Night" scenario to 10.2% in the "Thirdnight" scenario. This indicates that, despite the relatively low energy demand, the high daytime charging peaks will lead to higher peaks in transformer loading.

Table 4.8: Median relative increase of substation transformer loading following the introduction of heavy equipment charging loads.

Scenario	Average loading	Maximum loading
Night charging	+2.4 %	+5.2 %
Thirdnight charging	+2.2 %	+10.2 %

The contrast between average and peak impacts is visualized in Figure 4.16. Figure 4.16a confirms that the mean transformer loading is largely insensitive to the charging timing at all substations, as all data points are close to the unity line. In contrast, Figure 4.16b reveals significant variations in maximum loading. Most substations exhibit higher peaks in the "Thirdnight" scenario (below the unity line), driven by the concentration of high-power charging during daytime breaks. However, there are some substations where the maximum loading is actually higher in the night charging scenario. This indicates that in substations where the nighttime base load is already high, adding slow night charging can actually be worse than fast daytime charging.

The risk of overload caused by the heavy equipment fleet is lower than for the analyzed passenger car and long-haul truck fleets, as presented in Figure 4.17. The highest risk of overload due to the introduced charging is in substation 20, where the risk increases from 0% to 2.2% in the "Thirdnight" charging scenario. Interestingly, Substation 29 presents an anomaly where the "Night" scenario creates a higher risk than the "Thirdnight" scenario. This again suggests that in some cases, the common assumption that slow night charging would always have a lower impact on the grid than fast daytime charging is proven false. In Substation 29, the "Thirdnight" strategy, despite its higher power peaks, is preferable as it shifts the demand to the less congested daytime hours.

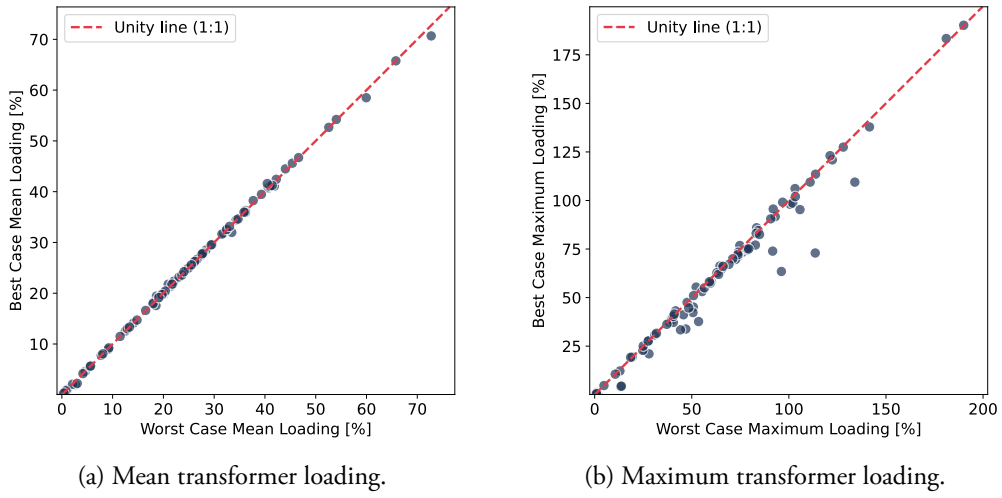


Figure 4.16: Comparison of transformer loading for the thirdnight charging scenario (x-axis) and night charging scenario (y-axis). (a) shows the mean transformer loading, while (b) shows the maximum loading. Each data point represents one primary substation. The unity line ($y = x$) is included for reference.

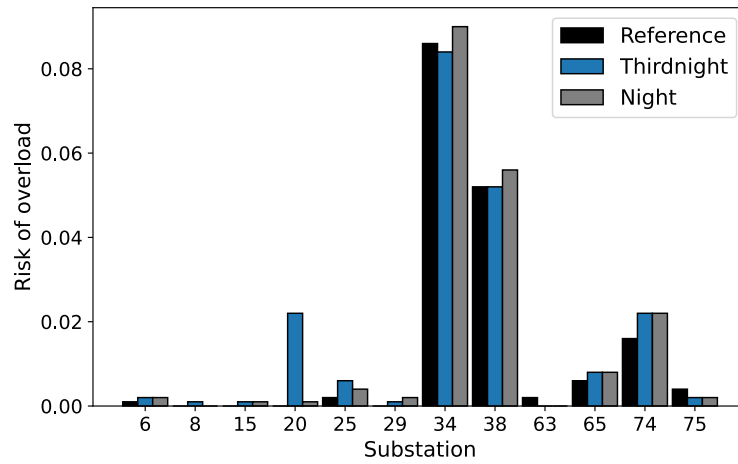


Figure 4.17: Risk of overload in the heavy equipment simulation, in substations where this is nonzero.

Total Impact of Combined Vehicle Fleets

Having established the individual grid impacts of the different vehicle fleets, this section focuses on the total impact of the combined fleets. The analysis is based on the full-scale simulation in Paper VI. By combining the different charging scenarios defined previously, this section explores the full range of potential scenarios.

First, the impact of the different scenarios on the transformer capacities was investigated. The results indicate that temporal load shifting strategies are far more effective at mitigating peak stress than average stress. As shown in Table 4.9, the choice of charging strategy affects the maximum loading impact significantly (from 12.2% to 32.6%), whereas the average loading remains nearly constant (17.1 - 18.2 %) across all scenarios. The scenario combination that results in the lowest transformer loading impact, the "Best Case" combination, is the same one that produced the lowest peak load magnitude, namely "Smart" car charging and "Night" heavy equipment charging. Likewise, the opposite combination gives rise to the highest transformer loading impact, referred to here as the "Worst Case" combination. The slight differences in average power despite the constant energy throughput are due to the non-linearity of resistive losses. Adding EV load during periods of high background demand (e.g., the evening peak) results in a non-linear increase in resistive losses and thermal stress compared to adding the same load during off-peak hours. This additional loss component increases the total apparent power measured at the transformer. However, as the results show, this effect is minor compared to the impact on peak magnitude.

Table 4.9: Median relative increase in average and maximum transformer loading under different scenarios.

