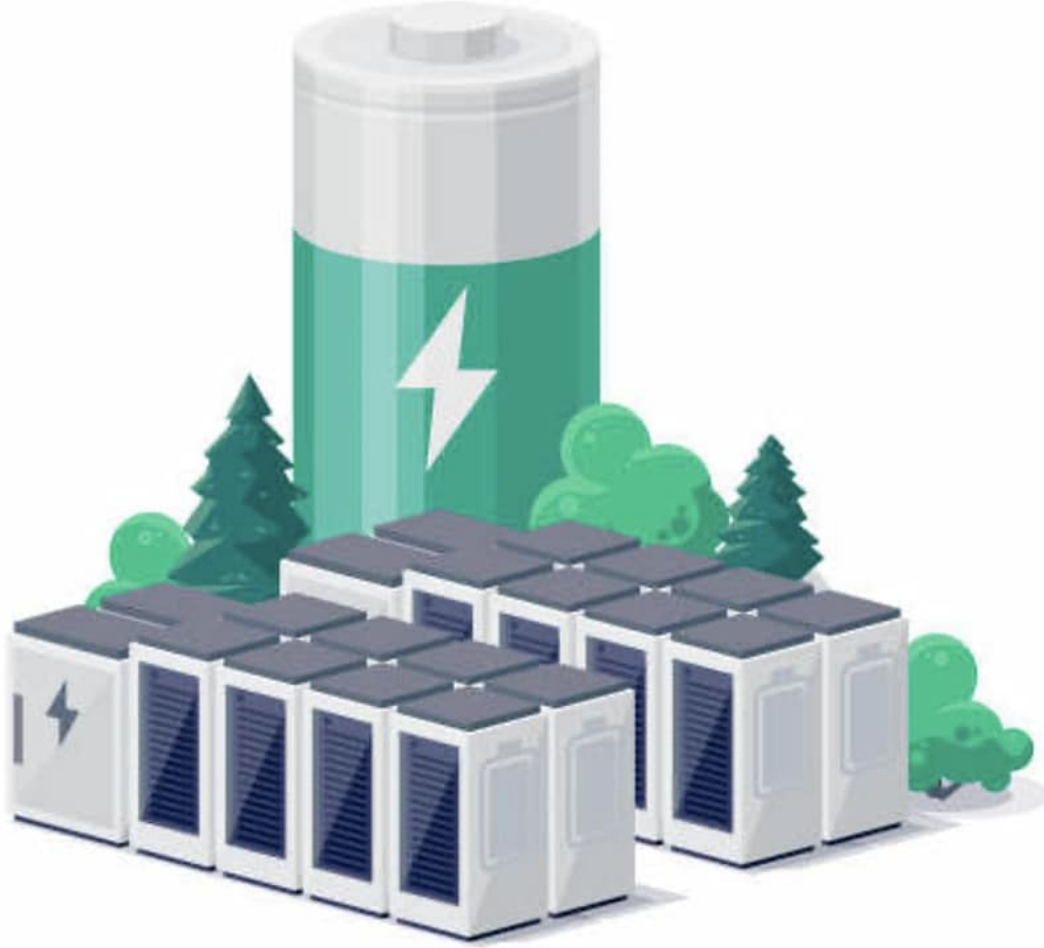
Impact of Alternative Transport Tariffs on Battery Performance

An Optimization and Distribution Network Model

Master Thesis

Pien A.C. Wetselaar



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phrase=battery+storage

Preface

Writing the preface marks the end of the thesis process. A couple days before the final deadline I sit in the glass hall of the university library, a place where I have spent countless hours listening to lectures, writing summaries and papers. Many of these hours have been spent with a much too expensive Coffee Star cappuccino by my side. And my final day is no exception.

I started my TU Delft career convinced I would become a chemical engineer. After a few months in the lab I accepted that, having loved subjects such as history and global perspectives just as much as I loved chemistry, the focused and abstract nature of the discipline wasn't a match made in heaven. TPM was. I relished the deep engineering in combination with policy, stakeholder management and economics. I never looked back. A highlight was, while in quarantine, modeling the optimal COVID vaccination tents, showing me the importance of the skills I was acquiring. The ultimate highlight lies in front of you, 6 months of research on the impact of tariffs on battery's profitability and congestion management performance.

Many thanks to my TU Delft supervisors, Dr. ir. Rudi Hakvoort and Dr. ir. Özge Okur. I am grateful for my bi-weekly meetings with Rudi, who was steered me on the right track and provide valuable insights during the entire process. I also would like to thank Özge for her valuable contributions during our meetings.

I'm grateful to the Accenture Strategy Consulting Utilities team for their daily support, whether through sharp insights or for our walks outside. Special thanks to Marc en Duco, my Accenture supervisors who helped me shape the research and understand the broader implications of the work. They consistently supported me throughout this process and were a source of energy and motivation.

Graduating would not be possible without my friends and family, I am forever grateful for their unwavering support and encouragement.

Pien A.C. Wetselaar
Delft, March 2025

Summary

The Dutch energy system is evolving rapidly, transitioning from centralized fossil-based generation to decentralized renewable sources. At the same time, electrification is increasing across heating, mobility, and industry, placing significant strain on the electricity grid. This imbalance between supply and demand leads to severe congestion issues, costing the Netherlands approximately 20-40 billion EUR annually. While expanding grid infrastructure is an option, it is costly, time-consuming, and constrained by resource shortages. As an alternative, market-driven flexibility solutions such as battery storage, alongside regulatory interventions like alternative transport tariffs, are being explored for their potential to relieve congestion.

This research examines how alternative transport tariffs impact battery behavior and grid stability in the Dutch distribution network. Specifically, it evaluates the effects of two newly introduced tariff structures: Time-of-Use (TOU) tariffs, which warrant flexible participation on the grid, and Time-Block (TB) tariffs, which provide discounts for energy usage within predefined time windows. The study assesses battery behavior, congestion relief, and financial viability under these tariffs, comparing their effects to a baseline scenario without alternative transport tariffs and without a battery. A key objective is to determine whether non-market-based mechanisms such as alternative transport tariffs can enhance congestion management and whether the TOU tariff should be extended to the distribution grid.

To analyze these effects, a quantitative modeling approach is used, combining a Mixed Integer Linear Programming (MILP) model, which optimizes battery operation in the day-ahead and intraday electricity markets, with a PyPSA distribution network model, which simulates battery interactions within the grid. The study evaluates three scenarios: no tariff, TOU tariffs, and TB tariffs. A sensitivity analysis is conducted to examine the robustness of results under different price fluctuations and seasonal variations.

The results show that battery storage significantly improves congestion management by reducing line overloading, renewable energy curtailment, and peak loads. However, the extent of these benefits depends on the tariff design. The Time-of-Use tariff proves to be an effective mechanism, providing a structured yet flexible approach that allows batteries to optimize charging and discharging based on real-time grid conditions. This improves both their financial viability and their role in congestion relief. In contrast, the Time-Block tariff imposes rigid constraints that limit battery owners' ability to adapt to market signals, significantly reducing both the financial attractiveness and technical effectiveness of batteries for congestion management. Seasonal variations also affect battery performance, with winter periods exhibiting higher volatility due to fluctuating energy demand and supply conditions. While some peak shaving occurs under all tariff scenarios, its effectiveness is reduced under the TB tariff because of its restrictive design.

From a socio-technical perspective, implementing Time-of-Use tariffs at the distribution level presents both opportunities and significant challenges. The research identifies three key barriers to TOU implementation:

- Financial feasibility: Without appropriate subsidies or incentives, battery owners may struggle to invest in the necessary infrastructure to fully leverage TOU tariffs.
- Regulatory uncertainty: The extension of TOU tariffs to the distribution grid requires adjustments in existing regulations and approval from policymakers. There is currently a lack of cost transparency and participation clarity that creates uncertainty for market participants.
- Implementation feasibility: DSOs need advanced congestion forecasting capabilities but currently lack the financial means to invest in these technologies.

To overcome barriers in the system, the study proposes the following recommendations:

- Market-Based Subsidy Allocation for Battery Deployment: The study finds that battery investments require an 18% subsidy to meet the OECD benchmark IRR of 10%. Rather than implementing a fixed subsidy, a competitive bidding system should be introduced where energy providers, battery owners, and flexibility service providers bid for the lowest subsidy required to deploy storage solutions. This mechanism fosters

competition, reduces the overall cost to taxpayers, and ensures that public funds are allocated efficiently. Large-scale projects could benefit from economies of scale, potentially reducing the required subsidy further.

- Establishing a Transparent and Standardized Regulatory Framework: A lack of cost transparency, tariff standardization, and participation clarity creates uncertainty for market participants, discouraging investment in flexibility solutions. The Autoriteit Consument Markt (ACM) should introduce a nationally uniform TOU tariff structure aligned with existing congestion management mechanisms. This requires a comprehensive cost-benefit assessment to ensure that TOU pricing remains financially viable while protecting non-flexible consumers from excessive cost shifts.
- Financial Support for DSOs to Improve Forecasting and Grid Monitoring: TOU tariffs rely on accurate congestion forecasting and real-time grid monitoring, yet many DSOs lack the necessary technological infrastructure to manage congestion dynamically. To address this, targeted financial support should be allocated to fund investments in advanced forecasting models, AI-driven congestion prediction tools, and real-time data collection systems. A grid intelligence investment fund should be established, allowing DSOs to recover part of their investment costs while ensuring that forecasting capabilities improve in parallel with TOU tariff expansion. Without this investment, DSOs may continue to resist TOU implementation, limiting its potential as a congestion management tool.

Despite these insights, this study has several limitations. The use of a synthetic network model means that some real-world complexities are not fully captured. The financial feasibility analysis is based on modeled price forecasts rather than actual market transactions, introducing some uncertainty regarding practical implementation. Additionally, regulatory and policy uncertainties surrounding TOU tariffs at the distribution level require further exploration. Future research is needed to validate these findings under real-world market conditions, examine the long-term economic sustainability of transport tariff-based congestion management, and explore additional policy measures to enhance battery integration into the electricity grid.

The study concludes that while alternative transport tariffs significantly influence battery behavior, their effectiveness in congestion management depends on their design. The Time-of-Use tariff provides a balanced approach that improves both economic feasibility and congestion relief. In contrast, the role of the Time-Block tariff remains uncertain, requiring further investigation to determine its practical impact. Based on these findings, this research recommends extending the TOU tariff to the distribution grid, as it effectively balances financial incentives, market participation, and congestion management objectives. Additionally, a market-based subsidy bidding mechanism should be considered to enhance financial support for battery adoption, ensuring cost-effective congestion management and optimizing the role of flexible assets in the energy transition.

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Nomenclature

Abbreviations

Abbreviation	Definition
DA	Day-Ahead
ID	Intraday
SOC	State of Charge
KPI	Key Performance Indicator
TOU	Time-of-Use
TB	Time-block
TSO	Transmission System Operator
DSO	Distribution System Operator
RES	Renewable Energy Sources
PyPSA	Python for Power System Analysis
ENTSO-E	European Network of Transmission System Operators for Electricity
AC	Alternating Current
DC	Direct Current
MILP	Mixed Integer Linear Programming
BESS	Battery Energy Storage System
IRR	Internal Rate of Return

Symbols

Symbol	Definition	Unit
C	Charging Power	[MW]
D	Discharging Power	[MW]
E	Energy	[MWh]
C	Capacity	[MWh]
Δt	Time Interval	[h]
P_t	Price at time t	[EUR/MWh]
c^{ch}	Battery Charging Costs	[EUR/MWh]
c^{dis}	Battery Disharging Costs	[EUR/MWh]
η	Efficiency	[%]
Pr	Profit	[EUR]
R	Revenue	[EUR]
C_{OPEX}	Operational Costs	[EUR]
Dp	Depreciation	[EUR]
I	Interest	[EUR]
C_{inv}	Investment Cost	[EUR]
L	Lifetime	[years]
C_{TCC}	Contracted transport capacity costs	[EUR/year]
C_{FCC}	Annual fixed charge costs	[EUR/year]
C_{CYMPC}	Contracted yearly maximum power costs	[EUR/year]
C_{OM}	Operation and maintenance costs	EUR/year]
r	Interest rate	[%]
T	Profit tax	[%]

1
Introduction

1.1. Problem Statement

To meet urgent climate targets, the European Union is advancing policies that accelerate the shift to renewable energy. The "Fit for 55" package, which aims to reduce greenhouse gas emissions by 55% by 2030, includes initiatives such as the European Wind Power Action Plan and substantial investments in solar capacity (European Commission, 2024). The Netherlands is one of the leading countries in this transition, generating almost 50% of its electricity from renewable sources in 2024 (Centraal Bureau voor Statistiek, 2024). This transition, while vital to combating climate change, brings complications to the stability and efficiency of the Dutch grid. As the electricity grid shifts from centralized, fossil-based generation to decentralized renewable sources, unpredictability in supply and demand is introduced. Meanwhile, the increasing electrification of sectors such as transportation, heating, and industry further intensifies electricity demand (TIBO Energy, 2024). Combined this leads to a mismatch in demand and supply, leading to congestion and balancing problems that, if not mitigated, will slow down the transition. For example, in the second quarter of 2024, to prevent congestion, the Netherlands curtailed enough green electricity to power the country for six full days — an amount of energy that could have saved 350 million cubic meters of natural gas and significantly reduced carbon emissions (Oerlemans, 2024).

Grid congestion poses significant economic and social challenges across the Dutch network, affecting producers, grid operators, and consumers with increased operational costs that raise electricity prices throughout the supply chain (TIBO Energy, 2024). According to the Netherlands Enterprise Agency (RVO), congestion interferes with both business efficiency and progress in the energy transition. Demand congestion, which limits local capacity to meet electricity demand, and injection congestion, which restricts renewable energy from feeding back into the grid, both slow economic progress and lead to financial losses of up to €50,000 and €121 per MWh, respectively (Thijsen et al., 2024). Without targeted interventions, these costs are likely to increase over the next few years (Energy StorageNL, 2024). According to the Dutch public news broadcaster NOS, the waiting list for a connection to the grid for a larger transport capacity takes 10 years, and has only grown more and more due to the electrification of processes and increased reliance on renewable sources. (Koster, 2024). Such inefficiencies slow the progress toward a fully decarbonized energy system in the Netherlands.

Managing grid congestion is critical to the success of the energy transition. Although expanding the capacity of the grid is an option, it is expensive and time consuming. In many areas, congestion occurs only during a few peak periods, making such investment inefficient there (Sagdur, 2018). Additionally, grid enhancement is a slow, capital-intensive solution (needing record investments by DSOs of EUR 8bn until 2026) that struggles with a shortage of technical workers (Wampack, 2023). Finally, there is a serious risk of material shortages, leading to logistical challenges and a price increase (Gielen & Papa, 2021). Addressing grid congestion requires a smarter approach, that incentivize a flexible use of the electricity grid. Practical alternatives like demand response, renewable energy curtailment, and energy storage systems already exist as market-based solutions, helping optimize grid use without extensive upgrades. These market-driven flexibility services, traded on energy markets, have shown promise in alleviating grid strain while supporting renewable integration. However, the impact of newly introduced, non-market-based policies—specifically alternative tariff structures aimed at encouraging grid stability—on market behavior is generally unexplored. The Netherlands has introduced alternative tariff structures targeting both transmission and distribution grid users, aiming to address congestion starting in April of 2025 (Autoriteit Consument en Markt, 2024). Time Block tariffs will be introduced on the distribution grid and Time of Use tariffs on the transmission grid. Time Block tariffs grant users predefined periods to access the grid, while time-of-use tariffs allow network operators to set usage windows based on anticipated grid conditions before the day-ahead market closes. By participating in these tariff systems, the assets gain a discount on their connected transport capacity fees (for Time of Use this is 100% discount, for Time Block this is dependent on the assigned hours). This tariff system also gives them the opportunity to connect to the grid instead of the alternative: join the ten year waiting list for a connection. It remains unclear how these changes influence the market dynamics and behaviors of flexible assets like battery storage systems.

This research will specifically investigate the effects of alternative tariff structures on battery storage behavior within the Dutch distribution grid. With the results it aims to advise Autoriteit Consument & Markt (ACM) on the use of alternative transport tariffs and whether the Time of Use tariff should be extended to the distribution grid. Batteries, as flexible assets, are particularly valuable in this analysis, given their dual capability to participate in market-driven activities and provide congestion relief. Understanding how these tariffs shape battery owner behavior will offer insights into the viability of non-market-based policies for improving grid stability. The Netherlands is an especially interesting case study because it is at the forefront of adopting renewables, distributed energy resources, and electrification. This leadership has brought early exposure to challenges likely to spread across Europe, making the issue internationally relevant. Given these uncertainties and social relevance, this research aims to explore whether market-driven flexibility solutions are enough to manage congestion, and how the implementation of alternative transport tariffs impacts their behavior, business case and impact on grid stability.

This leads to the main research question: "How do alternative transport tariffs impact battery performance and grid stability in the Dutch electricity distribution network?". Given the pressing nature of grid congestion and the inefficiencies caused by demand and injection limitations, identifying effective strategies for congestion management is essential for enabling the energy transition. The need to accommodate rising electricity demand while integrating a growing share of renewable energy sources underscores the importance of exploring alternative solutions to grid expansion. By comparing market-based and non-market-based solutions we can understand the types of policies that work better to incentivize flexible assets to aid in grid stability.

1.2. Background Alternative Transport Tariffs and ACM

In July 2024, the Autoriteit Consument & Markt (ACM) issued a new code decision on alternative transport rights. Under the new regulatory framework, two alternative transport rights are being implemented to optimize electricity grid utilization and address congestion issues. These are the Time of Use transport right (TOU) and the time-block transport right (TB). Both models aim to create more flexible and cost-efficient access to grid capacity, particularly for large electricity consumers with adaptable energy demand patterns (Autoriteit Consument en Markt, 2024).

The Time of Use transport right provides users with the ability to transport electricity for at least 85% of the hours in a year on TenneT's national high-voltage grid. This model is particularly relevant for businesses that can tolerate occasional unavailability of transport capacity in exchange for significant cost savings. One of the key incentives of this transport right is the zero tariff on contracted power (kW), which can lead to a 50% reduction in total transport costs compared to conventional fixed transport rights (Netbeheer Nederland, 2024). This financial benefit makes the TOU particularly attractive for industries that rely on flexible energy assets, such as battery storage, hydrogen production, and demand-response facilities. Grid operators will notify users at least a day in advance when transport capacity is unavailable, ensuring businesses have sufficient time to adjust their energy consumption. The 85% availability threshold is designed based on an analysis of expected congestion patterns, ensuring that these flexible consumers contribute to a more balanced grid load rather than exacerbating peak-hour congestion (Netbeheer Nederland, 2024).

The time-block-based transport right allows users to secure electricity transport capacity within specific, predefined time slots agreed upon with the regional grid operator. This model is designed for large electricity consumers that do not require continuous access to the grid and can concentrate their energy usage in off-peak hours. The example given by Netbeheer Nederland is electric bus depots that only need to charge vehicles during nighttime hours, or industrial processes that can be scheduled to run outside of peak demand periods (Netbeheer Nederland, 2024).

One of the main financial advantages of this transport right is that users only pay for the contracted hours, leading to cost reductions. If a business contracts transport for 8 out of 24 hours per day, they would receive a discount of approximately 66% on their contracted power fees. This pricing structure provides businesses with the flexibility to strategically manage energy costs by shifting operations to the most cost-effective periods. Unlike the TOU, which is focused on high-voltage grid users, the TB is available on regional distribution networks operated by regional grid operators (Autoriteit Consument en Markt, 2024).

Initially, system operators are not obligated to offer the new transport right but have the option to implement it voluntarily from April 1, 2025. However, from October 1, 2025, they will be mandated to offer this alternative transport right to qualifying consumers (Autoriteit Consument en Markt, 2024).

By offering discounts to businesses that reduce their peak-hour consumption, ACM and grid operators expect to fill up the remaining capacity left on the grid. However, it is important to note that alternative transport rights do not grant priority access to the grid. Applications for TOU and TB are processed on a first-come, first-served basis, just like conventional transport rights (Autoriteit Consument en Markt, 2024). However, if there are gaps that can be filled with these rights, these parties will be connected before the fixed contracts. Despite this limitation, these transport rights provide a key financial incentive for companies willing to adjust their electricity consumption patterns. For industries that can adapt their energy usage, this offers an opportunity to significantly lower costs while supporting the energy transition.

The question of whether to extend Time of Use tariffs to the distribution grid will impact many of the stakeholders in the system. The Autoriteit Consument & Markt (ACM) plays a central role in the Dutch electricity sector, overseeing market regulation and ensuring fair competition while maintaining system reliability (Autoriteit Consument en Markt, 2024). As the regulatory authority responsible for approving and enforcing transport tariffs, ACM is the key decision-maker in determining how flexibility resources, such as battery storage, participate in congestion management. The rapid expansion of renewable energy sources, combined with increasing electrification, has led to significant grid congestion, making it essential for ACM to develop policies that balance economic efficiency, market fairness, and grid stability. Given its authority over tariff structures and congestion management mechanisms, ACM is the primary problem owner in this research, as its regulatory decisions will shape the feasibility and effectiveness of alternative transport tariffs in addressing congestion challenges. The findings of this study provide critical insights for ACM, offering evidence-based recommendations to optimize tariff design and improve flexibility integration within the Dutch electricity distribution network.

In summary, the alternative transport rights framework marks a shift in how grid access is managed in the Netherlands. By linking financial incentives to flexible energy usage, these tariffs aim to balance electricity demand more effectively, reduce congestion, and accelerate the integration of renewable energy solutions into the Dutch grid. This research will help gain understanding of the impact of these tariffs on the business case of flexible assets, and the impact that they have on distribution grid stability.

1.3. Relevance

Network congestion and its optimization are highly relevant to the MSc Program in Complex Systems Engineering and Management. This stems from its technical complexity and the fact that the state of network congestion is part of a large socio-technical system. The issue involves multiple stakeholders with diverse objectives and viewpoints on the optimal solution and includes many different facets of complexity. In analyzing different pathways to an efficient solution to network congestion, a bottleneck in the Dutch energy transition can be further explored.

1.4. Structure

The report begins by identifying a knowledge gap through a comprehensive literature review, which leads to the formulation of the main research question. Next, a literature review is conducted to establish commonly used key performance indicators that will help measure the success of the introduction of non-market based policies. Subsequently, the methodology of the paper is described in detail, covering both optimization and network analysis models. This chapter will include input variables, tracked results, visualizations and other computations necessary to obtain the required results for the next chapter. The results chapter, chapter 4, will show the outcomes of the models to easily compare the outcomes. Next, a discussion will place the results in the context of the literature from the first literature review, and in the socio-technical context. This will help understand what stakeholders are involved and barriers there are for implementation. Finally, the conclusion will aim to answer all the sub-research questions and eventually the main research question. The paper will end with limitations, recommendations, further research and a reflection on the thesis process.

1.5. State of the Art

This section aims to find the literature that is relevant to the problem statement described in the introduction. The literature will help form an understanding of what is known about the problem and then identify areas of knowledge that are missing. This will then form the basis for the main research question. After stating the research question, the sub-research questions that will guide the paper towards answering the main research question will be presented.

1.5.1. Search Description and Selection Criteria

The key concepts for this research are the following terms:

- Congestion management
- Congestion management alternatives
- Flexible capacity or flexible asset portfolio
- Roles in congestion management
- Market-based alternatives to congestion management
- Non-market-based alternatives to congestion management

Subsequently, these core concepts were used as keywords in the search for relevant literature. This in turn yielded results whose title, abstract, method, and conclusions were screened and filtered based on the following criteria:

- Accessibility: if the full PDF of the article was not accessible then it was removed from the list
- Relevance: the article must be relevant to either the Dutch electricity network or congestion management alternatives

During the selection process, the sections 'related articles' and 'cited by' for each relevant article were also reviewed and findings were incorporated into the literature list. This review of the literature was divided into two parts. The first looked at the different alternatives for congestion management and mapping them on a scale of market/non-market-based and operational/procedural based. This gave a wide overview of the available alternatives and how many sources mentioned this alternative. The first part of the review, which focused on presenting all known alternatives, yielded four papers. The second part of the literature review looked at how the different alternatives are measured for success. These articles were placed on a scale based on whether they were optimized for costs or for grid optimization. For this review, 23 articles were identified as relevant for this study.

Various combinations of core concepts were used in the search for articles on different search platforms. For a summary of the articles generated through each search method, refer to Appendix A. For more information on the goal of each article, also refer to Appendix A.

1.5.2. Literature

The first step in understanding congestion management in the Netherlands is to understand what the different alternatives are for mitigating it. Thus, the first literature search focused on finding articles that examined the different alternatives currently used and used in the future. Table 1.1 shows the articles generated and consulted in this process.