Scenario	Average loading	Maximum loading
Best Case (Cars: Smart & HE: Night)	+17.1%	+12.2%
Worst Case (Cars: Uncoord & HE: Thirdnight)	+18.2%	+32.6%

The average transformer loading on the individual substation level is presented in Figure 4.18. The results clearly show that while introducing EV charging increases average transformer loading, the specific choice of charging strategy has a minimal impact on this metric. The relative increase in average transformer loading when moving from the "Best Case" to the "Worst Case" is only 0.6 ± 1.6 percentage points across all modeled substations. This reflects that the total energy throughput is identical across scenarios. The temporal shifts introduced in the different strategies do not significantly alter the accumulated thermal stress or resistive losses over time.

The transformer peak loadings are to a greater extent dependent on the temporal shifts in charging, as seen in Figure 4.19. The increase of maximum loading in the "Worst Case" scenario is 8.4 ± 11.1 percentage points higher than in the "Best Case" scenario across

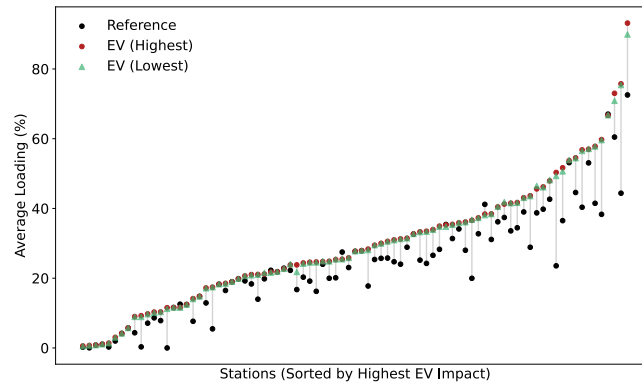


Figure 4.18: Average transformer loading in percent for the reference case in black, the "Worst Case" ("Uncoordinated" car charging and "Thirdnight" heavy equipment charging) in red, and the "Best Case" ("Smart" car charging and "Night" heavy equipment charging) in green. The substations are ordered by the loading in the "Worst Case" scenario.

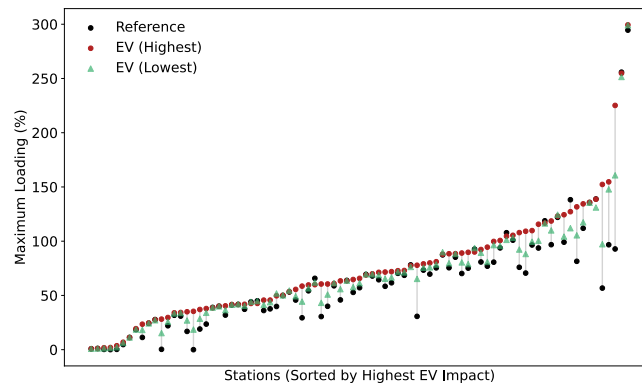


Figure 4.19: Maximum transformer loading in percent for the reference case in black, the "Worst Case" ("Uncoordinated" car charging and "Thirdnight" heavy equipment charging) in red, and the "Best Case" ("Smart" car charging and "Night" heavy equipment charging) in green. The substations are ordered by the loading in the "Worst Case" scenario.

all substations. Comparing these findings with Table 4.9 shows that while the average loading experiences a consistent increase of 17–18% regardless of the scenario (due to the added energy volume), the maximum loading is largely determined by when that energy is delivered. Consequently, while smart charging strategies can suppress the peak impact to levels below the average impact (+12.2%), uncoordinated charging can cause the peak impact to nearly double the average impact (+32.6%).

Just as for the individual fleets, the introduction of EV charging provides a 'balancing' effect in substations with high levels of distributed generation. As seen in Figures 4.18 and 4.19, several transformers exhibit a decrease in average and maximum loading due to the introduction of EV charging loads. In these cases, EV demand coincides with periods of high local generation (CHP or wind), effectively consuming the surplus power locally and reducing the reverse power flow through the transformer.

To understand the overall impact on transformer stress, the risk of overload (the probability of falling above 100% loading level of the transformers) was studied. In 17 of the 86 substations, a non-zero risk of overload was identified (Figure 4.20). Crucially, 10 stations show a tipping point scenario, where the risk of overload is zero in the reference case, but non-zero when EV charging is introduced. Station 20 is the most extreme case of this, transitioning from zero risk in the reference case to a 32.2% risk in the "Worst Case". In contrast, other substations, such as substations 34, 38, and 74, show existing overloads that are largely insensitive to EV charging, indicating that those constraints are driven by other local grid conditions rather than the introduction of new EV loads.

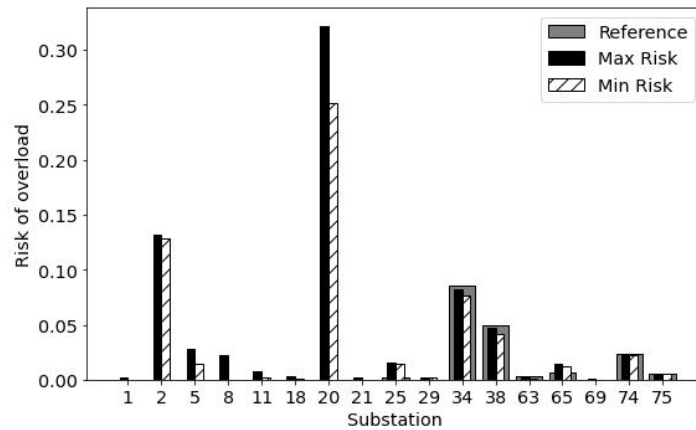


Figure 4.20: Risk of overload in the 17 substations where this is nonzero. The reference case is included in grey, the "Worst Case" in black, and the "Best Case" in white.

The effects of temporal shifts in charging have an effect in some cases, but not in others. The effect can be seen clearly in 4 substations (1, 8, 21, and 69) in Figure 4.20 where there is only a risk of overload in the highest loading scenario and not in the lowest. The impact can also be seen in other substations where the risk of overload, most notably again in substation 20, where the risk of overload is 32.2% in the "Worst Case", or 25.2% in the "Best Case". In most of the other substations, however, the effect of the temporal shifts is relatively low. This is especially true for the substations where the EV charging itself has a low impact on the overloads in the transformer.

Impact on Sub-transmission Power Lines

The primary focus in this work has been on the loading of primary substation transformers, as these have been identified as the main capacity bottlenecks. However, the work has also included analyses of the loading of sub-transmission power lines. Throughout the work of this thesis, the grid simulations have been performed under normal operating conditions (N-o), without explicit consideration of contingency scenarios. Under normal operation, no power lines violated thermal limits. This is expected, as sub-transmission grids are dimensioned to withstand N-1 contingencies, resulting in significant spare capacity during normal operation. However, the impact of the introduced charging demand was visible on several of the power lines studied. As shown in Figure 4.21, seven lines experienced loading increases of more than 10 percentage points. While these increases do not cause immediate failures, they substantially reduce the spare capacity available for redundancy. This suggests that while electrification may not trigger immediate line upgrades for normal operation, it could necessitate reinforcement to maintain N-1 reliability standards unless the inherent flexibility of EV charging loads is utilized to reduce demand during contingency events.

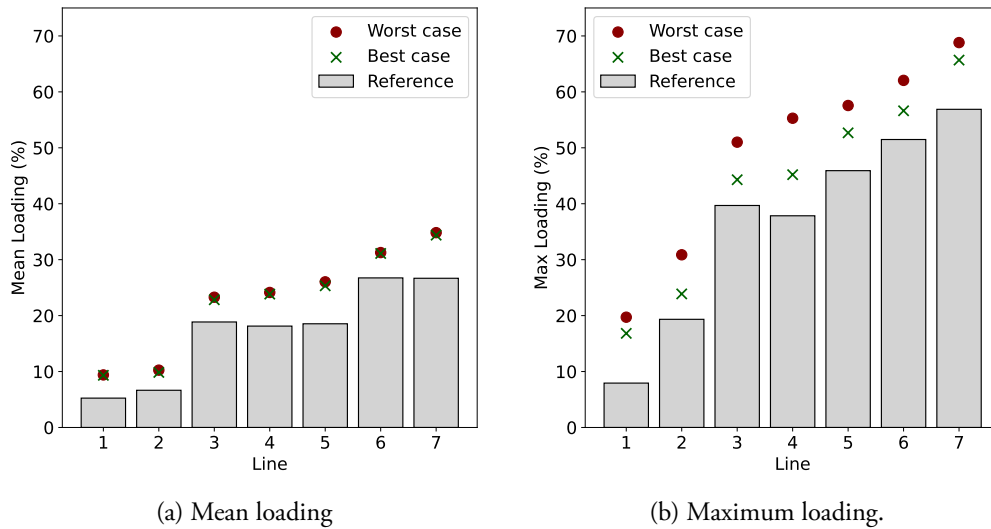


Figure 4.21: Mean (a) and maximum (b) loading of critical power lines in the reference scenario (grey), highest loading scenario (red), and lowest loading scenario (green).

Chapter 5

Discussion and Synthesis

The previous chapters have presented the development of the simulation framework and the specific quantitative results regarding the impact of charging demand and grid capacity. In this chapter, the key results are discussed to offer a comprehensive view of their meaning for the sector coupling between the transportation and power systems. This is followed by a summary of the implications of the results for different stakeholders: grid operators, regional planners and municipalities, charging point operators, vehicle manufacturers, and society in general. Finally, the limitations of the work are discussed.

5.1 Synthesis of Key Findings

This thesis has focused on the interaction between transport and grid simulations within the field of vehicle electrification. Both areas are established research fields with extensive experience in conducting simulations independently. Within transport research, transport simulations are often performed to estimate (or optimize) the charging demand of electric vehicle fleets, without looking at how the power grid responds to the simulated loads. A common assumption in this field is that high peaks in the charging loads are directly correlated to high stress on the grid. The results presented in this thesis demonstrate that the sub-transmission grid congestion is largely dependent on local grid conditions rather than the total charging demand itself.

Crucially, the highest charging load does not necessarily lead to the highest increase in transformer loading or the highest risk of overload. In fact, the results clearly show that the relation between energy or power demand and grid stress is not always proportional. As shown in the results, charging loads are often "dampened" by other loads and grid conditions. The impact of temporal shifting strategies (like smart charging) is very visible when

looking at the EV power peaks, but this effect is significantly reduced when looking at the total transformer loading in the sub-transmission grid. In practice, this means that flexibility services are still critical as a mitigation strategy in the distribution grid and for electricity market balancing, but less important as a mitigation strategy for congestion in the sub-transmission grid. In Sweden, the dampening effects can be attributed to the dimensioning of the grid, which is based on high levels of electric heating, heat pumps, and large industries. While this specific capacity margin is characteristic of the Swedish system, it is reasonable to assume that similar dampening effects would be observed in any power system where electric vehicle loads do not dominate the total magnitude of electricity consumption. This dampening effect can not be estimated without knowing and analyzing realistic local grid conditions. This emphasizes the need to perform realistic grid simulations to understand the grid impact of transport electrification. Furthermore, this highlights the value of the methodological framework developed in this thesis. Capturing the probabilistic nature of vehicle charging is necessary to avoid the overestimations associated with traditional deterministic grid planning.

Another key finding is that different transport fleets stress the grid in different ways and at different times, as shown in the comparison of the individual fleets in Section 4.2. For instance, passenger cars typically create a power peak in the evening or a more spread-out charging curve at night. In contrast, the fast en-route charging of long-haul trucks and the mid-day charging of heavy construction equipment create the largest power peaks during working hours. This temporal spread means that there is a natural mitigation factor between the different vehicle fleets. The total grid stress is lower than the sum of individual grid stresses created by the individual vehicle fleets. This implies that looking at any single fleet in isolation and stacking the power peaks might lead to an overestimation of the necessary grid reinforcement. Consequently, accurately assessing system capacity requires analyzing the diverse load profiles of interacting fleets, rather than modeling single vehicle categories in isolation.