Table 1.1: Overview of Articles Comparing Congestion Management Alternatives

Paper	Title
Gumpu et al., 2019	Review of Congestion Management Methods from Conventional to Smart Grid Scenario
Chondrogiannis et al., 2022	Local Electricity Flexibility Markets in Europe
Alavijeh et al., 2023	A Toolbox for Comparing Congestion Management Solutions for Distribution Networks
Hennig et al., 2023	Congestion Management in Electricity Distribution Networks: Smart Tariffs, Local Markets and Direct Control

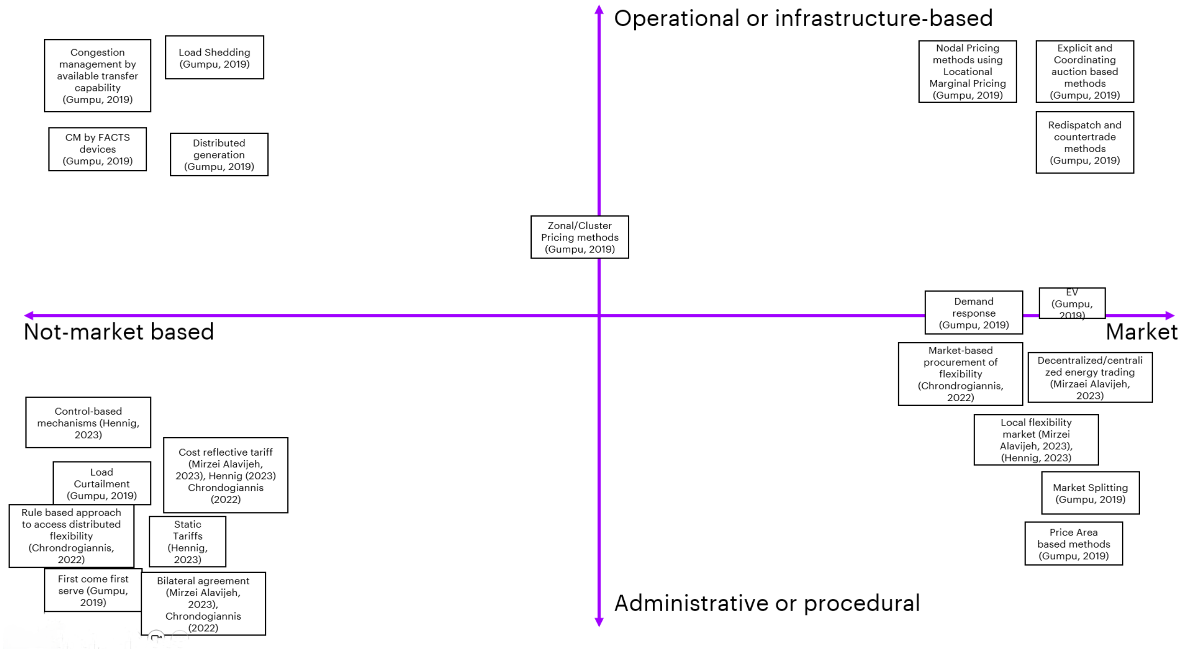

Figure 1.1: Comparing Different Alternatives

The above articles provide an overview of the possibilities for mitigating congestion. The image above (Figure 1.1) visualizes all these alternatives on an axis where they are compared on two different scales: whether they are market-based or not, and whether they are operational/infrastructure-based or administrative based. These axes capture two different dimensions that shape the function of congestion management strategies. The market/non-market-based axis captures the economic nature of the congestion management alternative, evaluating whether the solution uses market mechanisms or relies on non-market approaches. Market-based approaches use price signals, competition, and market characteristics to manage congestion, these include, for example, demand response, flexibility markets, or congestion pricing. Non-market approaches often involve direct control or mandates such as grid reinforcement or curtailment orders where decisions are made without market interactions. On the y-axis, one finds a differentiation on the solution's nature of implementation: whether they involve technical implications or administrative measures.

As can be seen by the image above, there is quite an equal spread of alternatives over the different axes. There are some hybrid operational/administrative alternatives on the market-based side; however, very few market/non-market hybrid alternatives. This image also shows that there are ample alternatives for congestion management, covering different dimensions of the electricity system.

The next part of the literature review covers the extent in which these different forms of congestion management are covered in academic papers. The review covers congestion management on both distribution and transmission grids. After presenting all the consulted works, they will also be compared on an axis scale, differentiating them between market/non-market-based methods, and deciding whether the research focused on minimizing costs for stakeholder or focusing on grid management. Also, using a yellow star, they will be differentiated on whether their congestion management alternative is a flexible alternative or not.

Table 1.2: Overview of Articles Used for Review

Paper	**Method**
Hadush and Meeus, 2018	Literature review
Salkuti, 2018	Multiobjective methodology that uses optimal transmission switching (OTS) strategies
Escudero–Sahuquillo et al., 2010	Algorithm development and simulation
Khan et al., 2023	Develop a multi-objective optimization scheme that uses Demand Side Management
Singh and Bohre, 2022	Literature review on FACTS devices
Chakraborty et al., 2023	Literature Review
Koltsaklis and Dagoumas, 2019	Multi-Integer Linear Programming Model
Lampropoulos et al., 2019	Literature review, case study, historical market data
Boroumand et al., 2015	Value at Risk and Conditional Value at Risk models
Kettunen et al., 2010	Multi-stage stochastic optimization model
Yun et al., 2022	Response Characteristic Model
Brummund et al., 2022	Pilot demonstration
Junhua et al., 2017	Power Flow Sensitivity Analysis
Khanabadi and Ghasemi, 2011	Mixed Integer Programming
Z. Wang et al., 2024b	Two-stage optimization model
Li et al., 2024	Used computational framework
Hennig et al., 2024b	Case Study
Safdarian, 2018	Mathematical modeling, simulation and coordination frameworks
X. Wang et al., 2012	Literature review and feasibility tests
Dhabai and Tiwari, 2023	Developed algorithm to manage curtailment and applied to a test system
Buchmann, 2020	Analytical framework assessing implication of local congestion markets
Gi and Xie, 2014	Analytical approach with iterative simulations
Singh et al., 2014	Integrated approach combining multiple methods (numerical and physical)

Table 1.2 presents an overview of the articles used for this literature review. Also, the method used in the article is shown. From this, it is clear that a wide range of different quantitative and qualitative methods are used to study congestion management. Also, many of the articles are recently published, suggesting the relevance of the issue of congestion.

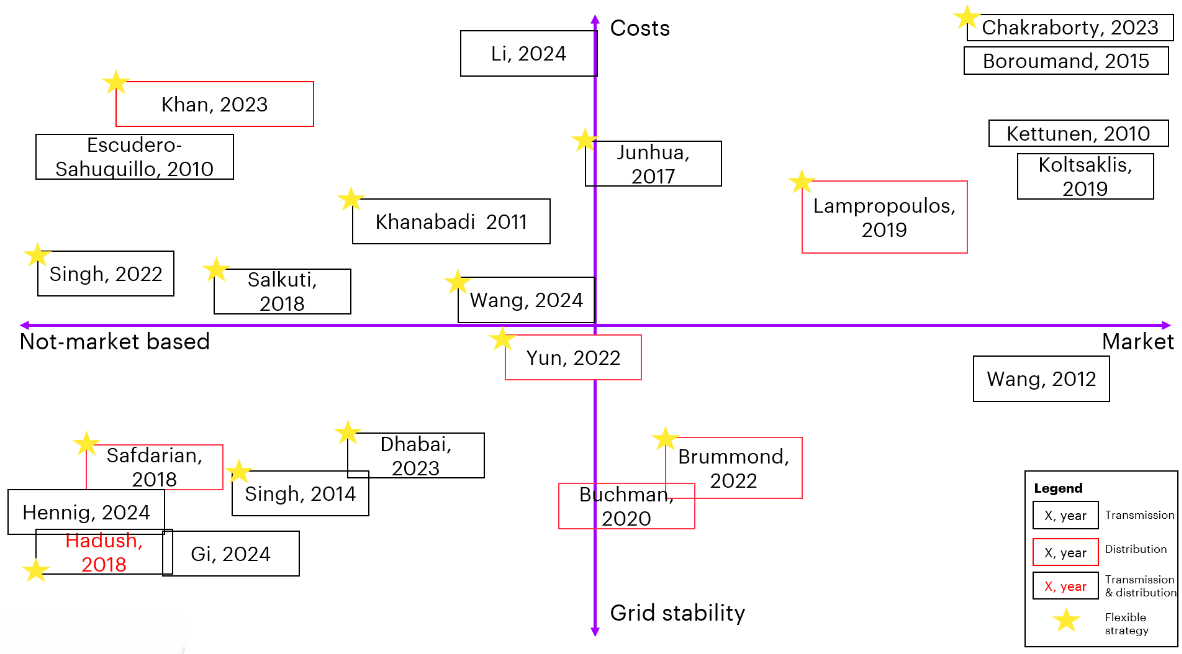

Figure 1.2: Comparing Different Articles

Figure 1.2 visualizes the articles from table 1.2. These are placed on two axes: whether the alternative they study are a market or non-market based measure, and whether it was judged on cost efficiency or grid stability.

1.5.3. Synthesis

Network congestion can be addressed using both market-based and non-market-based strategies, each presenting distinct challenges and opportunities. This review will assess the articles according to their positioning within the axes shown above, ultimately identifying a knowledge gap.

Non-Market-based Solutions Focused on Costs

Salkuti et al. (2018) improve operational costs in transmission networks by dynamically adjusting topology through transmission switching, enhancing both economic efficiency and system reliability. Similarly, Li et al. (2024) optimize wind and solar capacity allocation to reduce generation costs while managing renewable energy variability. Khanabadi et al. (2011) also explore congestion management, using transmission switching to lower generation costs and energy prices. Khan (2023) applies Demand Side Management (DSM) to shift consumer loads from peak to off-peak, aiming to cut electricity costs and the peak-to-average load ratio without congestion tariffs. Escudero-Sahuguillo (2010) presents an improved FBICM technique that reduces silicon area and costs while maintaining performance, and Singh et al. (2022) uses FACTS devices to reduce congestion in transmission networks by optimizing economic and operational placement.

The papers in this category concentrate on individual congestion management strategies with a shared focus on cost reduction. Also, all papers except one focus on tranmission grids over distribution grids. Li et al. (2024) found that network constraints nearly double electricity costs and suggest that adding battery storage could reduce costs by 7%. Salkuti et al. (2018), Escudero-Sahuguillio (2010), Singh et al. (2022), and Khanabadi et al. (2011) each analyze system (re)routing methods that improve costs but fail to consider market interactions. Similarly, Khan (2023), in modeling Demand Side Management, excludes market dynamics, focusing solely on consumer behavior. This emphasis on cost minimization and the choice to analyze only one alternative for congestion management reveal a gap in the literature — a need for a broad view that includes optimizing for other aspects of electricity networks, utilizing multiple management alternatives, and assessing market impacts on these approaches.

Non-Market-based Solutions Focused on Grid Management

Dhabai et al. (2023) examine renewable energy curtailment for congestion management, aiming to reduce energy waste and maintain grid stability. Singh (2014) integrates geographically indexed production, demand, and grid modeling to enhance reliability, providing useful insights for investors and policymakers. Similarly, Gi (2024) offers a decentralized network framework to assess wind curtailment impacts from transmission congestion, enhancing system effectiveness. Safdarian et al. (2018) develop coordination frameworks for demand response in smart grids, addressing autonomous home appliance operation and peak rebound risks. Lastly, Hadush et al. (2018) focus on improving grid management through cooperation between TSOs and DSOs to address congestion within the electricity market.

In this section, a broader range of methods is used, from modeling to integrated approaches and literature reviews. While there is a more balanced focus between transmission and distribution networks, transmission still dominates. Each paper examines a single congestion management solution rather than optimizing a combination and lacks consideration of market dynamics. This leaves a knowledge gap in the potential for combined alternatives within the distribution grid, particularly where market-driven mechanisms could play a role.

Market-based Solutions Focused on Costs

Koltsaklis et al. (2019) examine how vertically integrated utilities can use market mechanisms to manage congestion and minimize financial risks, particularly with renewables. Similarly, Boroumand (2015) demonstrates the value of hedging strategies in hourly markets to reduce congestion-related risks for retailers. Chakraborty et al. (2023) focus on optimizing load forecasting and profit in microgrid operations, while Kettunen et al. (2010) and Boroumand explore strategies to manage retailer costs and risks through electricity portfolios. Lampropoulos et al. (2019) analyze flexibility services traded in wholesale and ancillary markets for distribution and transmission operators, uniquely incorporating distribution networks. Junhua et al. (2017) use locational marginal pricing with a virtual power plant to reduce congestion costs and economic impacts.

This set of studies emphasizes the financial advantages of market-based congestion management strategies, highlighting their ability to minimize risk and optimize cost efficiency, particularly in systems with high renewable energy integration. However, the primary focus across these studies remains on the transmission level, with limited attention to distribution networks and flexible alternatives (with less than half analyzing flexible alternatives). Lampropoulos et al. (2019) stands out as the only study examining market-based flexibility at the distribution level, suggesting a notable gap in applying these strategies more broadly in distribution grids. This indicates an opportunity for future research to assess how market-driven congestion management tools could address cost efficiency, grid stability, and other performance indicators within the distribution network, particularly through flexible, distributed resources.

Market-based Solutions Focused on Grid Management

Wang et al. (2012) investigate the creation of an integrated marketplace aimed at balancing competitive wholesale prices with electricity supply reliability, addressing congestion through both reliability and operational costs. Brummond (2022) looks at building a flexibility value chain to manage congestion and support renewable integration in low-voltage grids, aligning with the European Clean Energy Package. Buchmann (2020) shifts focus to governance, proposing a framework for fair and efficient local congestion markets in Europe, blending regulatory oversight with market dynamics

It is immediately notable that only three papers fall into this grouping, indicating a limited exploration of market-based solutions optimized for grid management. Wang (2012) examines marketplace structure but does not apply congestion management alternatives within this framework, while Buchmann (2020) focuses on market governance without addressing specific congestion methods. Brummond (2022) concentrates primarily on facilitating flexibility procurement through markets, concluding that this approach supports renewable integration and grid stability. However, these studies collectively leave space for more research using simulation models to explore how market-based alternatives can directly impact congestion management.

Hybrid Research

Some studies adopt a more hybrid approach, positioning themselves toward the center of the axis. For instance, Wang et al. (2024) introduce a multi-energy system designed for independent planning and real-time operations, with the goal of minimizing operational uncertainty. Their system efficiently manages energy loads and accommodates renewable energy fluctuations in a cost-effective manner. Similarly, Yun et al. (2022) focus on creating an optimal combination of heterogeneous resources within virtual power plants. Their portfolio approach is aimed at maximizing expected returns while also managing congestion effectively. The hybrid approaches in these papers offer a more comprehensive view of congestion management by combining various optimization methods. Yun (2022) incorporates market dynamics with diverse resources within a virtual power plant but stops short of simulating the plant's flexible capacity directly in market settings. Wang's model, while simulating market demand effectively, relies on fossil-fuel-based congestion management alternatives, making it less aligned with future low-carbon grid goals. Together, these studies suggest that hybrid approaches could be strengthened by integrating both future-proof alternatives and direct market simulations of flexible resources.

Conclusion

While the literature provides a variety of solutions—market-based, non-market-based, hybrid, and flexible strategies—certain gaps remain unexplored. Hybrid solutions appear to address grid management in a more comprehensive way; however, there is a noticeable absence of studies comparing market-based and non-market-based strategies. This comparison could be highly relevant, especially in the context of the Dutch system, which currently relies on bidding flexible alternatives within the market and is implementing non-market strategies in the coming year. While markets offer flexibility, it may also highlight the need for non-market-based policies to improve overall system stability. Comparing the current system to a system in which non-market policies are added could provide interesting insights.

Figure 1.2 illustrates these gaps in research focus. The axes reveal less studies on distribution grids overall and more research on transmission grids. Also, the hybrid alternatives that were presented in the literature created optimal combinations of alternatives instead of focusing on the role that the market and non-market policies have on just one flexible alternative.

1.6. Electricity Grid Tariffication as a Non-Market Based Measure

The literature review above suggests that there is a gap in understanding of the impact of non-market based measures on flexible assets bidding on the market. Grid tariffication determines how electricity consumers and producers are charged for using the power grid, ensuring cost recovery, efficient grid operation, and congestion management. Traditional tariff structures rely on volumetric or capacity-based charges, while newer approaches, such as time-of-use and dynamic pricing, aim to better align electricity usage with grid conditions. By adjusting price signals based on demand, location, or time, tariffs can incentivize behaviors that reduce strain on the grid. In the Netherlands, transport tariffs specifically regulate access to the transmission and distribution network, influencing when and how flexible assets, like batteries, participate in the market. One of the most recent changes to the dutch electricity sector is the introduction of alternative transport tariffs. This form of tariffication determines when the asset can participate on the grid. The role of electricity grid tariffs in managing congestion and incentivizing efficient electricity consumption has been studied in recent literature. A key focus has been on how alternative transport tariffs, such as dynamic pricing and nodal pricing, can improve grid stability while maintaining economic efficiency. Several recent studies provide insights into different tariff structures, their impact on congestion management, and their interaction with demand-side flexibility. By looking into these studies, a more specific gap, focused on tariffs as a non-market based measure can be identified.

Abdelmotteleb et al. (2022) analyze the effect of dynamic distribution network tariffs on customer engagement in demand-side flexibility markets. Using a Norwegian case study, the study examines the interaction between demand response programs and tariff structures. The results indicate that dynamic tariffs, particularly those that include critical peak pricing, significantly enhance customer participation in demand response programs (Abdelmotteleb et al., 2022). The study finds that combining flexibility instruments (e.g., financial incentives for demand response) with dynamic tariffs leads to reduced grid reinforcement needs and overall system cost savings.

Boehnke et al. (2025) explore the value of decentralized flexibility in nodal market design, focusing on how locational marginal pricing (LMP) can optimize congestion management. The study simulates 2030 European electricity markets and finds that while nodal pricing provides better congestion signals, it also reveals geographical disparities in flexibility needs. The authors observe that zonal pricing creates inefficiencies, as it fails to incentivize flexibility at specific congestion points. While nodal pricing is widely implemented in North America, the study notes that political and regulatory challenges prevent its immediate adoption in Europe (Boehnke et al., 2025).

Belmonte et al. (2023) investigate recent developments in grid balancing services and their interaction with tariff structures in European electricity markets. Their findings suggest that balancing market reforms, such as shorter provision times and real-time flexibility auctions, improve overall grid stability (Blat Belmonte et al., 2023). However, they also highlight regulatory inconsistencies that limit market participation and price volatility challenges that can lead to inefficient cost allocations. The study concludes that more coordinated integration of balancing markets and distribution tariffs is needed to ensure that congestion management does not create unintended distortions.

Charbonnier et al. (2022) offer coordination strategies for distributed energy resources (DERs), examining peer-to-peer energy trading, transactive energy, and decentralized control mechanisms. The study finds that well-designed tariffs can incentivize local coordination of DERs, improving congestion management. However, it also highlights a key challenge: the lack of alignment between tariff structures and emerging decentralized energy markets. The findings suggest that without proper pricing mechanisms, decentralized flexibility markets may fail to deliver their full potential in grid management (Charbonnier et al., 2022).

Wanapinit et al. (2022) focus on how time-varying electricity tariffs influence demand response and congestion mitigation. The study finds that while time-of-use pricing is effective in shifting demand, it may lead to unintended consequences if not properly designed. For example, tariffs that incentivize load shifting based on wholesale market prices can sometimes exacerbate congestion at the distribution level. The study concludes that tariff structures need to be optimized to balance multiple objectives, including market efficiency, decarbonization, and congestion relief (Wanapinit et al., 2022).

Finally, Gunkel et al. (2023) examine the impacts of different grid tariff designs in the context of electrification. The study analyzes how alternative volumetric and peak-based tariffs affect different socio-economic consumer groups, using a case study of Danish households (Gunkel et al., 2023). The results show that tariffs designed to penalize peak consumption can disproportionately affect low-income households and small consumers, raising concerns about equity in cost distribution. The study suggests that new tariff designs should incorporate both efficiency and fairness considerations to ensure socially acceptable cost allocations.

Despite the extensive research on congestion management and alternative transport tariffs, several key gaps remain, particularly in understanding their impact on battery performance and grid stability in the Dutch electricity distribution network. While studies on dynamic distribution tariffs and demand response have demonstrated effectiveness in managing congestion, there is limited research on how these mechanisms interact with battery storage systems at the distribution level in the Netherlands. Most studies focus on broader European markets or other flexibility options, such as demand-side response, without isolating the role of batteries as a key flexible asset. Given the ability of batteries to both inject and absorb electricity, their market behavior under alternative tariff structures warrants closer examination.

Additionally, although nodal pricing is widely recognized as an efficient congestion management tool, its implementation in the Netherlands remains technically uncertain. Research is needed to determine whether alternative transport tariffs, such as timeblock tariffs or time-of-use (TOU) pricing, could achieve similar congestion management benefits while enabling batteries to operate efficiently. Understanding the incentives created by these tariff structures is particularly important because batteries can participate in wholesale markets, and their ability to optimize charging and discharging behavior under different pricing schemes may significantly affect their financial viability and contribution to grid flexibility.

Finally, studies on balancing market design have highlighted the need for better alignment between flexibility markets and transport tariffs, yet little research has examined how Dutch distribution tariffs could be optimized to support real-time balancing through battery storage. Batteries have demonstrated success in enhancing grid stability and flexibility in the UK and the US (EKU Energy, 2024; LSP Renewables, 2025), but their role in the Dutch distribution network remains underexplored. Given the increasing penetration of decentralized energy resources, assessing how alternative transport tariffs influence battery economics, grid congestion, and market participation is critical for shaping effective policy and market design.

1.7. Knowledge Gap and Research Questions

The literature review suggests that non-market-based measures are insufficiently studied in the context of flexible assets participating in market-based congestion management on the distribution grid. One of the most recent changes in the Dutch electricity sector is the introduction of alternative transport tariffs, which function as a non-market-based mechanism to regulate grid participation. These tariffs directly affect when and how an asset, such as a battery, can participate in the grid. Recent studies have explored how dynamic pricing and nodal pricing can improve grid stability while maintaining economic efficiency, yet there is a lack of research focused on transport tariffs as a non-market-based congestion management tool.

Despite extensive research on congestion management and alternative transport tariffs, several key gaps remain, particularly in understanding their impact on battery performance and grid stability in the Dutch electricity distribution network. While studies on dynamic distribution tariffs and demand response have demonstrated effectiveness in managing congestion, there is limited research on how these mechanisms interact with battery storage systems at the distribution level in the Netherlands. Most studies focus on broader European markets or other flexibility options, such as demand-side response, without isolating the role of batteries as a key flexible asset. Given the ability of batteries to both inject and absorb electricity, their market behavior under alternative tariff structures warrants closer examination.

Research is needed to determine whether alternative transport tariffs, such as timeblock tariffs or time-of-use (TOU) tariffs, could achieve congestion management benefits while enabling batteries to operate efficiently. Understanding the incentives created by these tariff structures is particularly important because batteries can participate in wholesale markets, and their ability to optimize charging and discharging behavior under different pricing schemes may significantly affect their financial viability and contribution to grid flexibility.

Given the increasing penetration of decentralized energy resources (DERs), assessing how alternative transport tariffs influence battery economics, grid congestion, and market participation is critical for shaping effective policy and market design.

This leads to the following research question:

"How do alternative transport tariffs impact battery performance and grid stability in the Dutch electricity distribution network?"

To address this research question in a structured manner, the study is divided into sub-questions, each targeting a specific aspect of the problem. Together, these questions contribute to a comprehensive understanding of the research objective:

1. How is the performance of congestion management alternatives in distribution grids measured in the literature?
2. How well does a battery perform based on the identified KPIs?
3. How does a battery perform after the introduction of the new Dutch timeblock transport tariff, based on the identified KPIs?
4. How does a battery perform after the introduction of the new Dutch time-of-use transport tariff, based on the identified KPIs?
5. How do market-based and non-market-based congestion management policies interact with battery performance in distribution grids?

The main research approach employed in this study is a quantitative modeling technique, specifically using a mixed integer linear programming (MILP) model and a Pypsa network model. The motivation for using this approach lies in addressing a significant knowledge gap: how the behavior of flexible assets, such as battery storage, changes when governed by market-based policies versus non-market-based policies. This question is particularly relevant as the Dutch electricity grid continues to evolve with a mix of market-driven and regulatory strategies aimed at optimizing grid performance and reliability. By modeling these behaviors under different policy scenarios, the research aims to capture shifts in battery owner decision-making that could impact grid stability and efficiency.

While the primary methodology is quantitative, the inputs and parameters that feed into the MILP model are derived from a comprehensive literature review. This review examines relevant studies and reports to identify the factors most critical to successful congestion management on the grid. By identifying key metrics for congestion management and stability, the literature review helps establish the key performance indicators (KPIs) that will be used to evaluate the model's outputs. These KPIs may include measures of peak reduction, battery utilization rates, or changes in congestion levels, each serving as a benchmark for assessing the effectiveness of the modeled tariff impacts on battery performance. The KPIs used in the rest of the paper will be identified in the next chapter.

2

Key Performance Indicators

2.1. Introduction

The transition to renewable energy has introduced unprecedented challenges to electricity grid management. One among these is congestion management, a critical aspect of ensuring the stability and reliability of power systems while integrating variable renewable energy sources such as wind and solar. The increasing complexity of energy systems demands advanced strategies to address congestion effectively, without compromising economic, social, or environmental goals.

Performance evaluation is important to determining the impact of congestion management mechanisms, and finding the best alternative for congestion management for the involved stakeholders for this situation. This is achieved through the application of Key Performance Indicators (KPIs) — quantifiable metrics that assess how well a system meets predefined objectives. KPIs have been extensively used in industries to measure success and guide improvements, offering a standardized framework for evaluation (Velimirovic et al., 2011). In the context of electricity grids, KPIs serve as tools to compare various congestion management strategies, identify their strengths and limitations, and align their outcomes with policy and operational goals. The chapter seeks to answer the following subquestion: "How is performance of congestion management alternatives measured in the literature and how do batteries and tariffs perform on these KPI's?

2.2. Method

To determine commonly used and trusted measures for assessing the performance of congestion management strategies, a structured literature review was conducted. The primary goal of this review was to examine existing studies that compared various congestion management approaches and, through those comparisons, identify widely accepted measurement practices. To ensure a systematic approach, relevant articles were identified and categorized based on the methods used to locate them. The following table presents the articles included in the review, along with details on the search methods employed to find them.

The literature review began by searching in two well-established academic databases: Scopus and ScienceDirect. These platforms were selected due to their extensive collections of peer-reviewed journal articles, covering a wide range of disciplines. Table 2.1 provides details on the database each article was sourced from and the specific search method used to retrieve it.