A primary objective of this thesis was to determine if the existing sub-transmission grid in the study area can accommodate the full electrification of road transport. The results indicate that the sub-transmission grid in Skåne generally has enough capacity to handle the aggregated power requirements of a 100% electrified vehicle fleet under normal operating conditions (N-o). However, the grid simulations show that there are substations where the transformers experience congestion. These can be divided into two groups: the transformers that are within limits in the reference scenario, and the ones that are already close to the capacity limit. This thesis has presented a methodology to quantify the risk of overload, which opens up the potential of mitigating the overloads with flexibility measures in the first category. It is important to acknowledge that this analysis focused strictly on the N-o scenario. In traditional grid planning, capacity is typically dimensioned to maintain full supply even during component failures (N-1). Consequently, the results presented

here should be interpreted as an upper bound of the hosting capacity, meaning that if the grid is constrained in N-o, it will certainly be constrained in N-1. However, unlike static industrial or residential loads, electric vehicles inherently possess the flexibility to react to grid signals and reduce power demand during emergencies. In the future, EV charging loads could function as a curtailable resource rather than a driver of grid failure in N-1 contingency scenarios. While N-1 compliance remains a strict requirement for current grid connections, this thesis highlights that future planning strategies could evolve to account for the inherent flexibility in EV loads.

Lastly, this thesis has found that the location of the charging stations is just as crucial as timing in terms of grid impact. In several of the case studies, there have been substations where the transformer loading has decreased when EV charging loads are introduced. These are areas with high levels of distributed generation, either in the form of wind power or CHP. This indicates that there are possibilities to balance distributed generation if charging stations are placed strategically. This may turn the challenge of integrating high-power charging loads, such as the fast charging of heavy-duty trucks, into an opportunity to counteract the impact of the integration of distributed renewable generation.

5.2 Implications for Industry and Society

The methodology and results presented in this thesis have a range of implications for stakeholders involved in the energy transition. This section outlines the possible applications for different stakeholders as well as some discussion on questions to consider moving forward.

For grid operators

The probabilistic framework presented here serves a dual purpose: estimating the energy and power requirements from large-scale electric vehicle fleets, and analyzing the grid capacity impact of these new loads. The methodology can be applied to any grid model, as long as the required data sources are available. This capability is especially useful for European grid operators, who are required to apply probabilistic methods in the stability analysis starting 2027 [8]. The probabilistic methodology also enables the quantification of flexibility requirements. This is particularly valuable in the context of conditional connection agreements, where the required level of flexibility must be estimated. For the specific case study of Skåne, the thesis provides detailed estimates of EV power requirements at the substation level. It analyzes the readiness of the sub-transmission grid to handle full transport electrification, identifying specific substations where severe overloads are expected. However, as the results only consider the N-o scenario, it should be noted that the grid capacity impact is probably underestimated.

Several questions have arisen during the work of this thesis regarding the practical application of these methods in grid operations. Probabilistic methods deal with risk rather than absolute numbers, which requires a strategic decision on what risk levels are acceptable. This thesis has not defined those thresholds, but highlights that they must be established. Additionally, the acceptable loading levels of transformers and power lines should be more strictly defined. In real-life grid planning or operations, accepting transformer loading levels of 100% may or may not be realistic, depending on the time frame. To apply the methodology and results in this thesis, these questions need to be dealt with by the grid owners.

For regional planners and municipalities

This thesis presents a general methodological framework to estimate the energy and power demands of electric vehicle fleets. The method is flexible in the sense that any input data can be modified to explore different future scenarios. For the Skåne region specifically, detailed estimates of power requirements for a 100% electrified car fleet are available per Demographic Statistical Area (DeSO) [9]. These profiles can be directly utilized to map the spatial distribution of future capacity requirements. Furthermore, the openly available source code can be used to run the models with parameter variations to explore different scenarios than those presented in this thesis.

The thesis also provides an overview of the sub-transmission power grid's readiness to accommodate large-scale fleets of electric vehicles. Previous research has often focused on the local grid near the chargers themselves. This "zoomed-out" view is essential for coordinating municipal planning with regional grid capacity.

For charging point operators

Charging point operators manage the aggregation of EV loads, similar to the fleet-level analysis performed in this thesis. With the introduction of power-based grid tariffs in Sweden, there is a strong financial incentive to lower charging peaks. The results presented here demonstrate that temporal load shifting has a major impact on peak reduction. Specifically, the analysis in Papers II and III examines how different load shifts in passenger car charging impact the resulting peak power, serving as a guideline for tariff optimization strategies. The geographical aspect of the results is also essential to charging point operators, considering the placement of new projects. The grid impact results show that the location is essential when considering if the grid can handle large charging loads. This information is highly relevant to customers looking for grid connections, especially considering the long lead times of these requests. As of today, no such information on available grid capacity is openly available. This thesis presents a method to provide this type of information, al-

though the detailed results can not be openly published due to security constraints. Future developments, such as the introduction of capacity maps, may help to move the industry in this direction.

For vehicle manufacturers

For the automotive industry (OEMs), the thesis provides market confidence by demonstrating that the sub-transmission grid can largely support a fully electrified fleet with existing capacity, provided that some flexibility is utilized. This removes a key perceived barrier to market entry and supports the continued scale-up of electric heavy vehicle production and introduction to the market. Furthermore, the results in this thesis highlight the need to apply smart or controlled charging strategies to avoid unnecessary stress on the grid. To ensure reliability without expensive grid redundancy, OEMs should integrate smart charging logic directly into vehicle software. This capability allows vehicles to react to external grid signals during constrained scenarios (N-1), transforming them from passive loads into active, flexible assets.

For policymakers and society in general

The need to decarbonize the transport sector is pressing. In Sweden, electrification provides a straight-forward means to quickly reduce greenhouse gas emissions, due to the low carbon intensity of the Swedish electric power sector. A common question that arises is whether the power grid is capable of supporting these new, large-scale demands on the system. This thesis has provided a detailed case-specific analysis, showing that full transport electrification is feasible with regards to the sub-transmission grid. Furthermore, the scenario analysis gives a starting point in the investigation on possible ways to mitigate the grid impact from aggregated electric vehicle loads.

5.3 Limitations

Several limitations have been identified during the work of this thesis, which will be discussed in this section. Models of future scenarios naturally involve uncertainty, since there is no way to accurately predict the future. In this thesis, the present-day behavior is assumed as a best estimate of what future electric vehicle fleets may look like. This should not be interpreted as a prediction, but rather as a possible representation consistent with current data and trends. The vehicle fleets in this thesis are already electrified to varying degrees, which has influenced both the modeling choices and the interpretations of results. Consequently, the findings are specific to both the study area and dependent on the avail-

ability and quality of charging, travel, and operational data. The modeling framework also assumes simplified charging characteristics, such as fixed charging power levels and connection types, which do not fully reflect the diversity of real-world charging technologies and user behavior. As electrification progresses and richer datasets become available, the models should be continuously refined to incorporate updated and more representative data. To facilitate this ongoing development, the core simulation framework and underlying scripts for the passenger car model have been made openly available [9]. This allows the research community to easily adapt the models as new empirical data becomes available.