The process started with the identification of key terms relevant to congestion management and its evaluation. These keywords were then combined to form search strings, which were subsequently applied within Scopus and ScienceDirect. The initial results were screened based on multiple criteria. First, articles published before the year 2000 were excluded to ensure that only recent research was considered. Next, the relevance of each article was assessed based on its title and abstract, ensuring that only studies directly related to congestion management evaluation were retained.

Once this initial selection process was completed, a technique known as backward snowballing was implemented to expand the review set. This involved examining the reference lists of the selected articles to identify additional relevant studies (Wohlin, 2014). The selection process for backward snowballing followed a two-step approach:

first, articles were assessed based on their title and publication year; if deemed potentially relevant, their abstracts were reviewed. If an abstract indicated that the study was suitable for inclusion, the full article was incorporated into the review.

Following the backward snowballing phase, forward snowballing was conducted. This method involved identifying newer studies that cited the already selected articles (Wohlin, 2014). By reviewing the cited papers, additional relevant research could be incorporated into the review process. The same selection criteria applied to backward snowballing were used here—initially filtering based on title and publication year, followed by an abstract review to confirm relevance before adding the study to the final set of reviewed literature.

By applying these search and selection methods, the literature review ensured that a comprehensive and well-rounded set of studies was analyzed. This process allowed for the identification of common measurement practices used in evaluating congestion management strategies, ensuring that the findings were based on well-established research methodologies. The performance indicators were tallied across all the papers and the most commonly used were used for the rest of the analysis. Table 2.1 shows all the papers included in the review and the method used to find them.

Table 2.1: Articles and Search Method

Paper	Database	Search Method
Hennig et al., 2023	ScienceDirect	Keywords: Comparing congestion management alternatives
Abdelmotteleb et al., 2018	ScienceDirect	Backwards snowballing from Hennig (2023)
Anaya and Pollitt, 2015	ScienceDirect	Backwards snowballing from Hennig (2023)
Ansarin et al., 2020	ScienceDirect	Backwards snowballing from Hennig (2023)
Bjarghov et al., 2022	ScienceDirect	Backwards snowballing from Hennig (2023)
Borenstein, 2016	ScienceDirect	Backwards snowballing from Hennig (2023)
Brandstatt et al., 2011	ScienceDirect	Backwards snowballing from Hennig (2023)
Esmat et al., 2018	ScienceDirect	Backwards snowballing from Hennig (2023)
Fridgen et al., 2018	ScienceDirect	Backwards snowballing from Hennig (2023)
Kahn et al., 2001	ScienceDirect	Backwards snowballing from Hennig (2023)
OConnell et al., 2012	ScienceDirect	Backwards snowballing from Hennig (2023)
Passey et al., 2017	ScienceDirect	Backwards snowballing from Hennig (2023)
Radecke et al., 2019	ScienceDirect	Backwards snowballing from Hennig (2023)
Kumar et al., 2005	Scopus	Keywords: Comparing electricity network congestion management alternatives
Bindu et al., 2024	Scopus	Forwards snowballing from Kumar (2005)
Pillay et al., 2015	Scopus	Backwards snowballing from Bindu (2024)
European Transmission System Operators (ETSO), 1999	Scopus	Backwards snowballing from Bindu (2024)
Hirth and Glismann, 2018	Scopus	Backwards snowballing from Bindu (2024)
Perez–Arriaga and Olmos, 2005	Scopus	Backwards snowballing from Bindu (2024)
Ehrenmann and Smeers, 2004	Scopus	Backwards snowballing from Bindu (2024)
Z. Wang et al., 2024b	Scopus	Keywords: Performance indicators energy tariff policy
Hennig et al., 2022	Scopus	Performance indicators distribution tariff policy
Han et al., 2024	Scopus	Keywords: Performance indicators energy tariff policy
Velkovski et al., 2024	Scopus	Keywords: Performance indicators energy tariff policy
da Silva and Rato, 2024	Scopus	Keywords: Performance indicators energy tariff policy
Heider et al., 2024	Scopus	Keywords: Performance indicators energy tariff policy
Vogelsang, 2005	Scopus	Keywords: Performance indicators energy tariff policy
Shabbir et al., 2024	Scopus	Keywords: Battery performance congestion management
Zhang et al., 2024	Scopus	Keywords: Battery performance congestion management
Peesapati et al., 2024	Scopus	Keywords: Battery performance congestion management
Aghdam et al., 2023	Scopus	Keywords: Battery performance congestion management
Ayesha et al., 2024	Scopus	Keywords: Battery performance congestion management
Ansaripour et al., 2022	Scopus	Keywords: Battery performance congestion management
Medeiros et al., 2024	Scopus	Keywords: Battery performance congestion management
Cerna, 2022	Scopus	Keywords: Battery performance congestion management

As can be seen by Table 2.1, thirty-five articles are used in research to measure congestion management. Backwards snowballing was the method used most often to find articles, with many stemming from Hennig (2023).

2.3. Literature Review of KPI's for Congestion Management

The transformation of electricity grids, driven by the integration of renewable energy sources, distributed generation, and increased electrification, has necessitated the development of comprehensive frameworks to evaluate and manage grid performance. Key Performance Indicators (KPIs) serve as tools to measure the effectiveness of grid management strategies, encompassing economic and operational dimensions. By offering measurable parameters, KPIs provide insights into the efficiency, reliability, and adaptability of energy systems, ensuring that policies and strategies align with both technical and economic objectives.

2.3.1. Economic KPI's

Economic KPIs are critical for evaluating the cost-effectiveness and financial sustainability of grid operations, guiding investment decisions, and shaping tariff structures. At the heart of these metrics is economic efficiency, which seeks to minimize system-wide costs while aligning electricity prices with societal marginal costs. Studies such as Borenstein (2016), Hennig (2023) and Pillay (2025) highlight how efficient pricing mechanisms reduce redispatch and curtailment costs, ensuring that grid operations remain financially sustainable. Esmat et al (2018) extends this discussion by demonstrating how efficient congestion management reduces operational costs and defers infrastructure investments, providing a foundation for long-term system viability.

Complementing economic efficiency is cost recovery period and sufficiency, which focuses on the time it takes for utilities to cover both fixed and variable costs. This metric is particularly important in deregulated markets, where revenues must align with long-term investment needs. Volgelsang (2005) and Kahn (2001) emphasize the importance of balancing cost recovery with equitable pricing strategies, such as hybrid tariff models that combine fixed charges with variable rates. Abdelmotteleb (2018) highlights the role of tariff designs in maintaining grid sustainability, showcasing how appropriate pricing structures can incentivize grid use while ensuring the recovery of network maintenance and upgrade costs.

The concept of cost-effectiveness further examines the financial feasibility of congestion management strategies. Radecke (2019) illustrates how flexibility markets can dynamically address grid constraints, reducing the need for costly infrastructure upgrades. Similarly, Peesapati (2024) and da Silva (2024) explore how Battery Energy Storage Systems (BESS) optimize energy flows to alleviate congestion cost-effectively. Hirth (2018) underscores the importance of balancing short-term operational costs with long-term investments to achieve scalable solutions.

Another essential economic KPI is price stability, which evaluates the predictability of electricity prices. As highlighted by Kahn (2001), pricing mechanisms such as uniform auctions stabilize market prices, promoting efficient dispatch and bolstering consumer trust, while pay-as-bid models can introduce volatility, complicating market dynamics.

2.3.2. Operational KPIs

Operational KPIs are important for ensuring the reliability, adaptability, and scalability of grid systems under increasingly variable demand and generation conditions. Central to these metrics is reliability and security of supply, which measures the grid's ability to maintain stability under varying conditions. Compliance with the "n-1" security criterion—a standard for ensuring system resilience—is emphasized by Kumar (2005) and Hennig (2023). Esmat (2018) highlights how redispatch and dynamic market mechanisms play a critical role in preventing overloads and maintaining stability in grids with high renewable energy penetration.

Congestion Mitigation Effectiveness is one of the most critical KPIs in grid management, as it directly evaluates the success of strategies aimed at reducing congestion while maintaining reliability and minimizing costs. This KPI is typically measured by assessing congestion-related costs, such as redispatch, curtailment, and flexibility activation costs, as highlighted by Esmat (2018), Peesapati (2024), and Radecke 2019). Additionally, renewable energy curtailment is a key metric, with sources like Ayesha (2024) and Zhang (2024) examining the percentage of wind and solar energy that is curtailed due to congestion, a clear indicator of how well renewable resources are being utilized. The frequency and duration of transmission or distribution line overloading, as tracked using SCADA systems (Hennig et al., 2023, Medeiros et al., 2024), provide a direct measure of the grid's ability to handle high demand without breaching operational constraints. Other important metrics include the activation and utilization of flexibility resources, such as batteries and demand response mechanisms (Esmat et al., 2018, Radecke et al., 2019), which reflect the grid's capacity to dynamically address congestion. Furthermore, tools like power flow simulations (Hirth and Glismann, 2018, Peesapati et al., 2024) are used to evaluate deviations from optimal energy flows, while load curtailment logs indicate the extent of consumer demand reductions necessary to manage congestion (European Transmission System Operators (ETSO), 1999, Esmat et al., 2018). Reliability metrics such as SAIDI and SAIFI are also employed to monitor the grid's performance during congestion events and extreme weather events (Kumar et al., 2005, Hennig et al., 2023). Finally, avoided infrastructure costs, calculated by comparing the cost of congestion management solutions with proposed grid reinforcements, offer a financial perspective on the effectiveness of these strategies (Esmat et al., 2018, Radecke et al., 2019). Together, these measurements provide a holistic view of how well congestion management strategies alleviate constraints, optimize costs, and maintain operational stability.

Flexibility and scalability have emerged as critical operational KPIs in the context of integrating renewable energy and DERs. Flexibility markets, as described by Hirth (2018), dynamically engage distributed resources such as demand response and energy storage to manage congestion in real time. Aghdam (2023) demonstrates how BESS can enhance grid scalability, offering dynamic solutions to manage peak loads and integrate renewable resources efficiently.

Finally, an operational metric is operational feasibility, which evaluates the practicality of implementing congestion management strategies within existing frameworks. Perez-Arriaga (2005) and Bindu (2024) stress the importance of aligning solutions with regulatory and technical constraints to ensure their adaptability. O' Connell (2012) provides a concrete example of feasible demand-shifting tariffs that reduce congestion from EV charging without necessitating extensive infrastructure modifications.

2.3.3. Environmental and Innovation KPIs

As the grid transitions toward higher renewable energy penetration, environmental and innovation-related KPIs are gaining prominence. Voltage stability and reverse power flow prevention are critical metrics in this domain, particularly in grids with high DER penetration. Velkovski (2024) and da Silva (2024) highlight how innovative tariff designs can maintain voltage stability and reduce reverse flows, ensuring grid resilience. Hennig (2023) emphasizes the importance of equitable mechanisms to prevent congestion displacement across regions.

Wind curtailment measures the efficiency of renewable energy utilization. Ayesha (2024) and Zhang (2024) demonstrate how BESS reduces wind curtailment, ensuring that renewable energy is effectively harnessed and minimizing dependence on fossil fuels.

Incentives for innovation evaluate support for advanced technologies that enhance grid adaptability and efficiency. Peesapati (2024), Cerna (2022) , and Hirth (2018) showcase the role of BESS, smart contracts, and dynamic pricing in addressing congestion while reducing operational costs. These technologies not only enhance system resilience but also encourage investments in future-ready infrastructure.

2.4. Synthesis

For this literature review, 28 sources were used. To understand which KPI's are used most commonly to test the success of a congestion management system, the amount of times each indicator was used across all papers was tracked. The results of the highest scoring indicators can be seen in Table 2.2 below.

Table 2.2: Measurable Key Performance Indicators

Category	KPI	Count
Economic KPIs	Cost Recovery	8
	Price Stability	5
Operational KPIs	Congestion Costs (Redispatch, Curtailment)	5
	Line Overloading (Frequency and Duration)	6
	Activation of Flexibility Resources	5
	Optimal Power Flow Deviations	4
	Market Participation	4
Environmental and Innovation KPIs	Renewable Energy Curtailment	4
	Voltage stability	3

Table 2.2 counts the number of times different indicators were used to measure congestion management performance. From the literature review, it is clear that there are many different indicators that are often used in research on congestion management. The KPI's presented above are most commonly used in evaluating performance of congestion management strategies and will now be used in the next section of this chapter.

2.4.1. Battery Performance

Batteries play an important role in modern grid management by addressing challenges such as congestion, renewable energy integration, cost recovery, and grid efficiency. One of their most critical contributions is mitigating congestion costs by absorbing surplus energy during low-demand periods and discharging it during peak times. This capability reduces strain on the grid, alleviates line overloading, and delays the need for costly infrastructure upgrades, particularly in high-demand scenarios (Peesapati et al., 2024). In addition, batteries are highly effective in minimizing renewable energy curtailment, as they store excess wind and solar energy that would otherwise go unused due to grid constraints. By optimizing renewable energy utilization, batteries enhance sustainability and reduce dependency on fossil fuels (Ayesha et al., 2024).

From a financial perspective, batteries aim to recover costs by generating revenue through diverse services. These include participation in demand response programs, providing ancillary services such as frequency regulation, and performing optimal switching, which enhances the financial viability of power systems while improving grid stability (Aghdam et al., 2023, Medeiros et al., 2024). Their rapid response capabilities are important for maintaining stability during periods of high demand or unexpected disturbances, ensuring reliable electricity delivery. This also supports the activation of flexible resources, allowing batteries to respond dynamically to grid needs and integrate seamlessly into grid operations (Medeiros et al., 2024).

Batteries further enhance grid efficiency by reducing deviations from optimal power flow, ensuring that electricity is distributed in a way that minimizes losses and supports economic dispatch (Ansaripour et al., 2022). Their participation in energy markets, particularly in services like frequency regulation, energy arbitrage, and capacity support, helps create a more dynamic and efficient energy ecosystem. This market involvement not only generates revenue but also strengthens market liquidity and competition, facilitating broader participation from flexibility providers and prosumers (Zhang et al., 2024).

In addition to market participation, batteries play a vital role in addressing renewable curtailment. By storing surplus energy generated during low-demand periods, they reduce the need for curtailment and improve the economics of renewable energy generation (Ayesha et al., 2024). Their ability to scale and adapt make them highly compatible with evolving market structures and distributed energy systems, ensuring that they can align with future grid and market requirements (Zhang et al., 2024).

However, while batteries excel across many metrics, challenges such as high capital costs, limited storage capacity, and degradation over time can limit their effectiveness in mitigating grid congestion. Despite these limitations, advancements in technology and economies of scale are steadily improving the cost-effectiveness and efficiency of battery systems, solidifying their role as a cornerstone of modern, resilient energy systems.

2.4.2. Tariff Performance

Tariff structures play an important role in modern grid management by shaping consumer behavior, ensuring cost recovery, and promoting grid efficiency. Effective tariff designs, including dynamic pricing and time-of-use structures, incentivize consumers to shift energy usage to off-peak periods. This reduces congestion costs by alleviating stress on the grid during peak demand times and minimizes line overloading, which would otherwise necessitate costly infrastructure reinforcements (OConnell et al., 2012, Hennig et al., 2022). Locational pricing strategies further enhance grid performance by aligning energy consumption with generation patterns and addressing grid constraints. This approach minimizes renewable energy curtailment, ensuring surplus generation from wind and solar sources is effectively utilized and contributing to decarbonization goals (Radecke et al., 2019).

From a financial perspective, well-designed tariffs are vital for cost recovery, particularly for distribution system operators (DSOs). Tariffs that reflect the true costs of network usage not only ensure that DSOs recover investments and operational expenses but also promote fair cost distribution among users, balancing affordability and efficiency (Borenstein, 2016). Additionally, tariffs play an essential role in encouraging the activation of flexible resources, such as batteries and demand response systems. By providing dynamic price signals, tariffs incentivize consumers and operators to adjust energy use patterns or deploy flexible assets, enhancing grid reliability and reducing operational costs (OConnell et al., 2012).

Tariffs also improve overall grid efficiency by reducing deviations from optimal power flow. Pricing structures that align with real-time grid conditions encourage energy consumption patterns that support economic dispatch and minimize transmission losses (Kahn et al., 2001). Moreover, by enabling broader market participation, tariffs enable distributed energy resources and consumers to engage in energy markets. This expands market liquidity, promotes competition, and encourages innovation in grid management practices (Radecke et al., 2019).

A critical advantage of tariffs is their ability to address wind curtailment. Dynamic and locational tariffs incentivize energy use during periods of high wind generation, reducing the likelihood of curtailment and improving the economics of renewable energy projects (Radecke et al., 2019). Furthermore, their adaptability to existing and future market structures ensures their compatibility with wholesale and retail frameworks. Well-designed tariffs balance efficiency, equity, and simplicity, making them an essential tool for grid stability and sustainability (Hirth and Glismann, 2018).

However, while tariffs perform well across most metrics, challenges such as consumer response variability and administrative complexities can limit their full effectiveness. Despite these limitations, advances in data analytics and grid technologies are expected to further refine tariff structures, enabling more precise designs. As a result, tariffs remain important to achieving grid stability, promoting cost efficiency, and supporting the transition toward a more sustainable electricity market.

2.4.3. Resulting metrics

Both batteries and tariffs offer significant potential for effective congestion management. It is important to explore how well batteries perform when used without non-market-based strategies compared to when they are combined with them. Additionally, it is interesting to examine how well batteries and tariffs complement each other in addressing key performance metrics.

The most frequently cited metrics in the literature for each category are cost recovery period, line overloading, renewable energy curtailment. We assume that the more often a KPI is mentioned in academic studies, the more established and credible it is as an indicator of performance.

With this set of metrics, we can evaluate how non-market-based strategies influence the effectiveness of congestion management solutions. This approach allows us to assess performance across different themes, providing a clearer picture of how these strategies impact the key aspects of the grid.

3
Methodology

The following chapter will outline the methods used to answer the main research question "How do alternative transport tariffs impact battery performance and grid stability in the Dutch electricity distribution network?". The methodology used for the analysis of the impact of the newly introduced alternative transport tariffs is twofold. It starts with determining the optimal behavior for a battery on the electricity market. Next, it uses the key performance indicators to assess the performance the battery on a synthetic grid representing the mid-voltage grid in the Netherlands. The chapter will start with explaining the research flow, then an explanation per method, including input variables and other design choices.

3.1. System Boundary

To ensure a focused analysis, this thesis uses a defined boundary for assessing congestion management in electricity grids. The study specifically investigates the role of tariff structures on battery storage in mitigating grid congestion, while excluding broader aspects such as long term grid expansion and market dynamics outside the wholeslae market. This section covers the elements considered within and outside the scope of the research.

The study focuses on the electricity grid's distribution networks. The main lever that the research adjusts is adding different tariff systems to the battery's operation. These tariff systems impact when the battery can participate on the market, thus influencing their charging and discharging behavior. This is then measured on a synthetic grid to gain understanding of the impact of these changes in behavior on grid stability. These outcomes are compared to the system without the battery and compared to the system without tariffs. The system without tariffs isn't a plausible option for the Dutch system because the grid does not have the capacity to connect more batteries to the system without employing alternative transport tariffs.

Within the scope of this research, electricity grid infrastructure such as grid nodes, substations and interconnection points were included. Also, the synthetic grid was altered to simulate a Dutch distribution grid as much as possible by altering the renewable generation capacity, the capacity of the lines and adding in Dutch weather patterns. Battery storage systems are analyzed in terms of their technical and economic performance as congestion management tools. This includes a dispatch strategy to optimize profit, market participation, and impact on grid stability. The study evaluates this using key performance indicators (KPIs) such as congestion reduction and cost recovery period.

While this study focuses on congestion management through batteries and tariffs, several related aspects fall outside its scope. Long-term generation and grid expansion planning are excluded, as the analysis does not address investment decisions in new power plants or transmission lines. Similarly, the study does not delve into other electricity markets other than the Day Ahead and Intraday Market. The reasoning for this choice will be elaborated on in more detail in section 3.3.1. Detailed consumer behavioral modeling, environmental impact assessments, and cybersecurity aspects are also beyond the scope of this study. While price elasticity is considered in evaluating tariff effects, in-depth behavioral models of consumer response are not included. Additionally, extreme scenarios such as grid blackouts or resilience planning are not analyzed in detail. Most importantly, other flexible assets are not included in this study, meaning that only conclusions can be made on the impact of tariffs on a 40 MWh battery on the distribution grid.

3.2. Research Flow

Figure 3.1 is a visualization of the flow of the research. It shows how the different parts of the methodology are connected and dependent on each other for input. The three purple rectangles are the three methods used, the purple arrows show their main inputs and outputs. These inputs will be described in more detail in the subsections of this chapter dedicated to that specific part of the method.

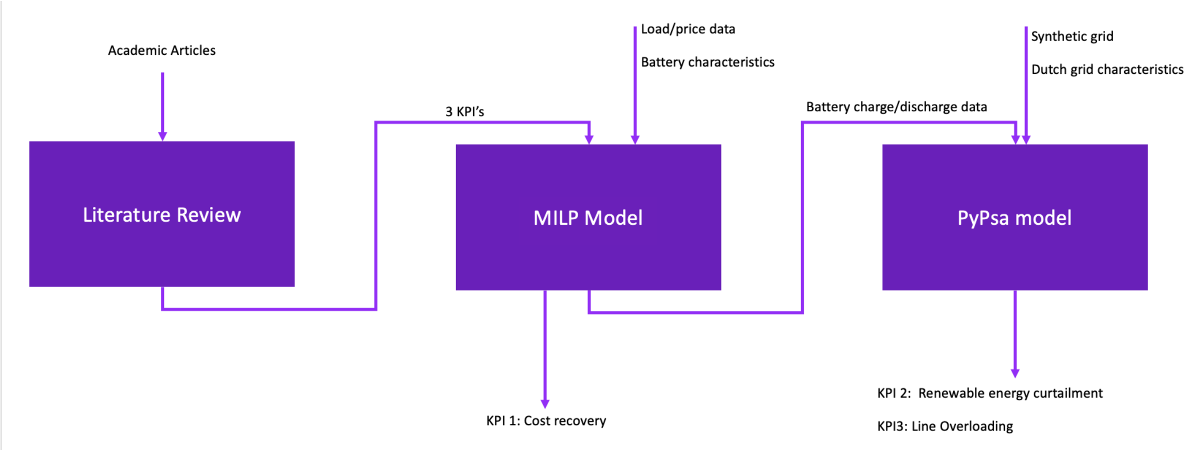

Figure 3.1: Conceptual Model

This framework outlines an approach for evaluating the integration of battery storage systems within an energy network, with a particular focus on the Dutch grid. It is structured into three interconnected components: a literature review, a Mixed-Integer Linear Programming (MILP) model, and a PyPSA model. Each element contributes to assessing both the economic and technical viability of battery storage solutions.

The process begins with a review of existing academic research, which aims to answer the first sub-question. This foundational step combines insights from academic sources to establish the key performance indicators (KPIs) often used in research to evaluate the effectiveness of congestion management strategies. These key performance indicators are subsequently used to evaluate the performance in the next two models.

Following this, the MILP model is used as a tool for economic optimization. It processes various data inputs, including electricity demand patterns, market price fluctuations, and battery specifications, to determine the optimal bidding strategy. The optimization evaluates the financial viability of the battery as an investment under the different tariff structures. One of its primary outputs is the assessment of cost recovery period, one of the three KPIs from the literature review. The MILP model also produces operational data regarding battery charging and discharging cycles, which serve as essential inputs for further grid analysis. While the MILP model is able to find the optimal bidding strategy for the battery and thus the new total load of the system, purely looking at decrease in peaks doesn't accurately represent a better congestion management strategy. Grid dynamics with distributed demand and supply must be considered, as they impact power flow across the entire distribution grid. Thus, the grid impact is calculated with the PyPSA model.

The PyPSA model takes these outputs and simulates their impact on a synthetic electricity grid. Incorporating a synthetic representation of the power grid along with key characteristics of the Dutch energy infrastructure, this model assesses the technical consequences of battery deployment. Specifically, it examines two additional KPIs: renewable energy curtailment and line overloading. The first metric measures the extent to which battery storage mitigates the wastage of surplus renewable generation, while the second evaluates whether the integration of batteries alleviates or exacerbates stress on transmission lines.

The MILP and PyPSA model together answer sub-questions two, three and four. Each model is run under the different tariff scenarios and thus answer how well the battery performs in these environments. By integrating economic optimization with power system simulation, this framework provides a comprehensive method for evaluating battery storage in energy grids. The combination of MILP and PyPSA enables a detailed analysis that considers both financial and technical dimensions. Which leads to valuable insights for policymakers, grid operators, and investors, facilitating informed decision-making regarding energy storage and grid modernization.

3.3. Mixed Integer Linear Programming

The second research method employed in this study is a quantitative modeling technique, specifically a mixed integer linear programming (MILP) model. The motivation for using this approach lies in addressing a significant knowledge gap: how the behavior of flexible assets, such as battery storage, adapts when governed by market-based policies versus non-market-based policies. This question is particularly relevant as the Dutch electricity grid continues to evolve with a mix of market-driven and regulatory strategies aimed at optimizing grid performance and reliability. By modeling these behaviors under different policy scenarios, the research aims to capture shifts in battery charge and discharge decisions that could impact grid stability and efficiency.

The MILP model is chosen for its ability to integrate both continuous and discrete decision variables, which is crucial in electricity market modeling. MILP is an optimization technique that allows for binary decisions (e.g., whether to activate or deactivate a battery storage system) as well as continuous decisions (e.g., the volume of energy to store, withdraw, or trade). This flexibility is important for simulating battery performance under a range of market conditions and regulatory frameworks (Fachrizal et al., 2020). In the context of electricity markets, many operational decisions involve a mix of binary and continuous variables, and MILP can effectively capture these dynamics, which are necessary to reflect real-world scenarios. The optimization problem is solved using Gurobi Optimizer. The key constraints include battery state-of-charge (SOC) limits, charging/discharging power constraints, and market-dependent operational restrictions.