The power grid simulations in this thesis were conducted at the sub-transmission level (130/50 kV), rather than the distribution level (0.4–20 kV) where electric vehicles actually connect. This choice was necessary to capture the aggregated regional impact of thousands of vehicles, and complements the wide range of research already focusing on the distribution grid. However, this implies that local grid constraints are not visible in the results. Consequently, the results presented here should be interpreted as an upper bound of the hosting capacity. If the sub-transmission grid is constrained, the underlying distribution grid is likely also stressed. However, the reverse is not necessarily true, as there may be local constraints even when the sub-transmission grid operates within its limits.

Several additional limitations were identified in the thesis work. All power grid simulations were conducted assuming a normal grid configuration (N-0), without modeling contingency scenarios. In practical grid planning, new loads are typically evaluated under N-1 conditions to ensure secure operation during component outages, even if these events last in the order of hours per year. The objective of this thesis was to quantify the steady-state loading effects of transport electrification under normal operating conditions. Extending the framework to include contingency analysis would significantly increase computational complexity and was therefore outside the defined scope. This is partly justified by the assumption that EV charging loads are flexible and can be curtailed during contingency situations. The absence of N-1 analysis implies that the results reflect steady-state capacity stress rather than a full security assessment. Future work may therefore investigate the interaction between probabilistic EV charging loads and contingency-based planning, including the potential role of EV charging as a curtailable resource during fault scenarios.

The analysis of these constraints has been limited by the fact that there are no clearly defined limits on how much overload is acceptable or for what time durations. As a result, the analysis could not establish clear thresholds for acceptable levels of congestion risk in daily operations. This opens up possibilities for the grid operators to continue the work on how these methods can be applied and how to interpret the results. Furthermore, the modeling framework does not account for electricity market mechanisms or price signals, but focuses only on technical constraints. In addition, consumption and generation within the study area are modeled stochastically, but external network dynamics, such as cross-border exchanges and external generation, are not explicitly modeled. These simplifications

allow for analysis of local grid capacity impacts but limit the ability to capture how the modeled charging demand interacts with external factors.

Finally, the developed framework applies a one-directional coupling between the transportation and power system models. Charging demand profiles are generated independently based on travel behavior and are then used as input to the power grid simulations, without feedback from grid constraints to charging or travel behavior. Moreover, no optimization or control strategies were implemented to minimize grid impacts. The focus has instead been on assessing the resulting charging loads and their implications for grid capacity under various behavioral and temporal scenarios. While this approach provides valuable insights into potential impacts, future work could extend the framework toward integrated optimization or co-simulation approaches.

Chapter 6

Conclusions and Future Work

This thesis has aimed to explore the sector coupling of the transportation and electric power systems following the trend of electrified transport fleets. This has been done through a grid simulation framework, where models of charging demand are combined with models of electric power consumption and generation.

The following research questions were defined at the beginning of this thesis:

- RQ1:** How can the aggregated energy and power requirements of a fully electrified road transport fleet be modeled?
- RQ2:** How can a simulation framework be developed to assess the impact of aggregated electric vehicle charging loads on sub-transmission grid capacity?
- RQ3:** To what extent can the grid capacity impact of electric vehicle charging be mitigated through temporal flexibility in charging demand?
- RQ4:** How can the developed modeling and simulation framework be applied to a real-world, large-scale case study to evaluate interactions between transportation and power systems under full transport electrification?

6.1 Conclusions

To address RQ1, this thesis presented probabilistic models of charging power demand for fully electrified fleets of passenger cars, long-haul trucks, and heavy equipment. By combining recent empirical data with scenario-based modeling, the work captured the uncertainty inherent in future transport demand. The results indicate that while the passenger car fleet

dominates the total energy demand, the aggregated peak power requirements are comparable across all three fleets. This highlights that for grid capacity planning, high-power commercial fleets (trucks and heavy equipment) are just as critical as the energy-intensive fleet of passenger cars. Furthermore, the results clearly show how the power peaks can be mitigated by the implementation of smart or controlled charging strategies.

To address RQ2, a probabilistic load flow simulation framework has been developed to assess the impact of aggregated EV charging loads on sub-transmission grid capacity. The choice of a probabilistic methodology means that the flexibility requirements can be quantitatively estimated. Results indicate that although many of the charging loads are located in the distribution grid, the aggregated effects on grid capacity can be seen on sub-transmission grid levels. However, the sub-transmission grid capacity is largely sufficient to provide the EV charging loads during normal grid conditions.

The investigation of RQ3 revealed a critical distinction between charging peaks and grid stress. The application of charging scenarios demonstrated that while smart or controlled charging strategies can significantly reduce the aggregated peak power of the EV fleet (by up to 32%), this reduction does not automatically translate to a proportional transformer unloading. The results show that local grid conditions, specifically the "dampening" effect of background loads, often dominate the outcome. Consequently, charging demand simulations alone are insufficient for predicting grid impact. To determine the actual grid impact of new EV loads on the system, the charging load estimations must be coupled to detailed grid simulations.

To show how the developed framework can be applied to a real-world and large-scale case study, in line with RQ4, the models and simulation have been applied to a case study of Skåne in Sweden. An actual grid model of the transmission and sub-transmission grid of the area was combined with data-based models of charging demand and electric power consumption and generation. The results and conclusions in this thesis are specific and realistic in the context of the Skåne study area. However, the framework can easily be adapted to other systems and areas.

In summary, this thesis has outlined a methodological framework for integrating transportation and power systems simulations. The specific application to the Skåne study area has led to insights into the required charging demand and its implications for the grid capacity of the sub-transmission grid in the area. These results could be directly utilized by the transportation or power systems communities to guide the future electrification of the transport sector. This thesis also contributes with a probabilistic framework to analyze the risk of grid congestion following installations of new loads on the system. This framework could be adapted to include the analysis of other loads than charging demand. This could be a useful tool for grid planners in the context of introducing conditional connection agreements or to meet the requirements of introducing risk-based approaches in power grid planning.

6.2 Future Work

Future research should aim to address the limitations identified in this thesis and could also seek to expand the study in several directions. The data-based models developed should be updated as new data becomes available, particularly as the electrification of transport progresses and empirical charging data for different fleets can be collected. The charging demand models could be further developed by incorporating agent-based simulations for the passenger car and heavy equipment fleets, or by expanding the parameters treated stochastically to capture a wider range of behavioral and operational uncertainties. This thesis has focused on three different vehicle fleets: passenger cars, long-haul trucks, and heavy equipment. Future work could include other vehicle fleets such as short- and medium-haul trucks, buses, or other vehicles.

The grid simulations could be expanded to include N-1 contingencies, detailed representations of cross-border flows, or voltage and dynamic stability analyses. Another important extension would be to include price signals and generation re-dispatch through optimal power flow instead of standard load flow analysis within the Monte Carlo framework. A natural expansion of the simulation would be to evolve the current one-directional coupling toward an integrated co-simulation framework that allows feedback between the transport and power systems. Such a framework could enable optimization of charging behavior and mitigation strategies for grid capacity impacts, rather than assessing outcomes for pre-defined scenarios.

Finally, this thesis has chosen the study area of Skåne in Sweden to illustrate the application of the developed frameworks. To draw wider and more general conclusions about the grid capacity impact from electrified transport, the study should be expanded to include areas with different power grid structures, resource, and transport mixes.

References

- [1] International Energy Agency, “Net Zero by 2050: A Roadmap for the Global Energy Sector,” IEA, Paris, Flagship Report, 2021. [Online]. Available: <https://www.iea.org/reports/net-zero-by-2050>
- [2] European Environment Agency (EEA), “Sustainability of europe’s mobility systems,” Web report no. 01/2024, 2024.
- [3] Ember, “Global electricity carbon intensity data,” <https://ourworldindata.org/energy>, 2025, data from Ember; Energy Institute - Statistical Review of World Energy (2025), CC BY.
- [4] L. Peiseler, V. Schenker, K. Schatzmann, S. Pfister, V. Wood, and T. Schmidt, “Carbon footprint distributions of lithium-ion batteries and their materials,” *Nature Communications*, vol. 15, no. 1, p. 10301, Nov. 2024.
- [5] DNV, “Energy transition outlook 2025,” DNV, Tech. Rep., 2025. [Online]. Available: <https://www.dnv.com/energy-transition-outlook/>
- [6] PowerCircle, “Elis – elbilen i sverige, distributed by powercircle,” 2024, available: <https://powercircle.org/statistik/>.
- [7] Svenska kraftnät, “Nätutvecklingsplan 2024–2033,” Svenska kraftnät, Technical Report, 2023.
- [8] European Union, “Commission Regulation (EU) 2017/1485 of 2 August 2017 establishing a guideline on electricity transmission system operation,” 2017. [Online]. Available: <https://eur-lex.europa.eu/eli/reg/2017/1485>
- [9] A. Callanan, “alicecallanan/ev-load-profiles-sweden: EV Charging Profiles Initial Release,” 2026. [Online]. Available: <https://doi.org/10.5281/zenodo.18670475>
- [10] European Commission, “Stepping up europe’s 2030 climate ambition: Investing in a climate-neutral future for the benefit of our people,” European Commission, Brussels, Communication, COM(2020) 562 final, 2020. [Online]. Available: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0562>
- [11] European Parliament and Council of the European Union, “Regulation (EU) 2023/851 of the European Parliament and of the Council of 19 April 2023 amending Regulation (EU) 2019/631 as regards strengthening the CO₂ emission performance standards for new passenger cars and new light commercial vehicles in line with

- the Union's increased climate ambition," pp. 5–20, 2023, published 25 April 2023. [Online]. Available: <http://data.europa.eu/eli/reg/2023/851/oj>
- [12] —, "Regulation (EU) 2023/1804 of the European Parliament and of the Council of 13 September 2023 on the deployment of alternative fuels infrastructure, and repealing Directive 2014/94/EU," pp. 1–47, 2023. [Online]. Available: <http://data.europa.eu/eli/reg/2023/1804/oj>
- [13] Sveriges riksdag, "Klimatlag (2017:720)," 2017, the Swedish Climate Act. Adopted by the Riksdag. [Online]. Available: https://www.riksdagen.se/sv/dokument-och-lagar/dokument/svensk-forfattningssamling/klimatlag-2017720_sfs-2017-720/
- [14] Elektrifieringskommissionen, "Två år med elektrifieringskommissionen – en sammanfattning," Regeringskansliet, Tech. Rep., sep 2022, a summary of the Commission's work from 2020 to 2022. The title translates to 'Two Years with the Commission for Electrification – a Summary'. [Online]. Available: <https://www.regeringen.se/contentassets/2d116eb604404aa7b09a1a414c6a2e40/sammanfattning-av-tva-ar-med-elektrifieringskommissionen/>
- [15] Energimyndigheten, "Scenarier över sveriges energisystem – vägar till ett energisystem med nettonollutsläpp 2050," Energimyndigheten, Tech. Rep. ER 2025:13, 2025, ISBN 978-91-7993-230-5. [Online]. Available: <https://energimyndigheten.a-w2m.se/System/TemplateView.aspx?p=Arkitektkopia&id=1173312576a844f5a08e2c4a2005ccfb&l=t&cat=%2FPrognoser%20och%20Scenarier>
- [16] Statistics Sweden (SCB). (2023) Number of passenger cars by fuel type. Accessed: 26 Sept. 2023. [Online]. Available: https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__TK__TK1001__TK1001A/PersBilarDrivMedel/table/tableViewLayout1/
- [17] Mobility Sweden. (2023) Databas nyregistreringar. Accessed: 26 Sept. 2023 (in Swedish). [Online]. Available: <https://mobilitysweden.se/statistik/databas-nyregistreringar>
- [18] European Alternative Fuels Observatory (EAFO), "Sweden: BEVs reach 35% share in april 2025," may 2025, news article, published May 8, 2025. [Online]. Available: <https://alternative-fuels-observatory.ec.europa.eu/general-information/news/sweden-bevs-reach-35-share-april-2025>
- [19] Energiforsk, "Scenarier för transportsektorns utveckling till 2030 och 2045," Energiforsk, Tech. Rep., 2024, accessed: 26 Sept. 2023 (in Swedish). [Online]. Available: <https://energiforsk.se/media/33165/2024-993-scenarier-fo-r-transportsektorns-utveckling-till-2030-och-2045.pdf>
- [20] Naturvårdsverket. (2025) Arbetsmaskiner, utsläpp av växthusgaser. <https://www.naturvardsverket.se/data-och-statistik/klimat/vaxthusgaser-utslapp-fran-arbetsmaskiner/>. [Online; accessed Jan. 9, 2025].