Moreover, MILP models enable the incorporation of technical constraints, which is important for a realistic representation of battery operations within the grid. For instance, the model can account for minimum and maximum charging and discharging rates, enforce state-of-charge limits, and incorporate grid transmission limits, all of which ensure that the behavior of the battery system is both feasible and aligned with actual technical limitations (Fachrizal et al., 2020). By capturing these constraints, the model can provide a more precise analysis of how batteries would operate in response to alternative transport tariffs, thereby yielding insights into potential grid impacts.

While the primary methodology is quantitative, the inputs and parameters that feed into the MILP model are derived from a comprehensive literature review. This review examines relevant studies and reports to identify the factors most critical to successful congestion management on the grid. By identifying key metrics for congestion management and stability, the literature review helps establish the key performance indicators (KPI's) that will be used to evaluate the model's outputs.

Figure 3.2 presents a conceptual diagram illustrating the decision-making process for battery participation in electricity markets under a Mixed-Integer Linear Programming (MILP) framework. The diagram breaks down the optimization process into four main stages: tariff checks, day-ahead market optimization, intraday market optimization, and profit calculation. The process begins with a tariff check, which determines whether the system is subject to regulatory constraints that may prohibit charging or discharging during certain periods. If no restrictions apply, the model proceeds to the day-ahead market optimization, where the battery's charging and discharging schedule is determined based on expected market conditions while adhering to operational constraints. Once the day-ahead schedule is established, the intraday market optimization adjusts the battery's operation in response to real-time market deviations while ensuring consistency with the commitments made in the day-ahead market. Finally, the model calculates the net profit by aggregating revenues from energy sales and subtracting costs such as charging expenses and potential tariff-related fees.

Throughout the optimization, decisions are made based on several factors, including market price forecasts, battery state-of-charge constraints, regulatory restrictions, and earlier Day Ahead commitments. Charging is prioritized when the expected future price is higher than the current price after accounting for charging costs, while discharging occurs when the current price exceeds the expected future price, considering discharging costs.

It is important to note that while the diagram illustrates the decision process as if it were sequential, the MILP model does not operate in a step-by-step manner. Instead, it optimizes all time-steps simultaneously over the entire planning horizon. The model accounts for all constraints and objectives at once, solving for the globally optimal charging and discharging schedule rather than making isolated decisions at each timestep. The sequential representation in the diagram is intended to provide an understanding of the underlying optimization logic while acknowledging that MILP finds an optimal solution across the entire period rather than iterating through individual time-steps.

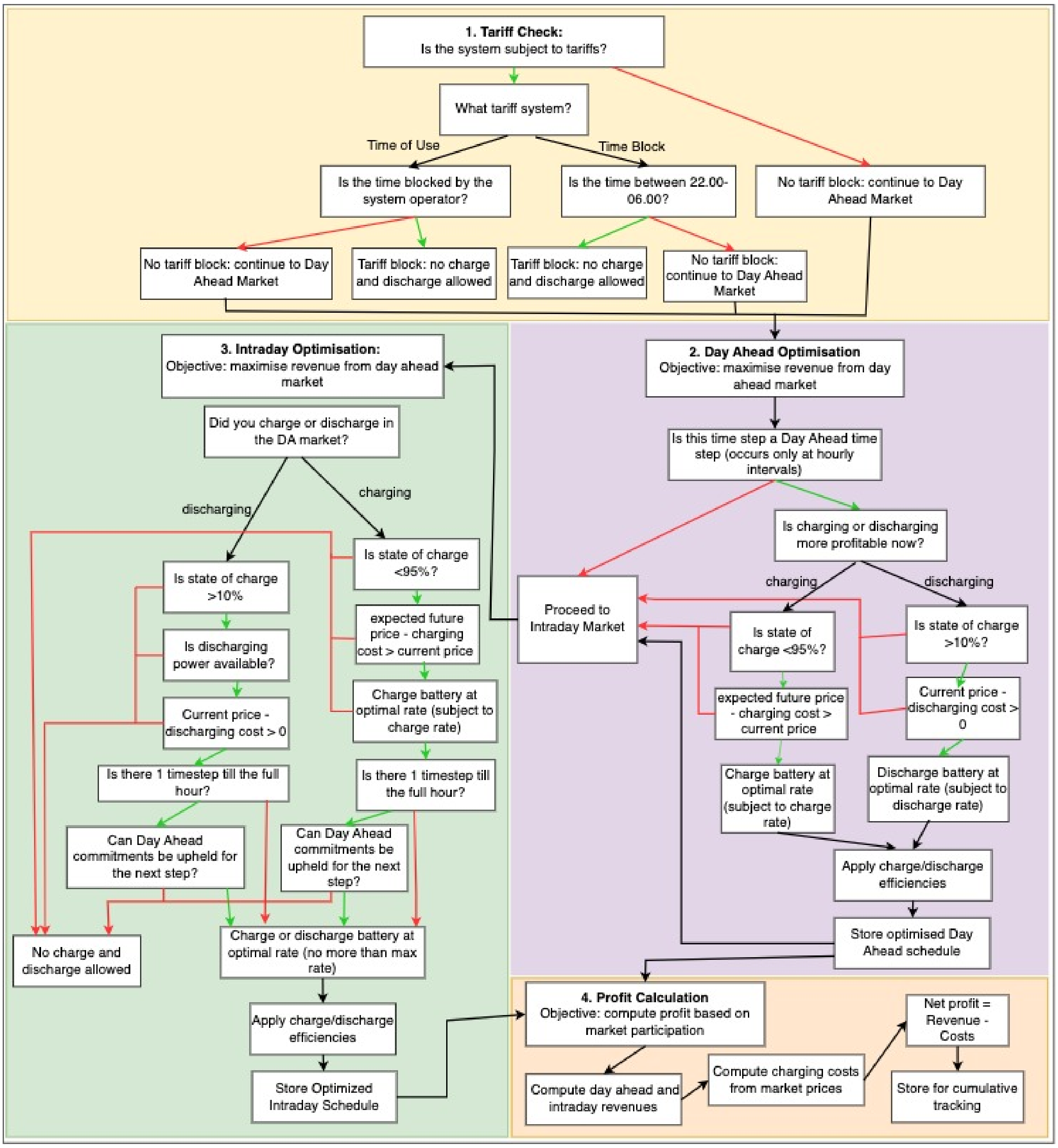

Figure 3.2: Conceptual Diagram Mixed Integer Linear Programming

3.3.1. Input Variables

An overview of all input variables utilized for the optimization process can be found in Appendix D. Below, these variables are described, and the rationale behind their selection is provided.

Time series

The optimization relies on AI-generated data, which was developed using historical load, pricing, and weather data. This approach resulted in the creation of two synthetic datasets: one representing two summer weeks and another representing two winter weeks in the Netherlands. The historical input data for this synthesis was sourced from the ENTSO-E Transparency Platform. The retrieved data had a temporal resolution of 15-minute intervals for all variables except for day-ahead electricity prices, which were only available at an hourly resolution. To ensure consistency in the dataset, the hourly day-ahead price values were duplicated across the corresponding 15-minute intervals. Refer to Appendix D for the exact prompt used to generate the data.

The synthesized dataset, referred to as "data," included the following key variables: 'Time', 'Total Load', 'Wind Load', 'Solar Load', 'Day-Ahead Prices', and 'Intraday Prices'. This dataset served as the foundation for the simulated environment in which the battery system made its operational decisions. The battery's bidding strategy was exclusively based on the available data at each time step, ensuring that its decision-making process remained data-driven.

The decision to use averaged data from the years 2022, 2023, and 2024 was made to mitigate the influence of short-term external factors that could introduce variability in load and pricing patterns. As the model does not explicitly account for such external influences, constructing synthetic two-week periods that represent an average winter and summer period over these three years was deemed the most appropriate approach. The exclusion of data preceding 2022 was based on the potential distortions introduced by the COVID-19 pandemic, which significantly affected electricity consumption patterns.

The selection of two-week periods for both summer and winter was driven by the need to create a representative dataset that accounts for seasonal variations in energy demand and supply. Using 15-minute granularity over a two-week span provided a sufficiently detailed dataset, capturing day and night fluctuations within the system. Additionally, by incorporating both winter and summer scenarios, it was possible to assess the battery's performance under two extreme weather conditions, allowing for a comparative analysis of its operational effectiveness across different seasonal contexts.

Electricity Markets

In this study, the focus is placed explicitly on the Day-Ahead Market (DAM) and Intraday Market for battery optimization, which aligns with the current electricity market structure and anticipated developments in the Netherlands. The DAM serves as the primary trading platform, setting hourly electricity prices through auctions conducted one day prior to actual delivery. Conversely, the Intraday Market provides market participants with the opportunity to adjust their trading positions closer to real-time via continuous trading. This shorter lead time significantly enhances price predictability, making it particularly suitable for battery operators seeking to capitalize on intraday price variations by charging when electricity is inexpensive and discharging during high-price periods.

Additionally, the Intraday Market permits trading in shorter intervals (fifteen-minute periods), greatly enhancing the operational flexibility and responsiveness of battery storage. As renewable energy sources, such as wind and solar, continue to expand, the Intraday Market becomes increasingly vital for managing the inherent variability and forecast errors associated with these resources. Consequently, trading volume in the Dutch intraday market is projected to grow significantly, from on average 500 MW in 2019 to over 1 GW by 2030 (Jongsma et al., 2021). With maximum market size up to 2,2 GW in 2030 from 500 MW in 2019. This anticipated growth underscores the importance of understanding and optimizing battery participation specifically within this market.

Battery Characteristics

Another important input variable in this research is the set of characteristics defining the battery system. For this study, a 40 MWh battery has been selected for analysis. This is a medium- to large- scale battery system. This choice is based on recent trends in energy storage deployment, where batteries of this scale are being installed in various regions worldwide, with high expectations regarding their potential to enhance grid stability and flexibility (EKU Energy, 2024; LSP Renewables, 2025). Despite these developments, there are currently no plans for implementing batteries of this size in the Netherlands. This absence of deployment makes it particularly relevant to examine how such a battery would perform within the specific conditions of the Dutch electricity network. By assessing its potential impact, this research aims to contribute to the broader discussion on integrating large-scale storage solutions into the national grid.

Furthermore, Lazard's research provides valuable insights into the operational characteristics of front-of-the-meter battery systems used within distribution networks. According to their findings, the typical charge rate for a battery of this size is approximately 10 MW, aligning with common industry practices (Lazard, 2020). The same study also determined that the round-trip efficiency of such battery systems averages around 90%, meaning that a portion of the stored energy is inevitably lost due to conversion and operational inefficiencies. This value is also backed by Alsym Energy Alsym Energy, 2025. In terms of financial considerations, Yuan et al (2022) reported that the variable cost per megawatt of storage capacity for this type of battery system is approximately 1,6 euros. This has been set as the bidding price for the battery, so it can cover its variable costs (Yuan et al., 2022).

The final input variables for the characteristics of the battery are the maximum state of charge and the minimum state of charge. Wang et al (2024) and Gul et al (2022) assumed a minimum state of charge of batteries as 10% and a maximum state of charge of 95% to minimize depletion of the battery over time (Gul et al., 2022; Z. Wang et al., 2024b). These parameters are also used in this study.

In this study, the initial state of charge (SoC) for the battery was set at 50% capacity. This decision was made to ensure that the battery had sufficient flexibility to participate in both charging and discharging activities within the optimization framework. By starting from a mid-range state of charge, the battery could respond dynamically to fluctuations in electricity prices and grid conditions, effectively simulating real-world operational scenarios. This approach provides a balanced and realistic assessment of how the battery could interact with market signals and system requirements within the Dutch energy landscape.

Bidding Strategy

The bidding strategy implemented for the battery was deliberately structured to be relatively straightforward, adhering to fundamental economic principles governing electricity markets with high shares of renewable energy. Specifically, the strategy was designed based on the assumption that electricity prices tend to decrease during periods of high renewable energy generation and high system load, creating a favorable condition for the battery to charge. Conversely, when renewable generation and overall demand are lower, electricity prices typically increase, making it more advantageous for the battery to discharge.

To operationalize this principle, the battery was programmed to charge when wind and solar generation were forecasted to exceed the 80th percentile of their respective historical distributions. This threshold was selected to ensure that charging occurred primarily during periods of surplus renewable energy, aligning with the goal of enhancing grid flexibility and optimizing economic returns. By structuring the bidding strategy in this manner, the battery's operations closely mirrored market dynamics, responding to fluctuations in supply and demand while maintaining a simple yet effective decision-making framework.

Tariffs

This research focuses on gaining a better understanding of the impact of the newly introduced alternative transport tariffs. Thus, the way these tariffs are structured in the code is very important. The way that the tariffs are defined are based on publications by Netbeheer Nederland, where they give examples of how the alternative transport tariffs would work for parties involved, as well as their prospective discount on their yearly contracted transport tariffs (Netbeheer Nederland, 2024). These examples were used to build the rules surrounding the new tariffs.

Time-block contracts are designed to provide certainty of transport capacity during specific, pre-agreed time windows. This type of contract is particularly relevant for consumers with flexible energy demands that are concentrated within predictable periods, such as electric bus depots where charging typically occurs overnight. Netbeheer Nederland used this situation as their example of the tariff, thus this model builds on these values. A bus company might contract transport capacity from 8:00 PM to 6:00 AM daily, aligning with the operational schedules of their fleet. Outside these contracted time windows, the consumer holds no right to transport capacity, and any energy demand would require separate arrangements. The financial benefits of time-block contracts stem from their structure. Network operators apply a discounted transport tariff proportional to the number of contracted hours relative to a full 24-hour period. This means that the fewer hours contracted, the higher the relative discount. For example, if a customer contracts capacity for 8 out of 24 hours, the discount reflects the reduced strain on the grid during off-peak periods (Netbeheer Nederland, 2024).

In contrast, time-of-use contracts offer a different form of flexibility. Rather than focusing on specific daily or monthly time windows, these contracts guarantee transport capacity for a minimum number of hours per year. The key characteristic here is not when the energy is transported, but that it is available for a specified duration annually. For example, a contract might stipulate that a customer has the right to transport capacity for 85% of the hours in a year. The exact hours when capacity is unavailable are communicated at least a day in advance (before the closing of the day-ahead market) by the network operator, allowing the consumer to plan accordingly Netbeheer Nederland, 2024, and don't neccessary mean that the 15% threshold is met every year. The tariff advantage of time-duration-bound contracts is substantial. Network operators apply apply a zero tariff for the contracted capacity component, leading to significant cost reductions (Netbeheer Nederland, 2024). These types of contracts are currently only available on the transmission network, by incorporating it into this research it can be tested if this method from the transmission world can be effective in the distribution network.

Yearly Grid Costs

An important part of the optimization of the battery is the profitability of the battery under different tariff scenarios. As explained above, each alternative transport tariff has different financial benefits. According distribution system operator Enexis, these are the periodic connection and transport tariffs for electricity on the distribution grid, for connections greater than 1500kW (Enexis Netbeheer, 2025):

- Fixed charge for transport service: This refers to a recurring fixed fee that consumers pay to the grid operator for maintaining access to the electricity network. This charge is independent of how much electricity is actually consumed or transported. It covers the administrative costs, infrastructure maintenance, and the availability of the network to ensure reliable service (BidonEnergy.org, 2024). In the Netherlands, the fixed charge on the midvoltage distribution network was **441 euros** (Enexis Netbeheer, 2025).
- Contracted capacity: Contracted capacity is the agreed-upon maximum amount of power (measured in kilowatts or megawatts) that a consumer is allowed to draw from or inject into the grid at any given time (Abdelmotteleb, 2023). This capacity is specified in the contract with the grid operator based on the consumer's needs. Consumers are billed for this capacity, even if they don't always use the full amount. On the midvoltage distribution grid in the Netherlands, the contracted capacity is 13,57 EUR/kW/year. For a 10MW battery, this is **135700 EUR/year** (Enexis Netbeheer, 2025). For batteries in the Time of Use tariffy system, they don't have to pay this fee, for batteries in the Time Block system, they pay this fee times the fraction that they do participate (8 hours connected means 8/24 * contracted capacity fee).
- Maximum capacity: Maximum capacity refers to the highest level of power that is actually used or technically possible within a given period. This can be different from the contracted capacity. For example, if a company has contracted 10 MW but only ever uses up to 7 MW, the maximum capacity in practice is 7 MW. Network operators often monitor this because exceeding the contracted capacity can cause strain on the grid and trigger additional charges or technical interventions (Brading, n.d.). The maximum capacity is 1,57 EUR/kW/month, this is **188 400 EUR/year** for this battery (Enexis Netbeheer, 2025).

3.3.2. Decision Variables

Let t be the time index every fifteen minutes.

State of Charge (SOC_t): The battery's energy level at time t (MWh) represents the state of charge, which is monitored at each time step to determine the maximum capacity available for charging and discharging at any given moment. Since the day-ahead market closes prior to the intraday market, intraday bidding strategies must account for the battery's state of charge as influenced by prior day-ahead commitments. It is important to note that day-ahead bids represent one-hour energy commitments, with energy delivery distributed evenly over the hour rather than concentrated at the beginning. To accurately reflect this in the model, the state of charge is updated at 15-minute intervals within each hour. This approach ensures that intraday bids, which operate on 15-minute time intervals, are based on the precise, real-time state of charge available for trading.

Charging Power (C_t): Charging power at time t (MW) represents the amount of electricity the battery can charge per hour. This charging rate limits the amount that the battery can charge per hour and thus the amount that it can buy on both markets. Because the intraday model operates on 15 minute intervals, it works by dividing the charging power by four.

Discharging Power (D_t): Discharging power at time t (MW) represents the amount of electricity the battery can discharge per hour. Discharging rates determine the amount that the battery can commit per hour, and thus the maximum bidding it can place. For intraday, this is divided by four because it bids per 15 minutes.

Binary Charging and Discharging Indicator: In the model it is important to be able to differentiate when the battery is charging, discharging or idle. This is especially important when defining constraints, as the battery cannot be charging and discharging simultaneously. The indicator x_t^C equals 1 if charging is allowed at time t, otherwise 0. The indicator x_t^D equals 1 if discharging is allowed at time t, otherwise 0.

$$x_t^C \in \{0, 1\}$$

$$x_t^D \in \{0, 1\}$$

3.3.3. Objective Function

The objective is to maximize the total economic profit from energy arbitrage, accounting for charging and discharging costs. The battery bids on the electricity market. The code is set up in a way that the energy bid placed by the battery is only accepted if the bid is the same or below the day-ahead or intraday price.

Day-Ahead Market Optimization

The profit function in the day-ahead market is formulated to maximize the net revenue generated from battery operations, accounting for both energy trading and operational costs. The objective function is defined as:

$$\max_{D_t, C_t} \sum_{t=1}^{T} \left(P_t^{DA} \cdot D_t - P_t^{DA} \cdot C_t - c^{dis} \cdot D_t - c^{ch} \cdot C_t \right) \tag{3.1}$$

The first term, $P_t^{DA} \cdot D_t$ captures the price of electricity (EUR/MWh) in the day-ahead market, as the battery discharges stored energy at time t. This price, P_t^{DA} is found in the input data and is multiplied by either 0 or 1 depending on if the battery is discharging at that time. The second term, represents the cost of purchasing electricity from the market for charging the battery. This is the price, found in the input data, multiplied by either 0 or 1 depending on whether or not it is charging at time t. The third and fourth terms, account for the operational costs linked to battery usage. These costs may include efficiency losses, degradation costs, and other expenses related to the energy conversion processes during charging and discharging cycles. Battery discharging and charging costs (EUR/MWh) are represented by c^{dis} and c^{ch}, respectively.

The goal of the optimization problem is to identify the optimal charging and discharging schedule that maximizes the battery's profit over the specified time horizon. This is achieved by balancing the revenue from energy sales against the costs of energy procurement and battery operation, while adhering to technical and market constraints such as capacity limits and state of charge restrictions.

Intraday Market Optimization

The intraday market optimization builds upon the day-ahead schedule by incorporating updated electricity prices and market conditions, allowing for real-time adjustments that enhance profitability. This optimization is designed to maximize the net revenue generated from battery operations, taking into account both energy trading opportunities and operational costs. The objective function for the intraday market is formulated as:

$$\max_{D_t, C_t} \sum_{t=1}^{T} \left(P_t^{ID} \cdot D_t - P_t^{ID} \cdot C_t - c^{dis} \cdot D_t - c^{ch} \cdot C_t \right) \tag{3.2}$$

In this formulation, P_t^{ID} denotes the intraday electricity price at time t (measured in EUR/MWh), which reflects the most current market price updates. The variables D_t and C_t represent the discharging and charging power of the battery at time t, respectively, both expressed in megawatt-hours (MWh). Similar to the day-ahead model, c^{dis} and c^{ch} refer to the operational costs associated with battery discharging and charging, measured in EUR/MWh.

The first term, $P_t^{ID} \cdot D_t$, captures the revenue generated from selling electricity in the intraday market when the battery discharges stored energy. This term reflects the real-time market price, which can fluctuate significantly compared to the day-ahead price, offering opportunities to capitalize on short-term price volatility. The second term, $P_t^{ID} \cdot C_t$, represents the cost of purchasing electricity from the intraday market to charge the battery. Both terms are influenced by binary decision variables (implicitly represented by D_t and C_t), which determine whether the battery is actively discharging or charging at time t.

The third and fourth terms, $c^{dis} \cdot D_t$ and $c^{ch} \cdot C_t$, account for the operational costs of battery usage, including factors such as energy conversion inefficiencies, battery degradation, and other maintenance-related expenses. These costs are critical for accurately modeling the economic performance of the battery in dynamic market conditions.

The primary goal of the intraday optimization is to refine the battery's charging and discharging schedule based on the most recent price signals, thereby maximizing profits while respecting technical and operational constraints. This includes considerations such as the battery's state of charge, capacity limits, and the commitments made in the day-ahead market. By continuously adjusting the operation in response to real-time market data, the intraday optimization enhances the flexibility and economic efficiency of battery storage systems in competitive electricity markets.

Constraints

No Simultaneous Charging and Discharging: The battery cannot charge and discharge at the same time

$$x_t^C + x_t^D \leq 1, \quad \forall t \tag{3.3}$$

SOC Limits: To prevent overcharging or depletion, SOC is constrained as

$$SOC_{\min} \le SOC_t \le SOC_{\max}, \quad \forall t$$

Renewable Generation and Load-Based Constraints: To further optimize battery performance, two additional constraints based on renewable generation and load conditions were introduced:

High Renewable Generation with Low Load: When wind or solar generation exceeds the defined threshold ($wind_{threshold}$ or $solar_{threshold}$), and total load is below a certain threshold ($load_{threshold}$), the battery is required to charge at a minimum rate:

$$C_t^{ID} \ge 0.7 \cdot (C_{\max} - C_t^{DA}) \cdot x_t^C, \quad \text{if } wind_t \ge wind_{threshold} \text{ or } solar_t \ge solar_{threshold}, \text{ and } load_t < load_{threshold} \tag{3.4}$$

Low Renewable Generation with High Load: Conversely, when wind and solar generation fall below their respective thresholds, and the total load exceeds the load threshold, the battery is incentivized to discharge at a minimum rate:

$$D_t^{ID} \ge 0.5 \cdot (D_{\max} - D_t^{DA}) \cdot x_t^D, \quad \text{if } wind_t < wind_{threshold}, \ solar_t < solar_{threshold}, \text{ and } load_t \ge load_{threshold} \tag{3.5}$$

These additional constraints ensure that the battery's behavior aligns with system-wide objectives, such as maximizing renewable energy utilization during periods of surplus generation and supporting grid stability during periods of high demand and low renewable output.

Battery State of Charge (SOC) Day Ahead market: The SOC is updated based on charging and discharging actions from the time step before.

$$SOC_t = SOC_{t-1} + \eta^{ch} C_t - \frac{D_t}{\eta^{dis}}, \quad \forall t \tag{3.6}$$

where: η^{ch} and η^{dis} are the charging and discharging efficiencies, respectively.

Battery State of Charge (SOC) Intraday Market: The SOC is updated based on the day ahead state of charge and the charging and discharging actions from the intraday market the previous time step.

$$SOC_t + SOC_{DA} = \begin{cases} \text{initial SOC} + \eta^{ch}(C_t + C_{DA}) - \frac{(D_t + D_{DA})}{\eta^{dis}}, & \text{if } t = 0 \\ SOC_{t-1} + SOC_{DA} + \eta^{ch}(C_t + C_{DA}) - \frac{(D_t + D_{DA})}{\eta^{dis}}, & \text{otherwise} \end{cases} \tag{3.7}$$

This equation models the evolution of the battery's state of charge over time. At the initial time step, the SOC is determined based on the initial SOC, adjusted for both intraday and day-ahead charging and discharging actions, accounting for charging and discharging efficiencies. For subsequent time steps, the SOC builds on the previous time step's SOC, adding the net effect of current charging and discharging activities while continuing to consider efficiency losses.

Charging and Discharging Power Limits Day Ahead Market: Charging and discharging rates must stay within the battery's capabilities

$$0 \le C_t \le x_t^C \cdot C_{\max}, \quad \forall t 0 \le D_t \le x_t^D \cdot D_{\max}, \quad \forall t \tag{3.8}$$

Charging and Discharging Power Limits intraday Market The intraday model refines decisions based on the day-ahead schedule. Here, if the day ahead model already charges or discharges at a rate, the intraday model can only charge or discharge at the remaining rate.

$$C_t^{ID} \le C_{\max} \div 4 - C_t^{DA}, \quad \forall t D_t^{ID} \le D_{\max} \div 4 - D_t^{DA}, \quad \forall t \tag{3.9}$$

Tariff-Based Constraints: For Time-of-Use (TOU) tariffs, charging and discharging are restricted based on congestion levels. The battery cannot participate in the market during congestion periods, which occur when the net load exceeds a predefined threshold. If this occurs:

$$C_t, D_t = 0, \quad \text{if } t \text{ falls in a high-congestion period} \tag{3.10}$$

However, to ensure market participation the total duration of these restricted periods cannot exceed 15% of the total operation time. When the next day is predicted to have more congested periods than 15%, the periods with most congestion are chosen as restricted periods.