- [21] Volvo Construction Equipment. (2026) Electric construction machines. Accessed: 23rd March 2026. [Online]. Available: <https://www.volvoce.com/europe/en/products/electric-machines/>
- [22] National Grid, “Commercial report,” National Grid, Tech. Rep., 2023, accessed: 26 Sept. 2023. [Online]. Available: <https://commercial.nationalgrid.co.uk/downloads-view-reciteme/64369>
- [23] My Electric Avenue. (2024) My electric avenue. [Online]. Available: <http://myelectricavenue.info/>
- [24] J. Quiros-Tortos, A. N. Espinosa, L. F. Ochoa, and T. Butler, “Statistical Representation of EV Charging: Real Data Analysis and Applications,” in *2018 Power Systems Computation Conference (PSCC)*. IEEE, pp. 1–7. [Online]. Available: <https://ieeexplore.ieee.org/document/8442988/>
- [25] K. N. Hasan, R. Preece, and J. V. Milanovic, “Probabilistic Modelling of Electric Vehicle Charging Demand based on Charging Station Data,” in *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. IEEE, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/9810600/>
- [26] C. Hecht, S. Das, C. Bussar, and D. U. Sauer, “Representative, empirical, real-world charging station usage characteristics and data in Germany,” vol. 6, p. 100079. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2590116820300369>
- [27] A. Weiß, F. Biedenbach, and M. Müller, “Probabilistic Load Profile Model for Public Charging Infrastructure to Evaluate the Grid Load,” vol. 15, no. 13, p. 4748.
- [28] L. Calearo, A. Thingvad, K. Suzuki, and M. Marinelli, “Grid Loading Due to EV Charging Profiles Based on Pseudo-Real Driving Pattern and User Behavior,” vol. 5, no. 3, pp. 683–694. [Online]. Available: <https://ieeexplore.ieee.org/document/8733835/>
- [29] D. Betancur, L. F. Duarte, J. Revollo, C. Restrepo, A. E. Díez, I. A. Isaac, G. J. López, and J. W. González, “Methodology to Evaluate the Impact of Electric Vehicles on Electrical Networks Using Monte Carlo,” vol. 14, no. 5, p. 1300.
- [30] B. Borlaug, M. Muratori, M. Gilleran, D. Woody, W. Muston, T. Canada, A. Ingram, H. Gresham, and C. McQueen, “Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems,” vol. 6, no. 6, pp. 673–682. [Online]. Available: <https://www.nature.com/articles/s41560-021-00855-0>
- [31] K. Walz, K. Rudion, C.-M. Moraw, and M. Eilers, “Probabilistic Impact Assessment of Electric Truck Charging on a Medium Voltage Grid,” in *2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. IEEE, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/9960621/>
- [32] E. Ivarsoy, B. N. Torsater, and M. Korpas, “Stochastic Load Modeling of High-Power Electric Vehicle Charging - A Norwegian Case Study,” in *2020 International Conference on Smart Energy Systems and Technologies (SEST)*. IEEE, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/9203102/>

- [33] F. Maurer, C. Rieke, R. Schemm, and D. Stollenwerk, "Analysis of an Urban Grid with High Photovoltaic and e-Mobility Penetration," vol. 16, no. 8, p. 3380.
- [34] M. Ingelström, H. Pourroshanfekr Arabani, M. Alaküla, and F. J. Márquez-Fernández, "Placement of fast-charging infrastructure for long-haul road freight based on spatio-temporal evaluation of en-route energy needs," *IEEE Transactions on Transportation Electrification*, vol. 12, no. 1, pp. 53–65, 2026.
- [35] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand," vol. 3, no. 3, pp. 193–201. [Online]. Available: <https://www.nature.com/articles/s41560-017-0074-z>
- [36] W. Shoman, S. Yeh, F. Sprei, P. Plötz, and D. Speth, "Battery electric long-haul trucks in Europe: Public charging, energy, and power requirements," vol. 121, p. 103825. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S1361920923002225>
- [37] G. Yousefi, A. Dimovski, L. Radaelli, and M. Merlo, "Estimating the impact of electric mobility on distribution networks through GIS techniques," vol. 38, p. 101379. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2352467724001085>
- [38] G. Li and X.-P. Zhang, "Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 492–499, 2012.
- [39] P. V. Dahiwalé, Z. H. Rather, and I. Mitra, "A comprehensive review of smart charging strategies for electric vehicles and way forward," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 9, 2024.
- [40] Y. Kobayashi, M. Taljegard, and F. Johnsson, "Assessment of real-world driving patterns for electric vehicles: an on-board measurements study from Sweden," *Applied Energy*, vol. 401, p. 126608, 2025, data is based on GPS logging from 334 EVs in Sweden over one year.
- [41] Pacific Northwest National Laboratory (PNNL), "Grid capacity – what is it, what determines it, does one number work, and how does it relate to electric vehicles?" Pacific Northwest National Laboratory (PNNL), Richland, WA, Tech. Rep. PNNL-SA-192631, sep 2021, prepared for the U.S. Department of Energy under Contract DE-AC05-76RL01830. [Online]. Available: <https://www.osti.gov/servlets/purl/2221804>
- [42] S. Rivera, S. M. Goetz, S. Kouro, P. W. Lehn, M. Pathmanathan, P. Bauer, and R. A. Mastromauro, "Charging infrastructure and grid integration for electromobility," *Proceedings of the IEEE*, vol. 111, no. 4, pp. 371–396, 2023.
- [43] J. D. Glover, T. J. Overbye, and M. S. Sarma, *Power System Analysis and Design*, 6th ed. Cengage Learning, 2016, ISBN-10: 1305632133.
- [44] European Commission, "Commission regulation (eu) 2017/1485 of 2 august 2017 establishing a guideline on electricity transmission system operation," <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32017R1485>, 2017, official Journal of the European Union.