For Time Block tariffs, restrictions apply outside predefined hours:

$$C_t, D_t = 0, \quad \forall t \notin [\text{TIME\_BLOCK\_START}, \text{TIME\_BLOCK\_END}] \tag{3.11}$$

3.3.4. Tracked Results

Upon completion of the optimization model, the following key variables are systematically tracked to facilitate the next stages of the modeling process. The tracked results for each optimized market model—Day-Ahead and Intraday—are presented in the table below.

Table 3.1: Tracked Results from the Day-Ahead and Intraday Optimization Models

Day-Ahead (DA) Market	
Variable	**Description**
DA_Charge	Energy charged into the battery during each day-ahead period (MWh)
DA_Discharge	Energy discharged from the battery during each day-ahead period (MWh)
DA_SOC	Battery State of Charge at each time step in the day-ahead market (MWh)
Day-Ahead Profit	Total profit generated from day-ahead market operations (EUR)
Net DA Volume	Net volume of energy traded in the day-ahead market (MWh)
Intraday (ID) Market	
Variable	**Description**
ID_Charge	Energy charged into the battery during each intraday period (MWh)
ID_Discharge	Energy discharged from the battery during each intraday period (MWh)
ID_SOC	Battery State of Charge at each time step in the intraday market (MWh)
Intraday Profit	Total profit generated from intraday market operations (EUR)
Net ID Volume	Net volume of energy traded in the intraday market (MWh)
Combined Results	
Variable	**Description**
Total_Charge	Sum of DA and ID charging across all periods (MWh)
Total_Discharge	Sum of DA and ID discharging across all periods (MWh)
Total_SOC	Combined battery State of Charge from both markets at each time step (MWh)
Total Profit	Total combined profit from both day-ahead and intraday operations (EUR)

Profit Calculation

The calculation of profits is a key metric tracked to evaluate the economic performance of battery operations in both the Day-Ahead and Intraday markets. The profit is determined by accounting for market revenues from discharging, costs associated with charging, and operational costs related to battery use.This profit calculation offers insights into the economic viability of battery operations under different market conditions and regulatory frameworks. It helps in determining the first key performance indicator that was identified in the literature review: cost recovery.

To calculate the cost recovery period for the battery energy storage system, we consider the following components:

1. Profit Calculation: In this paper it is assumed that the battery is fully financed through debt. This is payed for by using all profit to repay the debt until the full debt is paid off. To calculate profit per year, the following equation is used.

$$Pr = R_{Total} - C_{\text{OPEX}} - Dp - I \tag{3.12}$$

Where:

- Pr = Profit (€)
- R_{Total} = Revenue (€)
- C_{OPEX} = Operational Costs (€)
- Dp = Depreciation (€)

- I = Interest (€)

2. Net Cash Flow:

Net cash flow is another important metric when calculating profit which plays a role in the amount of debt payed off each year, and thus in the yearly interest payments. Net cash flow is the same as profit, except without the depreciation:

$$C_{\text{net}} = Pr - Dp \tag{3.13}$$

3. Annual Revenue Calculation:
The Day-Ahead Revenue (R_{DA}) is calculated using hourly data, incorporating revenues from energy discharged at day-ahead market prices and deducting the costs for both charging and operational expenses:

$$R_{DA} = \sum_{i=1}^{n} \left(p_{DA,i} \cdot E_{dis,i} - p_{DA,i} \cdot E_{ch,i} - C_{op} \cdot (E_{ch,i} + E_{dis,i}) \right) \tag{3.14}$$

where:

- $p_{DA,i}$ represents the day-ahead price at hour i,
- $E_{dis,i}$ is the energy discharged at hour i,
- $E_{ch,i}$ is the energy charged at hour i,
- C_{op} denotes the operational cost per unit of energy.

The Intraday Profit (R_{ID}) is derived from 15-minute interval data:

$$R_{ID} = \sum_{j=1}^{m} \left(p_{ID,j} \cdot E_{dis,j} - p_{ID,j} \cdot E_{ch,j} - C_{op} \cdot (E_{ch,j} + E_{dis,j}) \right) \tag{3.15}$$

where:

- $p_{ID,j}$ represents the intraday price at time interval j,
- $E_{dis,j}$ and $E_{ch,j}$ are the discharged and charged energy at time interval j.

The **Total Revenue** (R_{Total}) is the sum of day-ahead and intraday revenues over the period of a year.

$$R_{Total} = 13 * (R_{ID} + R_{DA}) \tag{3.16}$$

Because the analysis is run for two winter weeks and two summer weeks, the total profit from winter and summer is multiplied by thirteen. This creates 52 weeks worth of data (2 weeks of summer data + 2 weeks of winter data * 13), representing a full year.

4. Depreciation Depreciation represents the reduction of value of an asset over time, this has to be included in the yearly profit of the asset.

$$Dp = C_{\text{inv}}/L \tag{3.17}$$

Where:

- C_{inv} represents initial investment cost: € 1649863 (Shin & Lee, 2024)
- L represents the lifetime of the battery: 25 years (Shin & Lee, 2024)

5. Total Operational Costs:

The total operational costs are the total annual operating expenditures.

$$C_{\text{OPEX}} = C_{\text{TCC}} + C_{\text{FCC}} + C_{\text{CYMPC}} + C_{\text{O\&M}} \tag{3.18}$$

Where:

- C_{TCC} = Contracted transport capacity costs: 135700 (€/year) (Enexis Netbeheer, 2025)
- C_{FCC} = Annual fixed charge costs for electricity: 441 (€/year) (Enexis Netbeheer, 2025)
- C_{CYMPC} = Contracted yearly maximum power costs: 188400 (€/year) (Enexis Netbeheer, 2025)
- $C_{\mathrm{O\&M}}$ = Operation & Maintenance costs: 98 216 (€/year) (Shin & Lee, 2024)

The costs vary depending on the applied tariff structure:

$$C_{\mathrm{OPEX}} = \begin{cases} C_{\mathrm{TCC}} + C_{\mathrm{FCC}} + C_{\mathrm{CYMPC}} + C_{\mathrm{O\&M}} & \text{if No Alternative Transport Tariff} \\ C_{\mathrm{FCC}} + C_{\mathrm{CYMPC}} + C_{\mathrm{O\&M}} & \text{if Time-of-Use Tariff (contracted capacity costs waived)} \\ (1/3)C_{\mathrm{TCC}} + C_{\mathrm{FCC}} + C_{\mathrm{CYMPC}} + C_{\mathrm{O\&M}} & \text{if Time Block Tariff (discounted contracted capacity costs)} \end{cases} \tag{3.19}$$

6. Interest:

The yearly interest costs for the loan are calculated as follows:

$$\mathrm{I} = (C_{\mathrm{inv}} - \sum_{i=1}^{t-1} C_{\mathrm{net,\,i}}) * r \tag{3.20}$$

Where:

- C_{inv} represents initial investment cost: € 1649863
- $\sum_{i=1}^{t-1} C_{\mathrm{net}}$ represents the sum of cash flow over the years preceding, or what has already been payed off to the bank.
- r = Annual interest rate: 6 % (Harris, 2023)

7. Cost Recovery Period and Total Profit:

To determine the cost recovery period, i.e., the number of years until the profit becomes positive:

$$N_{\mathrm{recovery}} = \min\{N \mid Pr_t > 0\}$$

Total profit of the asset is the sum of profit over the 25 year lifespan of the battery, after taxes:

$$Pr_{\mathrm{total}} = T \times \sum_{i=0}^{N} Pr_i \tag{3.21}$$

Where:

- T: profit tax at 25%
- $\sum_{i=0}^{N} Pr$: sum of profit over the lifetime of the battery

This paper assumes constant annual revenues and costs over the period of cost recovery. It also assumes that the investor first pays off all his debt with the available cash flow and until profit is made.

3.3.5. Summary

This chapter presented the mathematical formulation and implementation of the two-stage optimization model for battery operation. The day-ahead model determines an optimal schedule based on forecasted electricity prices, while the intraday model refines this schedule using real-time market updates. The optimization ensures economic feasibility while adhering to technical constraints, making the battery operation efficient and profitable.

3.4. Method: Synthetic Network

The next modeling step is to create a synthetic mid-voltage distribution network model. The goal of this network model is that it represents a distribution network in the Netherlands that experiences congestion. By inserting the original load profile of the system used in the optimization model, as well as the new net load of the system with battery, the network model aims to see what the impact of the battery is on a network. More specifically, this model aims to measure the other two KPI's: line loading and renewable curtailment.

In the evolving landscape of energy systems, the increasing integration of renewable energy sources, the electrification of various sectors, and the growing complexity of power grids necessitate advanced tools for system analysis and optimization. A tool for this analysis is Python for Power System Analysis (PyPSA). This section introduces PyPSA, its functionalities, and its relevance to the synthetic network method applied in this research. PyPSA, is an open-source software tool designed to model, simulate, and optimize electrical power systems. Developed to address the challenges posed by fluctuating renewable energy sources, PyPSA is a tool used by researchers, energy planners, and system operators (Brown et al., 2018). It facilitates the analysis of both operational and investment decisions in energy systems, making it highly suitable for long-term planning and policy development.

PyPSA supports modeling of conventional power plants, including unit commitment and operational constraints, as well as renewable energy sources such as wind and solar, which have variable generation profiles. Additionally, it accommodates energy storage systems like batteries and pumped hydro storage, which are essential for balancing supply and demand in power grids. The software is capable of simulating transmission networks, encompassing both alternating current (AC) and direct current (DC) grids.

The tool models power systems as interconnected networks of components, enabling detailed simulations of energy flows and system behaviors. The core components include buses, which serve as nodes where different elements such as generators, loads, and storage units connect, ensuring energy conservation through the enforcement of Kirchhoff's laws. Generators within PyPSA produce electricity, with outputs that can be optimized based on availability and cost considerations. Loads represent the demand for electricity across various sectors, while storage units play a critical role in maintaining grid stability by storing excess energy and releasing it when needed. The transmission of electricity over varying distances and voltages is facilitated through lines and transformers.

Power flow analysis is an important aspect of PyPSA's functionality, and used in this research to visualize and generate congestion data. The software performs both AC and DC power flow analyses, employing mathematical formulations based on Kirchhoff's laws to calculate voltage levels, power flows, and system losses under different load conditions.

In this paper, PyPSA is employed as the primary tool for implementing the synthetic network method. The synthetic network method involves creating representative models of power systems that capture key characteristics of real-world grids while allowing for controlled experimentation. PyPSA's flexibility in defining network topologies, component parameters, and optimization objectives makes it an ideal platform for this approach.

Because real-life network data is unavailable due to privacy reasons, it was necessary to use a synthetic network. To do this, Ding0 was used. This is a distribution network generator that creates synthetic medium and low voltage power distribution grids based on open data (Ding0, n.d.). It is part of the Open_eGo project, used by different universities in Europe (Amme et al., 2018). The 3608 synthetic topologies created by Ding0 are based on German mid-voltage networks, and cover many different types of distribution networks with different characteristics (% residential nodes, % industrial nodes, generation profiles). The grids were compared with modeled networks with real network data, and found that the grids generated were realistic grids that represent electrical energy systems well (Amme et al., 2018).

The downloaded Ding0 network consists of seven csv files of which four are compatible with PyPSA (buses.csv, generators.csv, lines.csv, loads.csv). Each of these files contains information neccessary for PyPSA to create the network.

- Buses.csv contains the list of buses in the network. Buses are the nodes in the system to which different characteristics can be assigned. For example, whether it is a generator, a household or an office. The buses.csv file contains information about the voltage of the lines connected to it and its the location in the grid.
- Generators.csv contains the list of generators in the system, the type of generator it is, to what bus it is

connected, its voltage level and it's nominal power.

- Lines.csv lists all the names of the lines, the two buses they are connected to, its length and the limit of power which can pass through branch.
- Loads.csv contains the power consumption of the different buses.

3.4.1. Structure of the Model

The synthetic network model developed in this research evaluates medium-voltage power distribution networks with and without battery storage under different tariff scenarios. The process begins with raw data acquisition from the Ding0 platform, which provides detailed datasets on network components. These datasets are cleaned, formatted, and validated to ensure accuracy.

The network is then adapted to reflect the Dutch medium-voltage grid by adjusting key parameters such as voltage levels, line capacities, and transformer settings. Fundamental components—buses, generators, lines, loads, and transformers—are added using the network.add function, ensuring a realistic infrastructure representation. Load profiles derived from the optimization model are integrated to simulate dynamic variations, and additional renewable generators are incorporated to align with the merit order.

To assess battery storage impact, a duplicate network model is created with an integrated battery system, allowing direct comparison with the baseline network. The battery's operational characteristics, including capacity, charge/discharge rates, and efficiency, are defined based on the optimization model.

Finally, power flow simulations analyze system behavior under varying conditions, providing insights into voltage profiles, power losses, line loading, and congestion. The final analysis measures key performance indicators such as line loading levels and renewable energy curtailment at both system and local levels.

3.4.2. Changes to the Network

Due to the size of the network and the fact that it included residential and industrial loads, grid 30901 was chosen (Amme et al., 2018). Initially the network had 24644 buses, 24394 lines, 18680 loads, 633 generators (including residential solar PV installations) and 428 transformers. It is a relatively large network with a significant number of buses and loads, indicating a distribution grid.

While the size of the grid is fitting for the research goal, there are some aspects that need to be altered to represent a Dutch distribution grid. This section explains the modifications to the synthetic power distribution network. The alterations include data preprocessing, network component adjustments, generator configurations, load scaling, and the incorporation of renewable energy profiles. These modifications are important in tailoring the network model to reflect the structural and operational characteristics of the Dutch power system, and important in gaining understanding of the impact of alternative transport tariffs on the dutch system.

Data Preprocessing and Initialization

The modification process starts with importing data from multiple Comma-Separated Values (CSV) files. These files, downloaded from Ding0, contain information on electrical loads, transmission lines, buses, transformers, generators, and switches.

Subsequent to data importation, preprocessing steps are undertaken to address missing values and standardize data types. For instance, the column corresponding to annual energy consumption within the load dataset is explicitly converted to a numeric format. The same logic is applied to the bus and transformer datasets, particularly for parameters such as resistance (r) and reactance (x), thereby ensuring uniformity and consistency across the network model, and avoiding errors in analysis.

Network Filtering and Component Refinement

Following data preprocessing, the network model undergoes a filtering process designed to isolate medium voltage (MV) components. The research focuses only on the mid-voltage grid, so all buses and lines that are part of the low-voltage grid are removed. This filtration is achieved by selecting buses with nominal voltages exceeding 0.4 kV, which typically correspond to MV distribution systems. Consequently, only lines and transformers connected to these MV buses are retained, effectively shrinking the network to focus on the medium voltage infrastructure. It is important to note that when removing the LV buses, their loads were combined to the remaining bus they were connected to, to maintain the distributed load of the system.

Modifications to Generator Configurations

To align the network with the Dutch energy landscape, some changes need to be made in the generation profiles of the network. One of the primary alterations involves the removal of hydroelectric (water-based) generators. This decision reflects the limited contribution of hydroelectric power to the Dutch energy mix. In contrast, the capacities of solar generators are standardized, with their nominal power ratings (p_nom) uniformly set to 15 MW. This helps to increase the solar generation to 14% of the total electricity generation.

To further change the network's renewable energy representation, a new wind park, named "WindPark1," is added into the system. This wind generator is connected to the bus previously associated with one of the removed hydroelectric generators, thereby using existing network infrastructure that can handle large electricity generation. The wind park is assigned a nominal capacity of 30 MW, reflecting the prominence of wind energy in the Netherlands' renewable energy portfolio.

These adjustments change the generation mix to:

- Solar power: 14,1 %
- Wind power: 30,0 %
- Conventional power: 55,6 %

These reflect results from CBS, stating that 48% of electricity generated in the Netherlands comes from renewable sources (Centraal Bureau voor Statistiek, 2024). Before these changes, the generation profile of the network was dominated by conventional generation (89% versus 11% renewables). Before these changes, the network barely had any congestion (1 out of 24394 lines), after adding the renewable generation capacity, congestion was introduced in the system, reflecting the changes that the energy transition has brought in the past decades (International Energy Agency, 2024).

Adjustment of Line Capacities

In the context of the Dutch electricity grid, medium voltage infrastructure exhibits varying capacity levels depending on the specific application and network configuration. MS stations typically have capacities ranging between 10–40 MW, influenced by factors such as station type, connected load, and operational requirements (Netbeheer Nederland, 2019). In industrial areas, particularly energy-intensive clusters like Rotterdam/Moerdijk, the demand for electricity is significantly higher, though specific line capacities are not explicitly defined in available documentation. Conversely, rural grids were historically designed to support lower power demands, necessitating infrastructure upgrades in response to the increasing integration of decentralized renewable generation, such as solar farms (Netbeheer Nederland, 2019). Urban networks, characterized by denser populations and more complex load profiles, typically feature higher redundancy and transport capacities to accommodate fluctuating demand and ensure reliability. While precise MW values for individual lines are not provided, these MS capacity ranges offer valuable benchmarks.

With this information in mind, the line capacities were upgraded to be organized by region and by what they are connected to. This process involves an analysis of each line's connectivity and associated load profiles. Lines connected to renewable energy generators, particularly wind and solar, are assigned capacities based on the connected generator's nominal power, with a multiplier of 1.4 applied to accommodate potential generation peaks. This approach ensures that the network can effectively integrate variable renewable energy outputs without compromising stability. Lines connected to industrial buses or urban buses are set to be minimum of 15 MW, and rural lines at 8 MW.

Construction of the Network Model

Upon completion of data preprocessing and component adjustments, the changed datasets are used to construct the synthetic network within the Python for Power System Analysis (PyPSA) framework. This construction process involves the step-by-step addition of network components, including buses, generators, transmission lines, loads, and transformers. Each component is defined with specific attributes, such as nominal voltage for buses, nominal power for generators, and impedance parameters for lines and transformers.

Integration of Time-Dependent Profiles

To simulate dynamic operational conditions, the network model is configured with time-dependent load and generation profiles. For this, the base load profile from teh optimization model is used (without the battery). Load time series data are distributed across the network based on proportional load weights derived from the static load dataset. This proportional distribution ensures that time-based load variations are accurately reflected in the network model.

Renewable energy generation profiles, specifically for solar and wind, are normalized and integrated into the model. These generation profiles are extracted from the same dataset as the optimizaiton set. Each renewable generator is assigned a time-dependent generation profile proportional to its nominal capacity. The marginal operational costs for these generators are set to zero, consistent with the negligible variable costs associated with renewable energy production, helping maintain the merit order.

Dispatch of Conventional Generators
Following the allocation of renewable generation, the residual system demand is distributed among conventional generators. This residual demand is calculated by subtracting the total renewable generation from the aggregate system load at each time snapshot. The remaining demand is then evenly distributed among available conventional generators, ensuring a balanced load-sharing mechanism. The marginal costs for conventional generators are set at a higher value relative to renewables, reflecting the greater operational costs typically associated with fossil fuel-based generation.

Placement of Battery
In the synthetic model there are no storage assets included. For this analysis, the battery from the optimization is added to the bus connected to the most congested lines. According to the American National Renewable Energy Laboratory, there is significant potential for battery storage systems when placed near highly loaded lines, including increased resilience against extreme weather conditions, reducing distribution losses, and lowering congestion Bowen et al., 2019. The load data resulting from the optimized battery under different tariff types is used as load data for this battery.

Summary of Modifications
In summary, the modifications applied to the synthetic network are designed to enhance its representativeness of the Dutch power distribution system. Key adjustments include the removal of hydroelectric generators, standardization of solar generator capacities, integration of a new wind park, refinement of load classifications, scaling adjustments, and the recalibration of transmission line capacities. Additionally, the incorporation of time-dependent load and generation profiles, along with the optimized dispatch of conventional generators, ensures that the network model can accurately simulate real-world operational conditions over time. These changes provide a foundation for the investigations conducted in this research, further building on the optimization model to gain a greater understanding of the impact of batteries under different tariff structures on power flow through Dutch distribution networks.

3.4.3. Network Analysis
After the network is modified to have more similarities with the Dutch distribution network and the load data from the optimization model is added, the PyPSA power flow analysis is conducted. The PyPSA model executes this with the command network.pf(snapshots = network.snapshots), which means that the power flow is run with a time series. In the background, the model formulates the following power flow equations, this is documented in more detail in the article PyPSA: Python for Power System Analysis by Brown et al (2018). For an overview of the equations built into PyPsa, please refer to Appendix C.

The power flow steps were all integrated into PyPSa, and thus don't need to be coded into the model. The outcomes of the power flow include voltage magnitudes at each bus, active and reactive power flows, system losses and line loadings. The line loadings are extracted from the results and used to calculate line loading and renewable curtailment of the system.

3.4.4. Tracked Results
Line Loading Analysis
Line loading represents the percentage of the transmission line's capacity utilized during power flow. It is calculated using the following formula:

$$\text{Line Loading} = \frac{|P_0|}{S_{\text{nom}}} \times 100 \tag{3.22}$$

where P_0 is the active power flow through the line, and S_{nom} is the nominal capacity of the line. The analysis compares two scenarios: with and without battery integration.

For each network, the maximum line utilization, most congested line, and associated buses are identified. The analysis outputs include:

- Maximum Line Loading: Identifies the line experiencing the highest load.
- Congestion Metrics: Number of lines loaded above 90
- Average Maximum Loading: Indicates general network stress levels.

Congestion Duration Analysis

Congestion duration measures the time a line remains overloaded (loading). It is computed by counting the time steps during which this condition holds:

$$\text{Congestion Duration (hours)} = \sum(\text{Line Loading} > 100\%) \tag{3.23}$$

The analysis identifies:

- Total congested lines.
- Congestion duration for each line.
- System-wide congestion hours.

Curtailment Analysis

Curtailment refers to the reduction in generator output to alleviate line congestion. For each overloaded line, the following steps are performed:

1. Identify connected generators (wind/solar).
2. Calculate the overload amount:
$$\text{Overload} = |P_0| - S_{\text{nom}} \tag{3.24}$$
3. Determine the available curtailment based on actual generation.

The results include:

- Number of curtailment incidents.
- Total wind and solar generation vs. required curtailment.
- Curtailment percentages relative to total generation.

Battery Impact Analysis

The impact of battery integration is assessed both locally (near the battery) and system-wide:

- **Local Impact:** Changes in line loading for lines connected to the battery bus.
- **Congestion Prevention:** Number of overloads prevented or caused.
- **System Metrics:** Average and maximum number of congested lines with/without battery.

Key metrics include:

- Total overloading incidents with and without battery.
- Net change in congestion hours.
- Hours with improved or degraded network conditions.

These analyses provide comprehensive insights into network performance under different configurations, highlighting the role of battery systems in mitigating congestion and enhancing grid stability.

3.4.5. Summary

This chapter presented the method used to measure line loading and renewable curtailment of the Dutch distribution network after the introduction of a battery under new alternative transport tariffs. It discussed the way that PyPSA works and the adjustments made to the synthetic network to more accurately represent the Dutch system. Finally, the method for calculating results were explained.

4 Results

As discussed in previous chapters, this study investigates the impact of different tariff structures on battery performance. The key performance indicators from the literature review will be the foundation upon which the three different tariffs are compared. This chapter shows and discusses the results from the optimization and network model for the Current situation (named No Alternative Transport Tariff), Time of Use tariffs and Time Block tariffs.

The results are presented per type of tariff scenario. The graphs visualize the operations on the two markets over the period of two summer and two winter weeks, the battery's state of charge over time and the distribution of peak loads. The results from these graphs are from the optimization model. They aim to show the battery behavior under different tariff circumstances and understand how non-market measures impact the market behavior of the battery.

Subsequently, the results of the three tariffs are directly compared over the course of a year compared to the absence of a battery. The grid results are from the battery being applied to the network analysis. This helps gain insight into the worth of a battery of this size in a distribution system, and whether it is important to add more storage opportunity to the grid with correct tariff systems. Since grid is so full, the real dilemma for DSOs is either no battery on the grid, or the battery under alternative transport tariffs. This direct comparison helps us gain insight into the mutual concessions and compromises that are made when implementing alternative transport tariffs.

Finally, results from the sensitivity analysis are presented, showing how sensitive the model is to small changes in the input variables.

4.1. No Alternative Transport Tariff

The "No Alternative Transport Tariff" results show how the battery performs without tariff bounds and discounts to their yearly contracted connection costs. The battery can participate on the market whenever is most beneficial to the battery, but has to pay full contracted transport tariffs. In the graphs below the behavior of the battery on the market can be found.

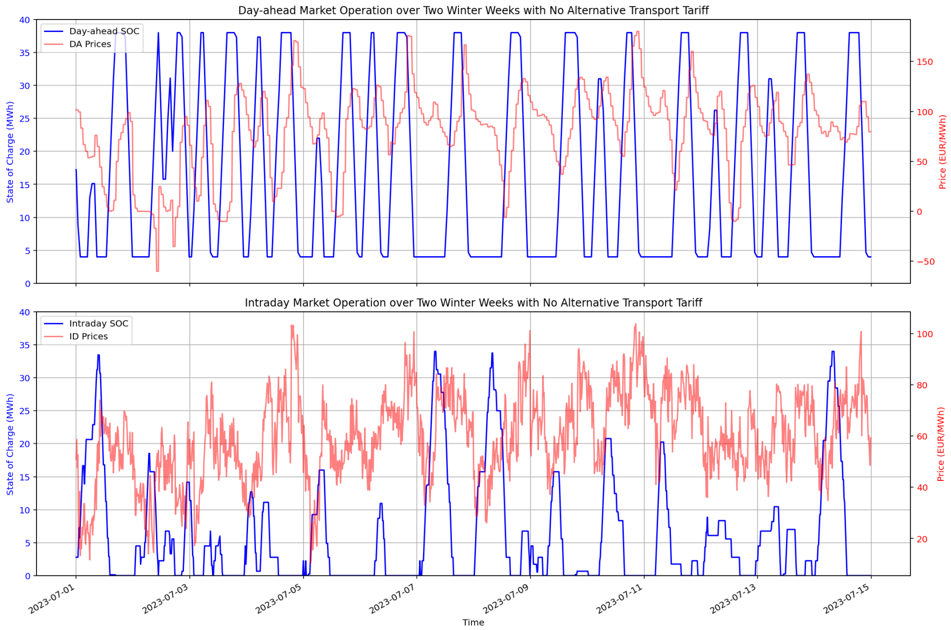

Figure 4.1: No Alternative Transport Tariff: Market Operation Summer

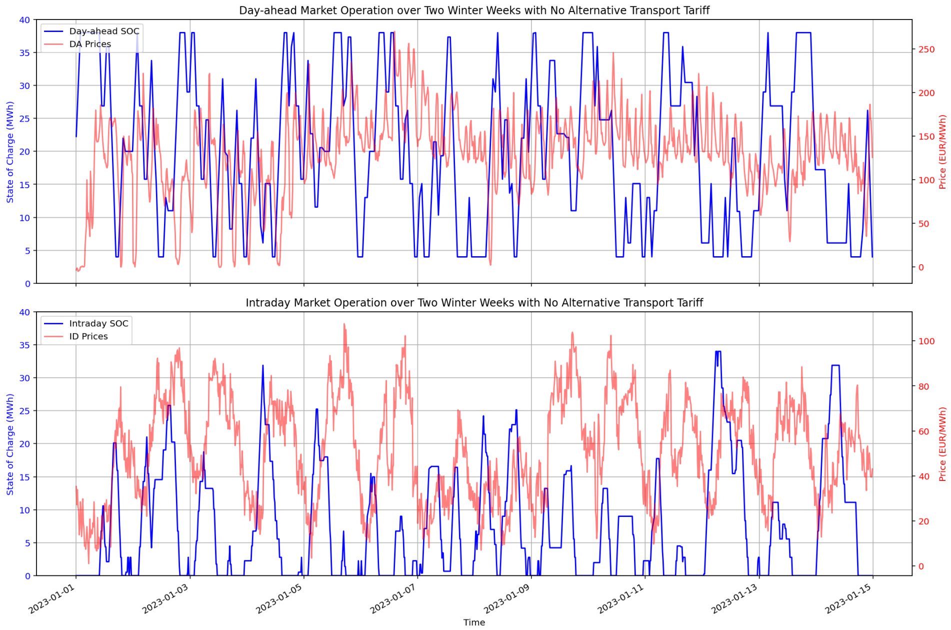

Figure 4.2: No Alternative Transport Tariff: Market Operation Winter

These graphs show the state of charge of charge of the battery over time on the day ahead and on the intraday markets. In red, the day ahead and the intraday prices are shown. From these graphs the behavior of the battery can be clearly seen, As prices increase, the battery discharges the stored electricity and as prices decrease, the battery charges. This is also an important verification visualization as the granularity of both markets are clearly shown: day-ahead prices and also day ahead participation are per hour, for intraday this is every 15 minutes.

The results of the day-ahead and intraday market operations show seasonal differences in battery behavior and price volatility. During the summer, the state of charge (SOC) reveal a cyclical and predictable pattern, driven by consistent daily charge-discharge routines, likely influenced by stable solar generation. Day-ahead prices show some volatility, with the battery discharging during higher price periods, indicating price-responsive operation.

In contrast, winter operations are marked by irregular SOC fluctuations and less pronounced peaks, reflecting the unpredictability of renewable generation and higher demand volatility. Day-ahead prices in winter are more volatile, with sharp spikes suggesting supply constraints. In the intraday market, summer SOC patterns are less regular compared to the day-ahead market but still relatively balanced, responding to moderate price fluctuations. However, in winter, intraday SOC becomes more unpredictable, with extended periods at low levels as the battery aggressively discharges to capitalize on extreme price spikes. This heightened price volatility in winter, both in the day-ahead and intraday markets, highlights the battery's reactive operation, focusing on opportunities during periods of small supply and unexpected demand surges. Overall, the battery operates more predictably in summer, while in winter, its behavior is more reactive, driven by volatile market conditions and grid reliability needs.

The results also show that the battery is very active during both the summer and winter weeks, with more involvement of the intraday market during the winter operation. This can be due to the extremer bidding patterns in the day-ahead market, with the intraday often filling the moments where day ahead operations are low for longer.

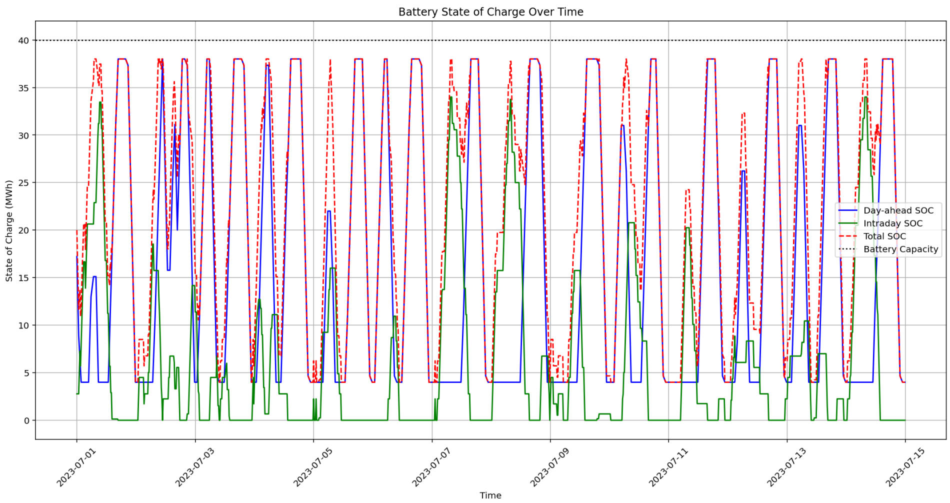

Figure 4.3: No Alternative Transport Tariff: State of Charge Summer

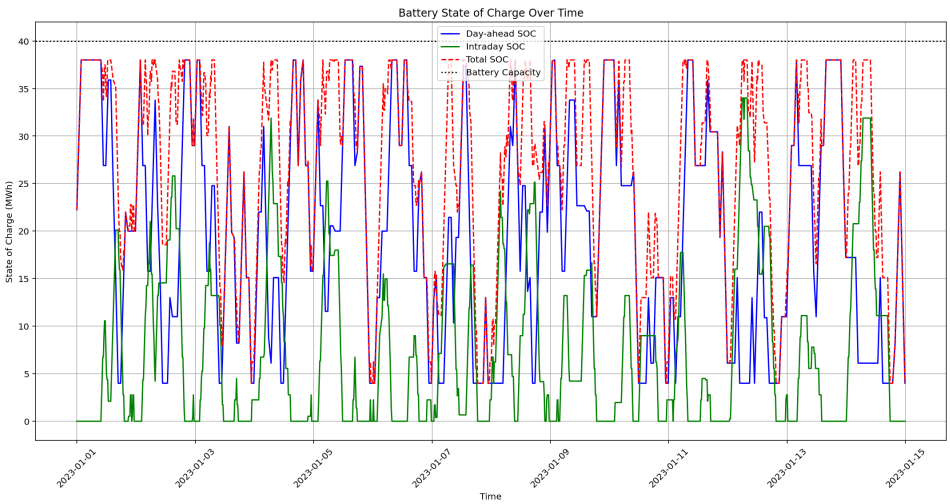

Figure 4.4: No Alternative Transport Tariff: State of Charge Winter

This graph shows the state of charge of the battery over time, the battery capacity, and the impact of the two different markets on the state of charge. Because the day-ahead market closes before the intraday market, the model optimizes behavior for this market first and then bids the remaining state of charge on the intraday market. This graph is also important for model verification as it shows the total state of charge of the battery over the selected period. Despite bidding on two markets, the battery cannot make commitments that exceed its technical constraints. As can be seen, the total state of charge never goes above the maximum or below the minimum allowed. The technical constraints apply only to the total state of charge, allowing the intraday SOC to reach zero as long as the total charge does not.

In the summer, the state of charge is more dominated by day-ahead market participation, with highly regular and cyclical patterns. This regularity is likely due to stable and predictable solar generation, allowing the battery to operate efficiently with consistent charging and discharging cycles. Most small bidding adjustments are managed by the intraday market, which fine-tunes the battery's operation without significantly altering the overall SOC trend. In contrast, during the winter, the intraday market plays a bigger role, as reflected in more irregular SOC patterns. The battery rarely reaches full capacity, and there are frequent periods of low or partial SOC, indicating reactive behavior driven by volatile market conditions and reduced renewable generation. The divergence between day-ahead and intraday SOC is more pronounced in winter, showing that the battery adjusts more dynamically in response to intraday price fluctuations.

Overall, the day-ahead market still dominates the battery's bidding strategy, but the intraday market's influence becomes more significant in winter. The results of this graph complement the previous one, as the summer SOC appears more patterned and predictable, while winter operations are more erratic, reflecting the battery's need to respond to greater price volatility and grid reliability demands.

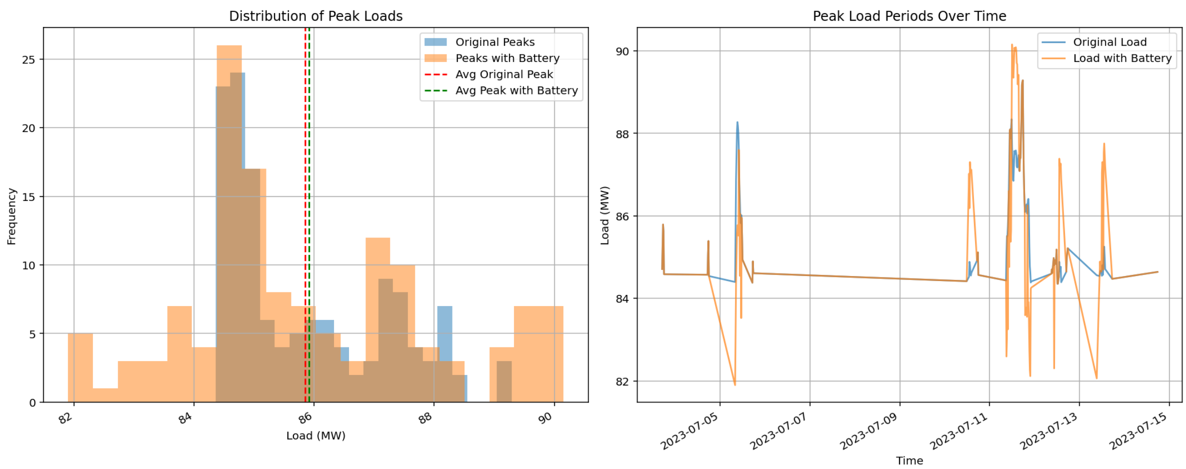

Figure 4.5: No Alternative Transport Tariff: Load Distribution Summer

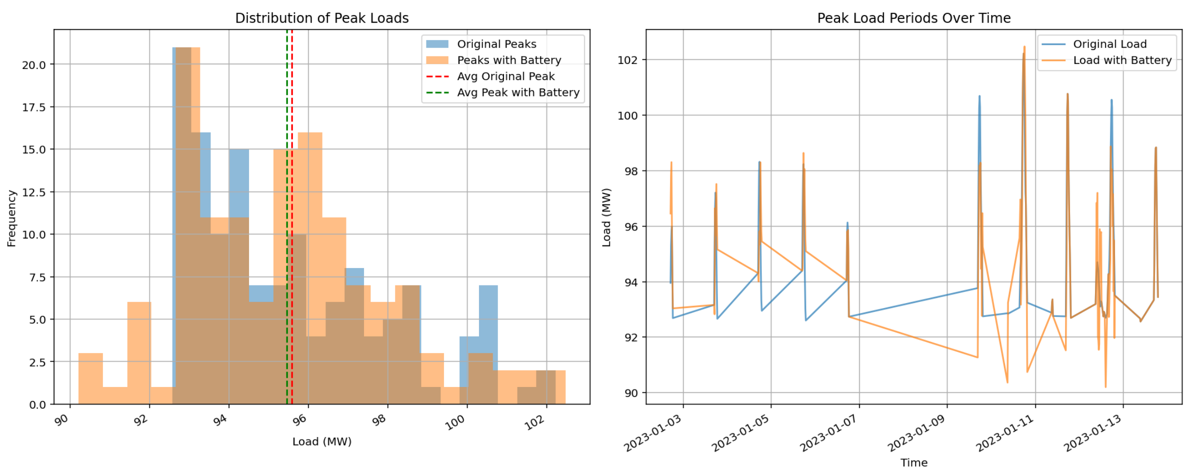

Figure 4.6: No Alternative Transport Tariff: Load Distribution Winter

The figures above illustrate the impact of a battery on load distribution during the summer and winter periods, respectively. In Figure 4.5, the summer load distribution shows that the battery shifts peak loads, though not always positively. The histogram indicates an increase in the frequency of higher peak loads in the winter, with the average peak load (green dashed line) slightly higher than the original (red dashed line). However, the shift is not uniform: while some peaks are reduced, others remain relatively unaffected as can be seen by the image on the right. This suggests that the battery's impact is conditional, likely influenced by market conditions, demand patterns, and the battery's operational constraints. The time series graph shows periods where the battery flattens load spikes, but also instances where its effect is minimal, indicating that a battery's market participation doesn't always result in flattening peaks.

In contrast, Figure 5.6, representing the winter load distribution, shows a slightly more effective reduction in peak loads. In winter, the battery reduces the overall peak load but also introduces some new peaks, however to a lesser extent than in summer. The battery smooths out the load profile more effectively, as evident in the time series graph, where peak periods are slightly flattened. Unlike in summer, the battery does not introduce as many new fluctuations, suggesting a more consistent focus on peak shaving. This could be due to the higher and more sustained demand levels in winter, where the battery's operation is driven by the need to manage prolonged peak periods rather than frequent short-term arbitrage opportunities. Additionally, the volatile winter market conditions may create stronger price signals that align battery operation.

Overall, the battery demonstrates a more effective peak load reduction in winter compared to summer, though its impact is limited and sometimes negative. In summer, the battery's frequent cycling behavior, driven largely by economic optimization strategies in response to market signals, results in a mixed effect: while the battery successfully reduces some of the highest peaks, it also introduces new, smaller fluctuations. This suggests that the battery's operation prioritizes short-term opportunities, responding to price volatility rather than focusing on load smoothing. As a result, while some peak loads are mitigated, the overall load profile exhibits increased variability, suggesting the limited ability of the battery's effectiveness in reducing aggregate peak demand. In contrast, during winter, the battery operates with greater consistency in peak load reduction. The higher and more sustained demand levels, coupled with pronounced price spikes, create conditions where peak shaving aligns more closely with economic optimization. The battery responds by targeting significant load peaks more effectively, reducing both the magnitude and frequency of extreme load events. The load profile in winter appears smoother, with fewer instances of sharp fluctuations compared to without the battery removing two high peaks.

This seasonal variation highlights the complex interplay between technical constraints, market dynamics, and operational strategies. While the battery performs some peak shaving in both seasons, its behavior adapts to external conditions: in summer, market-driven cycling introduces variability, whereas in winter, sustained demand and stronger price signals enhance its role in effectively mitigating peak loads but also leading to some new peaks also. The battery's constraints that include charging in periods with high renewable forecasted and discharging with low renewable forecasted also play a role in this. Since the battery's operation is solely market-driven and does not account for real-time grid congestion, its ability to provide consistent peak shaving is limited.

4.2. Time of Use Tariff

The Time of Use tariff is one of the newly introduced alternative transport tariffs in the Dutch electricity system. For now it has only been introduced on the transmission grid, here we test whether it can positively impact the distribution grid. The tariff structure allows connections to the grid to forego the contracted transport costs for limiting their participation of the grid for a maximum of 15% of the time. This tariff has been applied to the 40 MWh battery and the following results were extracted.

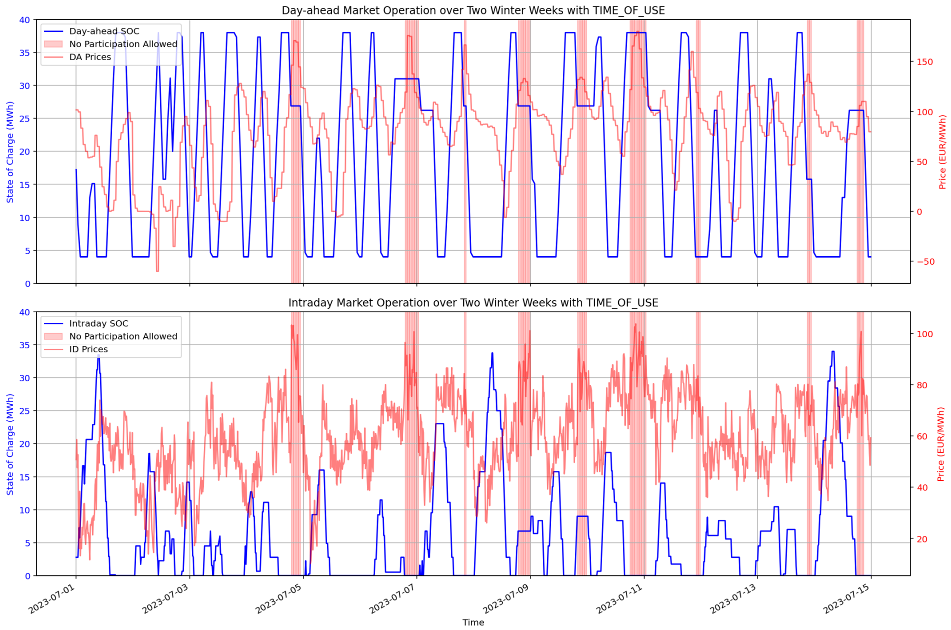

Figure 4.7: Time of Use Tariff: Market Operation Summer

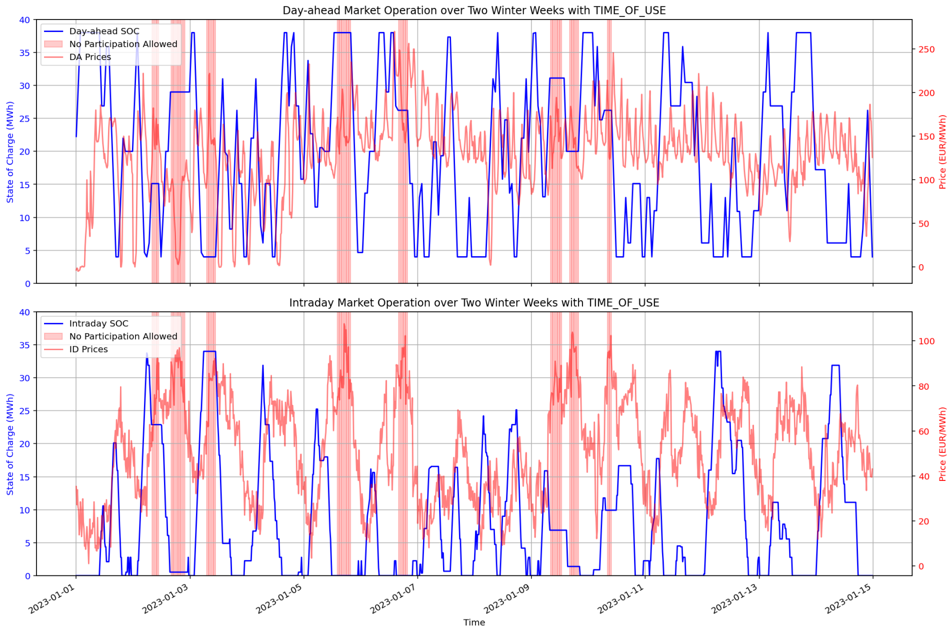

Figure 4.8: Time of Use Tariff: Market Operation Winter

The figures above show the battery's operation in the day ahead and intraday markets under the Time of Use (TOU) tariff during summer and winter periods respectively. They illustrate the impact of TOU restrictions on battery behavior on both electricity markets. The goal of this is to find out what impact this tariff has on the battery's participation and the grid's congestion. The areas shaded red are the periods that the battery cannot participate on the market.

In the day-ahead market during summer (figure 4.7), the battery's state of charge (SOC) exhibits the similar cyclical pattern as seen in the no tariff situation, with frequent charging and discharging cycles. The SOC often reaches its maximum capacity, suggesting aggressive charging during low-price periods and discharging during price peaks. This pattern reflects the battery's ability to optimize for price changes effectively when market signals are stable and predictable. However, the TOU restrictions create periods of inactivity, where the SOC remains flat despite the presence of price spikes. This suggests that while the battery is economically optimized outside restricted periods, its flexibility is constrained during TOU windows, potentially limiting revenue opportunities.

In contrast, the winter day-ahead market (figure 4.8) presents a more irregular SOC pattern with longer periods at partial charge levels. The battery's operation appears less predictable, driven by the higher volatility of winter DA prices. Although the battery still targets price peaks, its response is less consistent compared to summer. Notably, TOU restrictions in winter have a bigger effect, as the battery is unable to respond to some of the highest price events. This indicates a trade-off between tariff compliance and the ability to fully exploit market opportunities, particularly in volatile conditions.

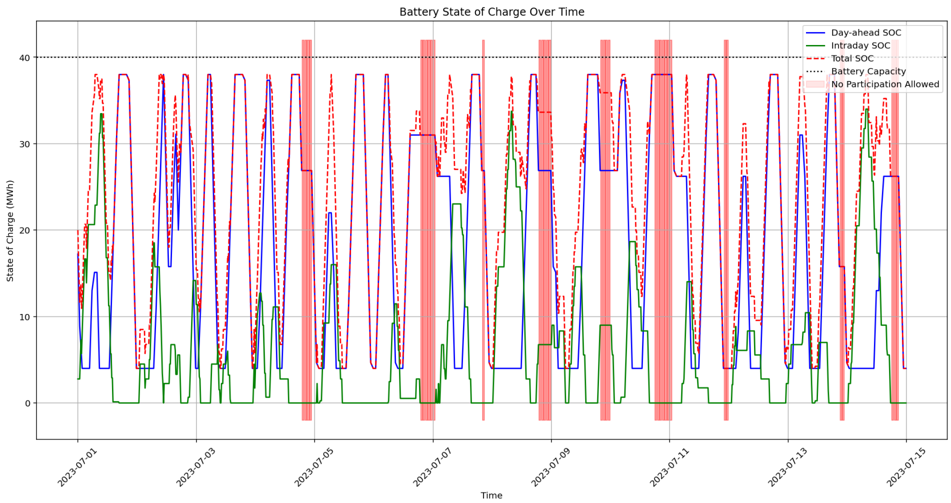

Figure 4.9: Time of Use Tariff: State of Charge Summer

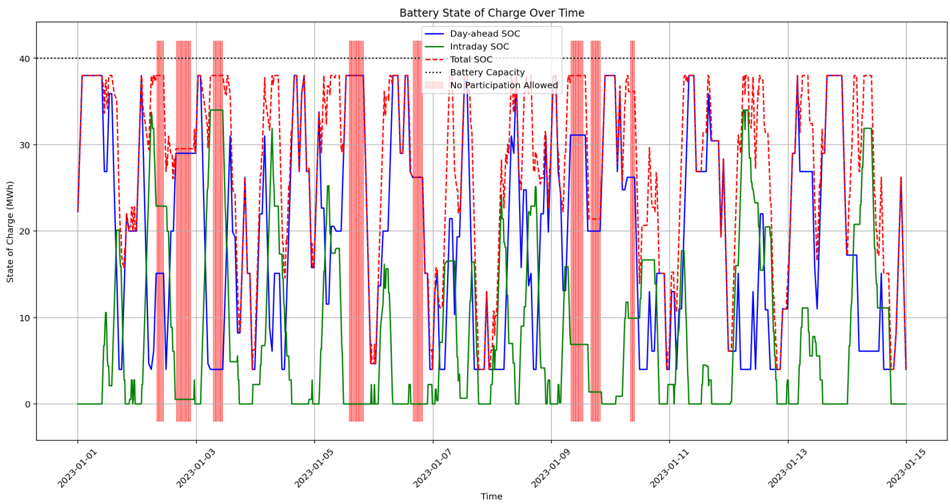

Figure 4.10: Time of Use Tariff: State of Charge Winter

While the market operation graphs suggested that both the day-ahead (DA) and intraday (ID) markets play significant roles, the SOC plots make it clear that the DA market heavily dominates battery behavior in the summer. The regular SOC cycles align closely with DA patterns, indicating that the battery optimizes its charging and discharging around DA commitments, with the ID market making only marginal adjustments. This wasn't as apparent in the price operation graphs, where ID activity seemed more prominent due to price fluctuations. In the market operation figures, TOU restrictions were visible through gaps in participation, but the SOC graphs reveal their deeper operational impact. The SOC remains completely flat during these restricted periods, even when there's available capacity and potential economic opportunities. This implies not just missed profit opportunities but also that the battery's operational flexibility is constrained. It's not merely avoiding trading—it's essentially "frozen," as is mandated by the tariff system. The SOC graphs highlight that in winter, the battery frequently reaches both its maximum and minimum capacity limits—something not as evident from the market operation graphs. This suggests the battery is under more operational stress in winter, aggressively cycling in response to volatile price signals. It indicates a more reactive behavior, driven by price spikes and the need to quickly shift between charging and discharging. This extreme cycling could have long-term implications for battery degradation, which isn't visible in the market operation data. While the market operation graphs showed volatile intraday prices, the SOC graphs illustrate that the intraday market serves as an important corrective mechanism in winter. The SOC frequently adjusts after DA market decisions, indicating that intraday trading is used to re-balance the battery's position in response to unexpected price shifts or DA forecast errors. This dynamic corrective behavior wasn't fully visible when focusing only on price and participation graphs. These SOC insights reveal that battery operation isn't just about following price signals—it's a complex balancing act between technical constraints, market optimization, and regulatory compliance. The SOC graphs expose hidden dynamics, such as the battery's limited flexibility during TOU restrictions, aggressive cycling in winter.