- [45] S. Babaei, D. Steen, L. A. Tuan, O. Carlson, and L. Bertling, "Effects of Plug-in Electric Vehicles on distribution systems: A real case of Gothenburg," in *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*. IEEE, pp. 1–8. [Online]. Available: <http://ieeexplore.ieee.org/document/5638947/>
- [46] Y. Yu, D. Reihs, S. Wagh, A. Shekhar, D. Stahleder, G. R. C. Mouli, F. Lehfuss, and P. Bauer, "Data-Driven Study of Low Voltage Distribution Grid Behaviour With Increasing Electric Vehicle Penetration," vol. 10, pp. 6053–6070, 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9667519/>
- [47] F. Safdarian, D. Wallison, J. L. Wert, O. Oshinkoya, J. K. Jung, T. J. Overbye, and Y. Xu, "Technical Impacts of Light-Duty and Heavy-Duty Transportation Electrification on a Coordinated Transmission and Distribution System," pp. 1–1. [Online]. Available: <https://ieeexplore.ieee.org/document/10630833/>
- [48] U. H. Ramadhani, M. Shepero, J. Munkhammar, J. Widén, and N. Etherden, "Review of probabilistic load flow approaches for power distribution systems with photovoltaic generation and electric vehicle charging," vol. 120, p. 106003. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0142061519341730>
- [49] A. Lojowska, D. Kurowicka, G. Papaefthymiou, and p. d. u. family=Sluis, given=Lou, "Stochastic Modeling of Power Demand Due to EVs Using Copula," vol. 27, no. 4, pp. 1960–1968. [Online]. Available: <http://ieeexplore.ieee.org/document/6193193/>
- [50] A. C. Melhorn and A. Dimitrovski, "Correlation between EVs and Other Loads in Probabilistic Load Flow for Distribution Systems," in *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. IEEE, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/8440435/>
- [51] C. Crozier, T. Morstyn, and M. McCulloch, "The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems," vol. 268, p. 114973. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0306261920304852>
- [52] J. L. Wert, K. S. Shetye, H. Li, J. H. Yeo, X. Xu, A. Meitiv, Y. Xu, and T. J. Overbye, "Coupled Infrastructure Simulation of Electric Grid and Transportation Networks," in *2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. IEEE, pp. 1–5. [Online]. Available: <https://ieeexplore.ieee.org/document/9372175/>
- [53] A. Birchfield, E. Schweitzer, M. Athari, T. Xu, T. Overbye, A. Scaglione, and Z. Wang, "A Metric-Based Validation Process to Assess the Realism of Synthetic Power Grids," vol. 10, no. 8, p. 1233. [Online]. Available: <https://www.mdpi.com/1996-1073/10/8/1233>
- [54] DigSilent GmbH, "Digsilent powerfactory."
- [55] Statistics Sweden. (2023) Open data for deso – demographic statistical areas. Accessed: 26 Sept. 2023. [Online]. Available: <https://scb.se/en/services/open-data-api/open-geodata/deso--demographic-statistical-areas/>

- [56] EV Database. (2023) Energy consumption of full electric vehicles. Accessed: 26 Sept. 2023. [Online]. Available: <https://ev-database.org/cheatsheet/energy-consumption-electric-car>
- [57] US Environmental Protection Agency. (2023) Fuel economy guide 2023. Accessed: 26 Sept. 2023. [Online]. Available: <https://www.fueleconomy.gov/feg/pdfs/guides/FEG2023.pdf>
- [58] Transport Analysis. (2023) The swedish national travel survey 2022. Accessed: 26 Sept. 2023. [Online]. Available: <https://www.trafa.se/kommunikationsvanor/RVU-Sverige/>
- [59] National Grid. (2023) Electric nation data. [Online]. Available: <https://www.nationalgrid.co.uk/electric-nation-data>
- [60] A. Horni, K. Nagel, and K. W. Axhausen, *The Multi-Agent Transport Simulation MATSim*. Ubiquity Press, 2016.
- [61] M. Ingelström, A. Callanan, and F. J. Márquez-Fernández, “Investigating the impact of public en-route and depot charging for electric heavy-duty trucks using agent-based transport simulation and probabilistic grid modeling,” *World Electric Vehicle Journal*, vol. 17, no. 4, 2026. [Online]. Available: <https://www.mdpi.com/2032-6653/17/4/172>
- [62] M. Ingelström, “mattiasingelstrom/hd-ev-charging-profiles: Charging Demand Profiles for Heavy-Duty Electric Trucks — Skåne, Sweden,” 2026. [Online]. Available: <https://doi.org/10.5281/zenodo.18631297>
- [63] Energimyndigheten. (2025) Regionala elektrifieringspiloter för tunga transporter. (in Swedish). Accessed: 09 Jan. 2025. [Online]. Available: <https://www.energimyndigheten.se/utlysningar/utlysning-regionala-elektrifieringspiloter-for-tunga-transporter/>
- [64] D. P. Kroese, T. Taimre, and Z. I. Botev, *Handbook of Monte Carlo Methods*. New York, NY, USA: Wiley, 2011.
- [65] B. Efron and R. Tibshirani, *An Introduction to the Bootstrap*. Boca Raton, FL: Chapman & Hall/CRC, 1998.
- [66] G. Papaefthymiou and D. Kurowicka, “Using copulas for modeling stochastic dependence in power system uncertainty analysis,” *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 40–49, Feb. 2009.
- [67] DIgSILENT GmbH, *PowerFactory User Manual*, DIgSILENT GmbH, Gomaringen, Germany, 2022, technical Reference Documentation.
- [68] Naturvårdsverket. (2025, Dec.) Inrikes transporter, utsläpp av växthusgaser. Naturvårdsverket. Accessed: 2026-02-09. [Online]. Available: <https://www.naturvardsverket.se/data-och-statistik/klimat/vaxthusgaser-utslapp-fran-inrikes-transporter/>



Division of Industrial Electrical Engineering and Automation
Department of Biomedical Engineering
Faculty of Engineering

ISBN 978-91-985111-0-9
CODEN: LUTEDX/(TEIE1103)/1-160/2026