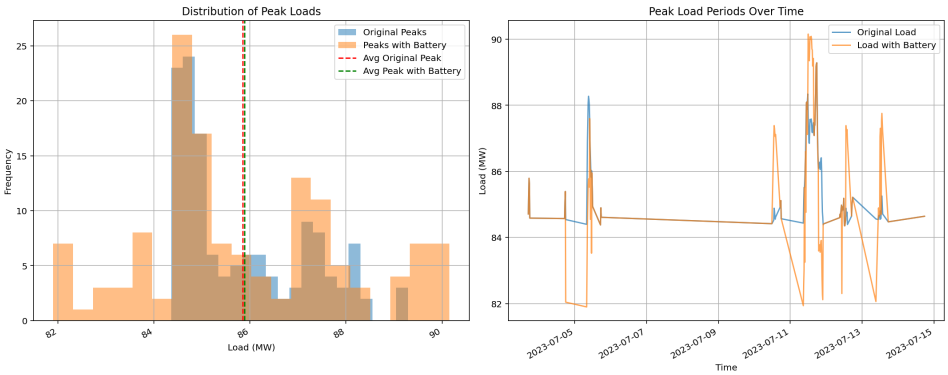

Figure 4.11: Time of Use Tariff: Load Distribution Summer

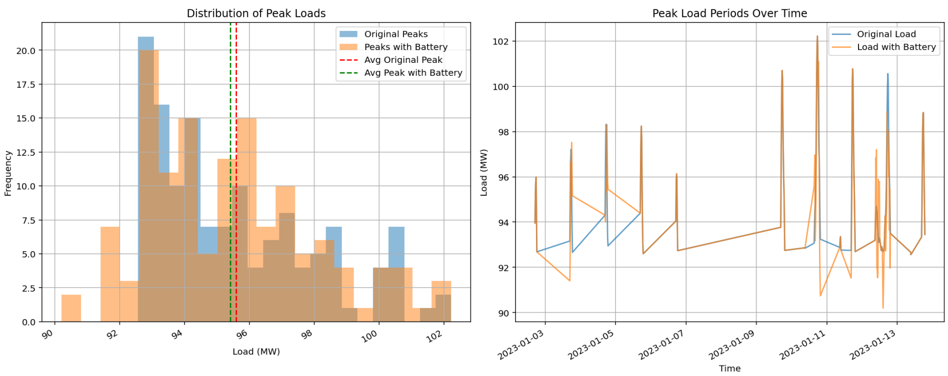

Figure 4.12: Time of Use Tariff: Load Distribution Winter

Figures 4.11 and 4.12 illustrate the load distribution and peak load periods under the Time of Use (TOU) tariff for summer and winter, respectively, providing a comparison with the No Alternative Transport Tariff (No ATT) scenarios from Figures 4.5 and 4.6. In the summer (Figure 4.11), the battery's impact on peak load reduction under TOU appears limited. The histogram suggests a redistribution of peak loads rather than a clear reduction. While the battery reduces some peaks, it also increases the frequency of others. These constraints limit the battery's ability to respond freely to all peak periods, reducing its overall effectiveness in load smoothing. The time series graph further supports this observation, showing that although the battery reduces certain peaks, it also introduces new fluctuations and, at times, closely mirrors the original load profile. This inconsistency suggests that the battery's ability to manage peaks is hampered by TOU restrictions, leading to missed opportunities for effective peak shaving.

In contrast, the battery's performance in winter (Figure 4.12) is slightly more effective under TOU. The histogram shows a shift in peak load distribution, with reductions in certain extreme peaks but also the persistence of others. While the average peak load appears slightly lower, the effect is not entirely consistent, suggesting that TOU-driven battery operations mitigate but do not eliminate peak occurrences. This suggests that the battery operates more effectively during winter TOU periods, likely driven by stronger economic incentives due to higher price volatility and increased demand variability. The time series graph confirms this trend, showing some reductions in peak load magnitudes and durations. In winter, TOU constraints align more closely with periods of high demand, improving battery effectiveness in peak shaving. However, the effect is not uniform—some peaks persist, and increased cycling may contribute to new fluctuations.

When comparing these results to the No ATT scenarios, it becomes clear that the battery's performance varies significantly with seasonal conditions and tariff structures. In winter, the battery achieves more pronounced peak reductions under TOU than under No ATT, suggesting that TOU tariffs help concentrate battery operations during critical periods, thereby improving load management when demand volatility is high. Conversely, in summer, the battery performs better without ATT, as the absence of operational constraints allows for greater flexibility in responding to market signals. Under TOU, the battery's peak shaving potential is restricted, leading to more variable load profiles and less effective reductions in average peak loads. Overall, while No ATT allows the battery to optimize freely for price signals and technical constraints, TOU tariffs encourage peak shaving in winter, but their effectiveness remains mixed.

4.3. Time-Block Tariff

Figures 4.13 and 4.14 illustrate the battery's operation in the Day-Ahead (DA) and Intraday (ID) markets under the Time Block Tariff (TB) for both summer and winter seasons. The grey shaded areas represent Time Blocks where market participation is restricted (22:00-06:00), impacting the battery's charging and discharging behavior.

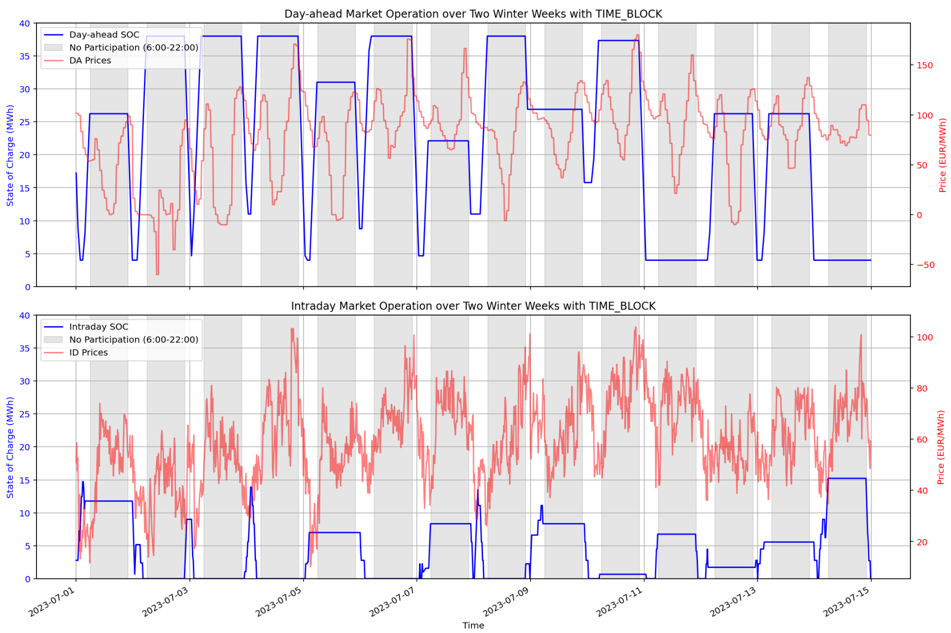

Figure 4.13: Time Block Tariff: Market Operation Summer

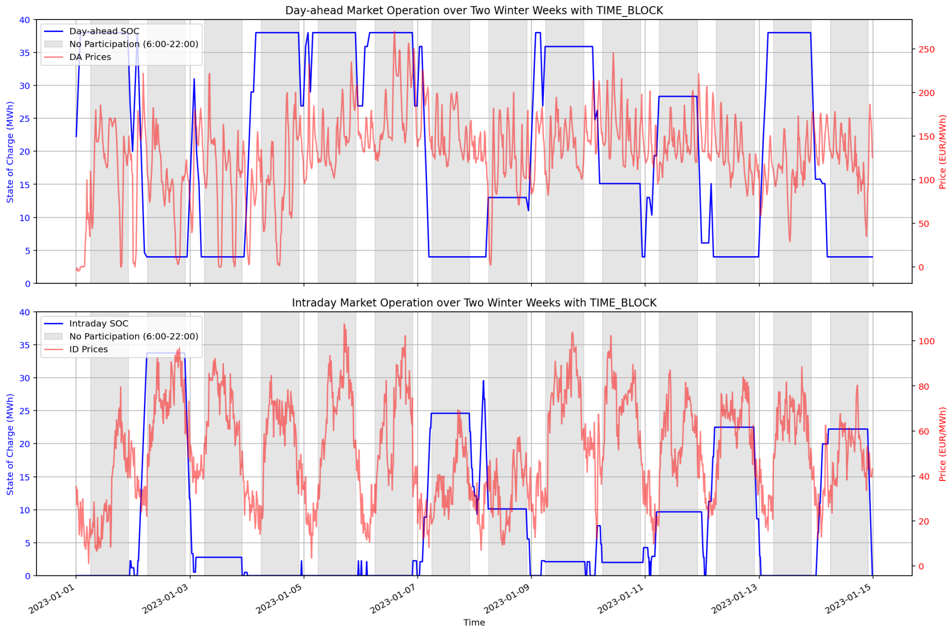

Figure 4.14: Time Block Tariff: Market Operation Winter

In the summer day-ahead market (Figure 4.13, top panel), the battery exhibits a regular and cyclical SOC pattern, with aggressive charging and discharging cycles outside the restricted Time Blocks. During the restricted periods, the SOC remains flat, indicating a complete halt in market participation. This leads to missed opportunities for arbitrage, especially when price spikes occur within these periods. To compensate, the battery adjusts its strategy by increasing its activity immediately before and after the restricted windows, as seen in the steep SOC changes during these transitions. In the intraday market (Figure 4.13, bottom panel), the SOC fluctuations are more erratic, reflecting frequent short-term adjustments to volatile price signals. Despite this, the operational gaps during restricted periods are evident, limiting the battery's ability to respond to sudden price spikes that occur within these windows.

In contrast, winter operations (Figure 4.14) present a more complex picture. In the day-ahead market (top panel), the SOC pattern is less predictable compared to summer, with the battery frequently reaching both its minimum and maximum capacity limits. This behavior reflects the higher price volatility and demand variability typical of winter. The restricted Time Blocks coincide with some of the highest price peaks, yet the battery remains inactive during these critical periods, resulting in significant missed revenue opportunities. The battery's ability to provide peak-shaving services is also limited, as it cannot respond during key periods of grid stress. In the intraday market (bottom panel), the SOC shows intense fluctuations outside the restricted periods, with rapid charging and discharging cycles reflecting the battery's reactive approach to volatile market conditions. Similar to the DA market, the battery remains idle during restricted periods, even when sharp price movements present profitable opportunities.

Key insights emerge from these observations. First, the impact of Time Block restrictions is significant, creating operational gaps during periods of high price volatility, particularly in winter. This results in missed opportunities for both profit and grid support. Additionally, the battery adjusts its activity by increasing operations before and after restricted Time Blocks to maximize market opportunities. Finally, the restrictions significantly limit the battery's peak-shaving capabilities, particularly in winter when peak demand events are more severe. This suggests that while Time Block tariffs may help manage grid congestion, they can also reduce the operational effectiveness of energy storage systems, especially during periods of high grid stress.

Time Block tariffs greatly impact the opportunities that the battery has to participate on the market. Under No ATT, the battery has greater operational flexibility, with frequent SOC fluctuations that closely follow price dynamics in both the day-ahead and intraday markets. This flexibility allows the battery to react quickly to price spikes, maximizing profit opportunities. In contrast, the Time Block Tariff significantly limits the battery's responsiveness during critical periods. The battery compensates for these limitations by increasing its activity immediately before and after the restricted Time Blocks, leading to steeper SOC gradients around these transitions. However, this compensatory behavior cannot fully offset the missed opportunities during restricted periods, particularly in the winter when price volatility is higher. Another key difference is how the battery interacts with the day-ahead (DA) and intraday (ID) markets. Under No ATT, the battery is able to use both markets to optimize its performance, responding to DA price forecasts while making real-time adjustments in the ID market. In contrast, the Time Block Tariff creates discontinuities in market participation, particularly in the intraday market. The battery is unable to adjust its position during restricted periods, reducing its ability to respond to real-time price spikes. This is especially important in winter, where intraday price volatility is high, and the inability to participate during critical hours leads to reduced profitability and less participation on the grid, possible making less impact on congestion and the grid.

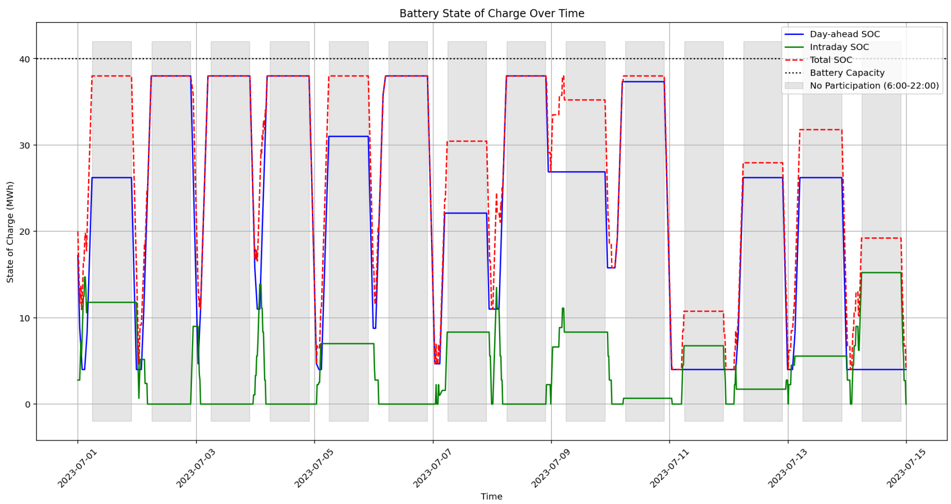

Figure 4.15: Time Block Tariff: State of Charge Summer

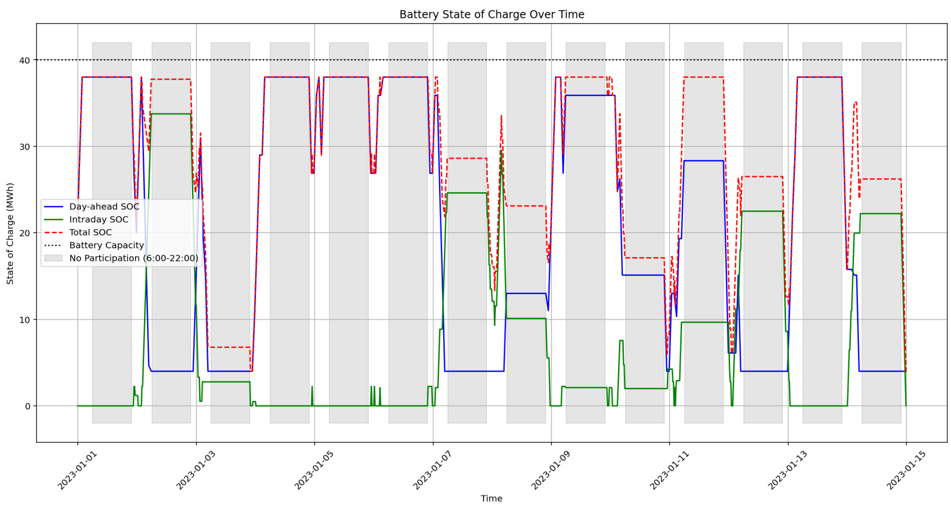

Figure 4.16: Time Block Tariff: State of Charge Winter

These graphs further visualize the findings from the previous section, highlighting that Time Block tariffs greatly impact the flexibility and participation of the battery on the grid. The hours in which the battery is active the battery can quickly charges or discharges, but cannot fully discharge or charge when that is profitable. In this case, the day ahead market has a dominant stake in SOC, with intraday acting as a corrective mechanism when possible.

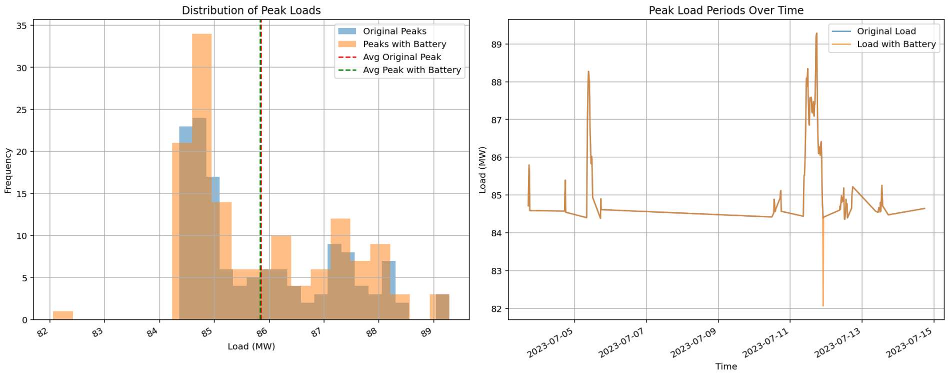

Figure 4.17: Time Block Tariff: Load Distribution Summer

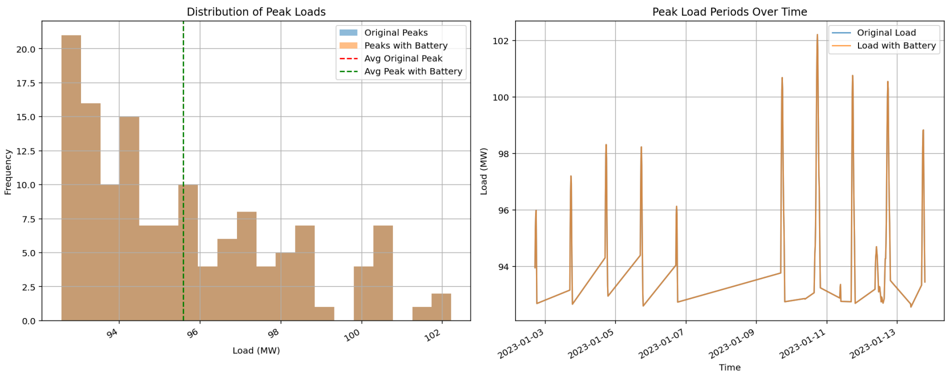

Figure 4.18: Time Block Tariff: Load Distribution Winter

The histogram shows that the battery has a limited impact on reducing peak loads in summer. While there's a slight shift in the average peak load (green dashed line) compared to the original (red dashed line), the reduction is minimal. The frequency of mid-range peaks increases, suggesting that although the battery reduces some extreme peaks, it also introduces new smaller peaks due to frequent cycling outside restricted periods. This indicates that Time Block restrictions limit the battery's flexibility, particularly during high-demand periods in the evening when the battery cannot operate.

The time series graph shows that the battery reduces certain peaks but lacks consistency, especially during restricted periods, where its impact is diminished. The load with the battery (orange line) often mirrors the original load (blue line), with only minor reductions in peak magnitudes. With one notable reduction halfway through the second week. Peaks occurring within restricted periods remain largely unaffected, highlighting missed opportunities for peak shaving during critical times.

In Figure 5.18, the addition of the battery under the Time Block Tariff (TB) shows minimal to no change in the load distribution and peak load periods over time. The histogram of peak loads reveals that the average peak load with the battery (green dashed line) is nearly identical to the original average peak load (red dashed line), with the frequency distribution of peaks remaining largely unchanged. This suggests that the battery has failed to meaningfully reduce peak loads during the winter period.

The time series graph further confirms this, as the load with the battery (orange line) almost perfectly overlaps with the original load (blue line). There are no significant reductions in peak magnitudes or changes in peak load timing. This indicates that the battery's operational constraints under the Time Block Tariff—particularly the restrictions on market participation during critical evening hours (likely 16:00–22:00)—are severely limiting its ability to provide any effective peak-shaving or load-smoothing services in winter.

These results above show the impact that tariffs have on battery behavior. Next, the results will be analyzed compared to the current situation in the Netherlands, namely the alternative that without the tariffs, the battery cannot be connected to the grid.

4.4. Annual Battery Performance

The previous results all stemmed from the optimization model, now the true impact of the battery on the grid will be discussed.

Annual KPI Results	**No Battery**	**No ATT**		**Time of Use**		**Time Block**	
		Value	**Δ**	**Value**	**Δ**	**Value**	**Δ**
Number of lines with overloading	582	361	-38%	361	-38%	593	+2%
Required Curtailment (MWh)	25	18	-28%	19	-24%	23	-8%
Cost Recovery Period (year)	N.A.	18.45	N.A.	18.63	N.A.	inf.	N.A.

Table 4.1: Annual Performance Metrics for Tariff Systems (Baseline: No Battery)

Table 4.1 shows the results of the battery over the course of a year, tested by the indicators from literature review. The data for summer and winter were combined by multiplying all metrics by 13 and adding summer and winter. Here it is assumed that combining thirteen times two summer weeks and thirteen times two winter weeks will even out and represent a Dutch year. These results highlight the trade-offs between technical efficiency and financial viability, with each tariff structure exhibiting its own strengths and weaknesses.

The number of overloaded lines was used as an indicator of network stress under each tariff structure. In the No Battery scenario, the system experienced significant congestion, with 582 lines exceeding their capacity limits during the year. Implementing No ATT and TOU tariffs resulted in a substantial 38% reduction, bringing the number of overloaded lines down to 361. This suggests that these tariff structures contribute to load redistribution, alleviating stress on critical network components. In contrast, the Time Block tariff led to a slight increase in the number of overloaded lines, rising to 593, which represents a 2% increase compared to the baseline. This result indicates that, while the Time Block tariff may influence consumption behavior, its effect on grid congestion appears to be counterproductive in this specific case.

Curtailment of excess electricity was also analyzed as a measure of the system's ability to balance supply and demand. In the No Battery scenario, the system required 25 MWh of curtailment to maintain stability. Under the No ATT tariff, curtailment was reduced by 28%, resulting in 18 MWh. Similarly, the TOU tariff led to a 24% decrease, requiring only 19 MWh of curtailment. These reductions suggest that pricing mechanisms such as No ATT and TOU can help shift demand patterns, reducing instances of surplus energy that would otherwise require curtailment. The Time Block tariff also contributed to a reduction in curtailment but to a lesser extent. Curtailment under this tariff was 23 MWh, reflecting an 8% decrease from the No Battery baseline. While this indicates some improvement, it is notably less effective than the other two tariff structures. The moderate reduction suggests that the rigid structure of Time Block pricing may limit its ability to efficiently balance load distribution across different periods.

The cost recovery period, representing the number of years required for investments in the tariff system to break even, varied significantly between scenarios. Since the No Battery case does not involve additional infrastructure investments, no cost recovery period was applicable. For the No ATT and TOU tariffs, the cost recovery periods were 18.45 and 18.63 years, respectively. These values are relatively close, indicating that both tariff structures yield comparable financial viability in terms of long-term revenue recovery. In contrast, the Time Block tariff resulted in an infinite cost recovery period, suggesting that under current conditions, the revenue generated from this tariff structure is insufficient to cover investment costs. This may be due to inefficiencies in the way the pricing structure influences consumer behavior or an imbalance between the incentives provided and the costs incurred by the system.

Overall, the results suggest that No ATT and TOU tariffs are more effective at reducing congestion and curtailment while maintaining financial viability. In contrast, the Time Block tariff appears to have a negative impact on overloading, a moderate impact on curtailment, and no feasible cost recovery period. These findings provide quantitative evidence of how different tariff structures impact grid performance and financial sustainability.

4.4.1. Additional Observations

Beyond the predefined KPIs, further analysis reveals additional insights related to congestion hours, market revenue, and total profit, which provide a broader perspective on the performance of different tariff structures.

An interesting pattern emerges when examining total congestion hours compared to the situation without battery. The No ATT scenario records an increase of congestion with 988 hours, indicating prolonged periods of network strain. In contrast, both TOU and Time Block tariffs result in negative congestion hours compared to the grid without battery (-845 and -429, respectively). This suggests that these tariff structures actively reverse existing congestion patterns, potentially through more efficient load redistribution. The TOU tariff demonstrates the strongest congestion reduction, likely due to its dynamic pricing model, which incentivizes battery discharge during peak periods, thereby alleviating grid stress.

From an economic perspective, the No ATT tariff yields the highest market revenues. It generates EUR 1,163,997.12 in day-ahead revenue and EUR 208,551.98 in intraday revenue, totaling EUR 1,372,549.10. This revenue dominance suggests that, despite its less effective congestion and curtailment performance, the No ATT tariff remains financially robust, possibly due to high market participation and stable pricing mechanisms. The TOU tariff follows with a total revenue of EUR 1,231,734.27, reflecting a more balanced approach between economic and technical performance. However, the Time Block tariff significantly underperforms, yielding only EUR 439,665.85 in total market revenue, which represents a substantial reduction compared to the other tariffs. This suggests that the Time Block pricing structure may introduce inefficiencies that limit market activity. For context, the initial battery investment cost was EUR 10,498,630, providing a benchmark against which these revenue figures can be assessed.

The overall total lifetime profit of the battery follows similar trends to the cost recovery period results. The TOU and No ATT tariffs yield similar total profits of approximately EUR 3.8 million, with the No ATT scenario generating around EUR 25,000 more in lifetime profit. This suggests that, while alternative tariffs may contribute to grid stability, they do not necessarily enhance the financial outcomes for battery owners. The absence of alternative transport tariffs appears to be the most profitable scenario, reinforcing the economic strength of the No ATT model.

It is interesting to note the difference between the grid results and the optimization's results on total load. The optimization peak load distribution suggested that the Time of Use tariff wouldn't greatly impact congestion, however after integrating it into a grid and allowing power flow analysis over multiple congestion metrics, it shows that it does impact congestion.

In conclusion, the performance metrics suggest that TOU offers the best overall balance between technical efficiency and economic viability. It excels in reducing congestion hours, and maintaining strong revenue streams. No ATT performs well economically but falls short in congestion and curtailment management. Time Block, while effective in reducing renewable curtailment, struggles with grid improvements and financial sustainability. These findings are consistent with the trends observed in the earlier curtailment and congestion graphs, where TOU consistently demonstrated superior performance in managing grid stability and economic outcomes.

4.5. Sensitivity Analysis

A sensitivity analysis evaluates how responsive the outputs of a model are to small variations in its input parameters (Razavi et al., 2021). This approach involves adjusting one input parameter at a time while holding others constant, then observing the corresponding changes in the model's results. By doing so, it becomes possible to identify which parameters have the greatest influence on the model's performance and to what extent these variations affect the overall outcomes. The second sensitivity analysis looks at the impact of choosing two summer and two winterweeks to represent a year. This is a simplified analysis with two Spring weeks and two Autumn weeks from 2023.

In the first analysis, input parameters of the optimization were modified to assess their individual impact. The sensitivity analysis is limited to the parameters of battery optimization because the state of the grid is viewed as given, and the focus is more on the impact of the battery behavior. Where feasible, the sensitivity testing values were selected to either halve or double the original parameter to capture the effect of significant proportional changes. In cases where doubling was not practical—such as parameters expressed as percentages with upper limits, like 80%, alternative values were chosen to create linear differences by adding or subtracting fixed amounts. This method ensures that the analysis captures both proportional and absolute shifts in input parameters, offering a better understanding of their influence on the model's results. Also, the uncertainty of the parameter is given, this means how likely it is for the parameter have this value. The values, uncertainty and reasoning for changes can be found in a table in Appendix C.

To visualize the sensitivity analysis, tornado charts were constructed per KPI. These show the percentage change that the new value had on the original value. The KPIs most impacted were day ahead profits, intraday profits, net improvement of lines and peak load change.

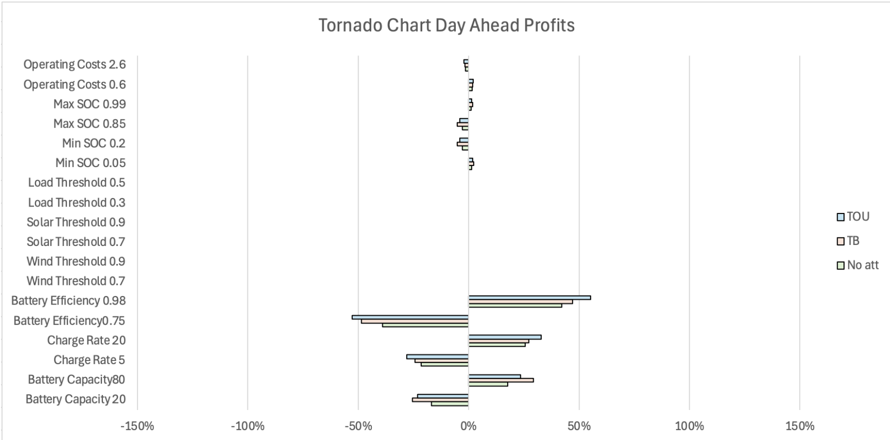

Figure 4.19: Tornado Chart Day Ahead Profit

The tornado chart for day-ahead profits highlights the sensitivity of profits to various parameters. The most influential factors appear to be charge rate, battery capacity, and battery efficiency, with significant variations observed under different tariff structures (TOU, TB, No Att). Higher charge rates and larger battery capacities tend to positively impact profits, while efficiency losses reduce profitability. The impact of operating costs and state of charge (SOC) constraints is smaller in comparison but still notable.

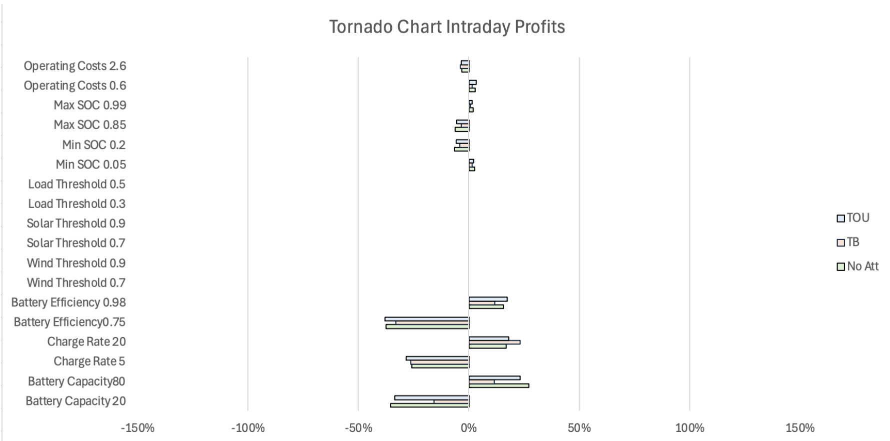

Figure 4.20: Tornado Chart Intraday Profit

The intraday profits tornado chart follows a similar pattern to the day-ahead profits but with generally lower variations. Battery-related parameters (efficiency, charge rate, capacity) remain dominant, showing that the ability to store and release energy efficiently is crucial for arbitrage opportunities. The operating cost variations also show an impact, but their influence remains secondary to battery performance. Differences between TOU and TB pricing schemes are present but do not drastically alter the hierarchy of sensitivity.

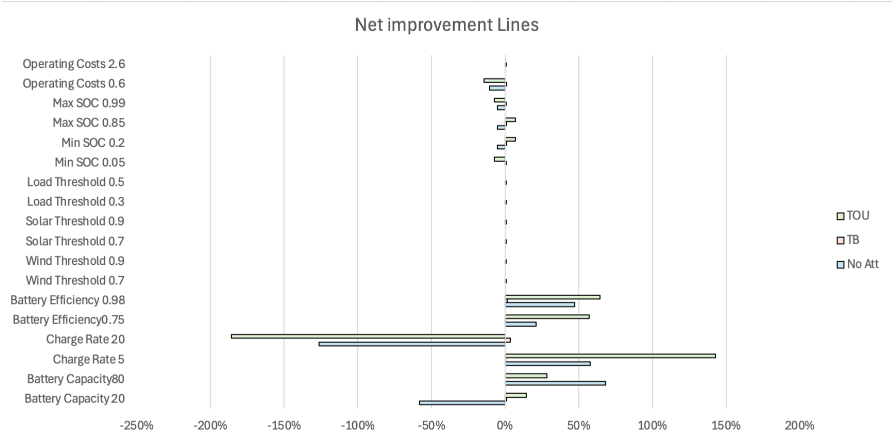

Figure 4.21: Tornado Chart Net Improvement Lines

This chart illustrates the net improvement in profits under different parameter variations. Interestingly, the impact of charge rate and battery efficiency becomes more pronounced, with some scenarios even showing negative net improvements, implying that certain parameter variations might cause losses. This suggests that while flexibility is valuable, operating outside optimal battery configurations can diminish the expected gains. Large negative swings indicate that poor battery sizing or inefficiencies can severely impact profitability.

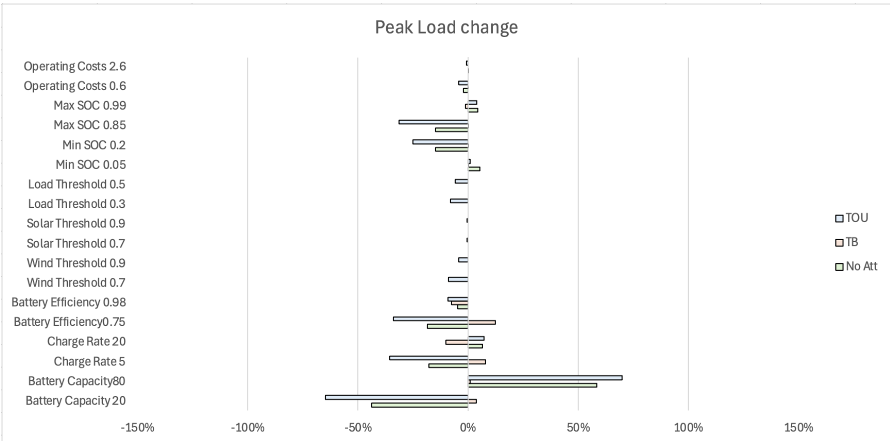

Figure 4.22: Tornado Chart Peak Load Changes

The peak load sensitivity chart shows a wider spread of variations, particularly with load and generation thresholds. This graph suggests that peak load reduction benefits are not just dictated by economic incentives but also by operational constraints. The results confirm that battery management strategies can influence grid congestion, but external factors like renewable generation and load profiles play an equally crucial role. The most sensitive parameters remain battery charge rate, capacity, and efficiency, reinforcing the idea that battery flexibility is a key driver of economic performance. The variations observed align with expectations, as higher efficiency and faster charge rates lead to better outcomes, while constraints on SOC and load/generation thresholds create deviations. One unexpected observation is the high degree of negative impact in the net improvement chart, particularly when charge rates and battery parameters deviate from optimal values. This suggests that suboptimal battery configurations can quickly erode potential gains, highlighting the importance of well-calibrated operational strategies.

Overall, the findings remain consistent with our initial assessments. However, the magnitude of certain impacts, especially negative net improvements, emphasizes the need for careful scenario planning when designing battery storage strategies. Overall innovations in batteries (better efficiencies, charge rates and capacity) leads to more profit, improvement of lines and in peak load changes. Meaning that further development of these factors make the battery more cost effective and better at managing congestion.

The second part of the sensitivity analysis looks at how sensitive the model is to changes in the seasons. The current study assumes that by using averages of summer and winter weeks, a representative year can be established. To check if this assumption has a lot of impact, data from two weeks in October 2023 (representing Autumn) and data from two weeks in April 2023 (representing Spring), have been used to run the model. This data is more difficult to draw conclusions from because it is less representative than the summer and winter data (which are averages over 3 years).

When running the model with weather and load patterns from April 2023 and October 2023, overall congestion of the grid is lower, possibly due to less extreme weather patterns. The battery is able to decrease the congested lines, but does this less effectively than in summer and winter months. No ATT and TOU score best in that metric, just as in the summer and winter. The battery also slightly lowers the total congestion hours and average peak under TOU and No ATT tariffs, and remains the same with Time Block battery configuration. Finally, profits are generally a bit lower during Spring and Autumn which hurts their business case compared to the situation sketched by this paper where high profits from Summer and Winter persist. This sensitivity analysis produces expected variations due to less volatile weather patterns. Refer to Appendix B for the full results.

5 Discussion

This chapter examines the research findings, placing them in the broader context of stakeholder perspectives and regulatory considerations. It explores the trade-offs between technical efficiency and economic viability, assesses how these findings align with existing literature, and evaluates the feasibility of implementing TOU tariffs at the distribution level. Additionally, it analyzes stakeholder positions and power dynamics, highlighting key challenges and opportunities for TOU expansion. The chapter continues with a discussion on regulatory and financial barriers, setting the stage for the final recommendations in the next chapter. The chapter ends with a discussion of the limitations of the study.

5.1. Interpretation of Results

At the system level, congestion and curtailment impose substantial annual costs on the Dutch economy. This is supported by research from Ecorys, which estimates that for every MWh not consumed, the Dutch economy loses between EUR 1,200 and EUR 4,000 in potential revenue (Thijsen et al., 2024). Given that nearly 9 million MWh of electricity demand is currently queued for grid access at the low- and medium-voltage levels, fully integrating these consumers into the grid could represent an added value of 10 to 35 billion EUR per year (Venema et al., 2024). Beyond these direct economic losses, grid congestion also weakens the profitability of energy-intensive industries, as it slows down decarbonization while simultaneously increasing CO_2 costs. If 5 to 10% of these industries relocate due to grid constraints, it could cost the Dutch economy an additional EUR 5 to EUR 15 billion annually (Venema et al., 2024).

These figures highlight the significant economic opportunity of reducing grid congestion. By mitigating congestion, market-driven flexibility solutions, such as battery storage, could play an important role in minimizing economic losses and improving overall system efficiency. However, the effectiveness and financial viability of congestion management strategies depend on how well tariff structures incentivize flexibility and investment.

The annual performance metrics clearly highlight distinct trade-offs between technical efficiency and economic viability across the evaluated tariff structures: No Alternative Transport Tariff (No ATT), Time of Use (TOU), and Time Block.

Firstly, the observed grid improvements reveal differences in the effectiveness of the tariff systems. Both the scenario without alternative transport tariffs (No ATT) and the TOU tariff scenario improved the load distribution across 221 congested lines. The effectiveness of congestion relief under No ATT reflects the battery's market-driven optimization, unconstrained by tariff-imposed operational restrictions. The positive performance of the TOU tariff specifically reflects its dynamic pricing mechanism, incentivizing the battery to strategically shift demand away from peak periods, closely aligning with fluctuating grid conditions. Conversely, the Time Block tariff negatively impacted grid conditions on 13 lines. This suggests that its rigid and static structure is counterproductive with dynamic grid demands, restricting battery operations and leading to operational inefficiencies.

While not an established KPI from the literature review, insights emerge from analyzing congestion hours. While No ATT resulted in a high number of congestion hours (988), both TOU and Time Block tariffs demonstrated reductions, reporting less congestion hours (-845 and -429, respectively) compared to the grid without battery.

This indicates that introducing batteries under these alternative tariff systems actively mitigates existing congestion events, improving overall grid efficiency compared to scenarios without battery operation or with unconstrained market-driven battery operation. The superior performance of the TOU tariff highlights its ability to redistribute energy loads effectively.

Economically, differences were observed between the tariff scenarios. The No ATT scenario yielded the highest total market revenue, outperforming both Time of Use and especially the Time Block scenario. This strong economic performance under No ATT is due to unrestricted market operations, allowing optimal battery participation in energy markets. Although slightly lower, the TOU scenario also demonstrated reasonable economic viability, balancing both market participation and grid-supportive operations. In contrast, the Time Block tariff's economic performance was notably weak, suggesting severe limitations in market flexibility and revenue generation capabilities under its rigid operational restrictions.

Financial assessments should go beyond simple cost recovery periods, as merely breaking even after approximately 18.5 years—observed in both the No ATT and TOU scenarios—may not make for an attractive investment proposition in practice. A more effective benchmark is the Internal Rate of Return (IRR), which reflects the effective annual return on investment over an asset's lifetime. This should be compared to the relevant benchmark, typically the weighted average cost of capital (WACC) for investors in grid infrastructure or storage assets (Fernando, 2024). The model predicts an IRR of 7.42% for a battery system operating under the TOU regime, primarily driven by energy price arbitrage—charging the battery when the system experiences congestion and marginal prices are low, and discharging when power is scarce and marginal prices are high. While battery systems can generate additional value through services such as ancillary markets, price arbitrage remains the primary revenue stream under the current regulatory framework. However, this predicted IRR falls well below the typical OECD cost of capital for Battery Energy Storage Systems (BESS) investments, estimated at 10-12% (Bush, 2024). To attract private investment, additional financial incentives will be necessary. The financial viability of the Time Block tariff scenario is even more concerning, as it lacks cost recovery altogether. Without supplemental incentives or regulatory support, investment in such a framework would be highly unattractive. This underscores the critical role of well-designed tariff structures in shaping the investment landscape and ensuring that energy storage solutions can compete effectively in the market. The absence of cost recovery in the Time Block tariff scenario further emphasizes financial troubles without supplemental incentives or regulatory support, underscoring the critical role well-defined tariff structures play in shaping investment attractiveness.

An interesting finding emerges from comparing initial optimization predictions with detailed grid analysis results. While the optimization suggested limited congestion mitigation impacts under TOU tariffs, the power flow analyses indicated positive congestion-reduction effects. This discrepancy highlights the necessity of integrating detailed grid dynamics and multiple congestion metrics into optimization models to accurately capture operational impacts.

In summary, these results highlight the TOU tariff as achieving the best balance between grid efficiency and economic viability, effectively reducing congestion while maintaining a degree of financial sustainability. The scenario without alternative transport tariffs performs well in terms of economic returns but fails to address congestion, limiting its long-term feasibility. Conversely, the Time Block tariff scenario significantly underperforms both technically and financially, reinforcing the critical need for dynamic and flexible tariff structures to enable effective battery integration. However, while the TOU tariff emerges as the strongest option, two major barriers remain. First, TOU is currently not permitted on the distribution grid, preventing its immediate implementation. Second, despite outperforming other scenarios, the TOU tariff fails to generate revenues high enough to attract private investment. This suggests that, under the current market structure, TOU tariffs alone are insufficient to drive private-sector participation. Without additional subsidies, incentives, or regulatory adjustments, private investors are unlikely to engage, meaning the benefits of TOU pricing for congestion relief and grid efficiency will remain unrealized. To unlock the full potential of this tariff structure, policymakers must introduce support mechanisms, such as direct subsidies, regulatory credits, or alternative revenue streams, to bridge the investment gap and make battery integration a financially viable and scalable solution.

While these results provide a clear comparison of tariff performance in the Dutch context, it is essential to position them within broader congestion management research. Existing studies on market- and non-market-based approaches have explored flexibility solutions, but few have directly analyzed their combined impact at the distribution level. The following section examines how these findings align with or challenge prevailing research, highlighting gaps that need further exploration.

5.2. Results in the Context of Literature

This study builds on existing research on congestion management in electricity networks, where strategies are broadly categorized into market-based and non-market-based approaches. While both aim to alleviate grid congestion, they differ in implementation, focus, and effectiveness. A key theme in the literature is cost optimization, often overlooking broader grid stability and market interactions. Most studies analyze a single congestion management alternative rather than assessing their combined effectiveness, particularly within distribution grids. This paper aims start bridging that gap and compare the impact of the introduction of non-market based measures on a system with only market-based measures, on performance indicators that include both profit as well as grid stability.

Non-market-based strategies primarily aim to reduce operational costs and improve grid management. Methods such as transmission switching, demand-side management, and renewable curtailment have shown potential to enhance efficiency. However, these approaches often neglect the role of market interactions, and most studies concentrate on transmission networks, leaving distribution-level solutions underexplored. Similarly, market-based strategies focus on financial risk management, flexibility services, and locational marginal pricing, primarily targeting cost optimization. While these mechanisms can enhance system efficiency, research on their application to distribution networks remains scarce. The limited number of studies addressing market-based solutions for grid management highlights the need for more modeling of flexible resources in congestion markets, measuring for grid stability.

There are hybrid approaches that have identified these gaps by integrating market and non-market mechanisms, offering a more holistic congestion management framework. However, existing studies do not fully explore how market-based and non-market-based policies interact, particularly in the context of future low-carbon grids. The Dutch electricity system, which currently relies on market-driven flexibility but is implementing new on-market-based policies, provides an opportunity to analyze this. Understanding how different tariff structures impact market-based solutions and their performance could offer new insights into future congestion management strategies.

The results of this research highlight the critical role of well-structured tariff systems in balancing grid stability and the financial viability of flexible assets, particularly batteries. The findings support existing literature that emphasizes the ability of batteries to alleviate line overloading by absorbing surplus energy during low-demand periods and discharging during peak times (Peesapati et al., 2024). However, while prior studies suggest that batteries can significantly minimize renewable energy curtailment (Ayesha et al., 2024), this effect was less pronounced in the current model.

Tariff structures have long been recognized as key tools for shaping consumer behavior, ensuring cost recovery, and improving grid efficiency. Time of Use tariffs were effective in achieving these objectives. The results align with previous research that found tariffs to be successful in reducing stress on the grid and minimizing congestion-related costs (OConnell et al., 2012). However, the more rigid time-block tariff structure showed limitations, as it did not allow for demand recovery, sometimes worsening grid conditions rather than improving them. This suggests that the flexibility of the tariff is essential in ensuring effective congestion management.

A major advantage of tariffs, as identified in previous research, is their potential to reduce wind curtailment (Radecke et al., 2019). However, this effect was not strongly observed in the present study, as the impact of tariffs on curtailment reduction was limited. This could be due to the battery's placement within the grid. While the battery was positioned at the most congested location, it was not directly adjacent to a wind farm, which may have affected the amount of curtailed wind energy. Curtailment in this study was calculated based on the reduction in wind generation required to alleviate congestion. If a wind farm contributes relatively little electricity to a congested line, the potential for curtailment reduction remains minimal, regardless of tariff structures. The research also confirms that pricing structures aligning with real-time grid conditions, such as TOU tariffs, contribute to grid stability, supporting earlier findings by Kahn et al., 2001. This is because TOU tariffs respond to predicted congestion periods, effectively distributing energy demand in a way that enhances overall system efficiency.

Comparing the grid and battery business case conditions in market operations with and without tariffs helps us gain a greater understanding of how well the newly introduced alternative transport tariffs will perform for batteries as flexibility measures. It gives insight into how well the market alone works as a congestion management incentive compared to the addition of non-market based measures. While TOU tariffs successfully reduced peak demand, congestion hours, and improved revenue generation, the time-block tariff struggled with grid improvements and financial sustainability. The findings suggest that while rigid tariff structures may work well in specific conditions, where the asset contracted to the tariff doesn't need flexibility, more adaptive and dynamic pricing strategies—such as real-time pricing or locational marginal pricing—could offer better solutions for congestion management and cost efficiency pertaining to batteries as asset.

Overall, the findings highlight a critical gap in current congestion management literature: while prior studies have focused on market-based solutions or technical grid reinforcements in isolation, this study demonstrates the importance of integrating both approaches. The results suggest that well-structured TOU tariffs can serve as an effective intermediate step before large-scale grid reinforcements, a perspective that has been underexplored in existing research. This underscores the need for future studies to evaluate dynamic pricing mechanisms that balance grid stability, market efficiency, and consumer fairness.

While the literature emphasizes the importance of balancing economic efficiency and grid stability, real-world implementation is shaped by stakeholder interests and regulatory constraints. The effectiveness of TOU expansion depends not only on technical feasibility but also on the willingness of market actors to support its adoption. The next section explores how stakeholder positions, economic concerns, and regulatory challenges influence TOU's feasibility at the distribution level.

5.3. Socio-Technical System

This section analyzes how extending TOU tariffs to the distribution grid interacts with stakeholder interests, technical feasibility, economic viability, and regulatory considerations. By examining these interconnected dimensions, this analysis identifies critical factors and stakeholder dynamics essential for the successful and economically sustainable implementation of TOU tariffs in conjunction with supportive subsidy frameworks.

5.3.1. Stakeholder Identification

Several key stakeholder groups have been identified, each playing distinct roles and having interests concerning congestion management through the extension of Time of Use (TOU) tariffs at the distribution grid level. Their views on the system were extracted from reactions submitted by their representative groups to the announcement of alternative transport tariffs.

The Authority for Consumers and Markets (ACM) serves as the regulatory body, ensuring market fairness, non-discrimination, and compliance with European regulations. Their primary objective is to balance economic efficiency with market equity (Autoriteit Consument en Markt, 2024). Meanwhile, Distribution System Operators (DSOs) play a direct role in local grid operations, particularly in congestion mitigation. Their main concerns revolve around operational feasibility, grid stability, and financial sustainability. At the same time, Transmission System Operators (TSOs), responsible for high-voltage network stability, may not be directly involved in distribution-level congestion management but still exert significant influence by ensuring that such measures align with overall network stability.

In parallel, battery storage companies represent key players in flexibility markets, prioritizing revenue maximization, operational adaptability, and favorable tariff structures. Similarly, renewable energy operators are highly invested in congestion management, as minimizing curtailment and securing stable grid access are essential for their business models. Their interests often align with those of storage operators, as both rely on efficient market conditions to optimize their operations.

Beyond these industry stakeholders, electricity consumers—both industrial and residential—are directly impacted by changing tariff structures. Since such changes can affect electricity costs, reliability, and fairness, their primary concerns center on affordability and service dependability. Lastly, energy suppliers are also closely tied to these developments, as tariff structures shape market prices, influence supply-demand dynamics, and ultimately dictate their strategies in energy trading and market participation.

Following this general overview of stakeholders and their roles, it is important to delve deeper into their specific perspectives regarding congestion management through alternative transport tariffs. To better understand stakeholders' positions, economic concerns, and regulatory or implementation challenges, insights were extracted from the ACM consultation responses (Autoriteit Consument en Markt, 2024). Table 5.1 summarizes these stakeholder positions, highlighting variations in their support and critical issues identified during consultations. This stakeholder analysis provides valuable context for interpreting the socio-technical implications of extending TOU tariffs at the distribution level.

Table 5.1: Overview of Stakeholder Positions from ACM Consultation Introduction Alternative Transport Tariffs.

Stakeholder	Stakeholder Type	Overall Position	Economic Concerns	Regulatory and Implementation Issues
Netbeheer Nederland	Grid Operator Association	Cautiously supportive	Potential negative tariff impacts on DSOs	Operational readiness; implementation delay (2026) due to forecasting and control systems
Vereniging voor Energie, Milieu en Water	Industrial Consumer Association	Strongly supportive	Need certainty for large industrial investments	Urgency for rapid regulatory approvals and timely implementation
Energie-Nederland	Energy Company Association	Mixed; cautious support	Concerns about tariff complexity, competitive distortion	Regulatory clarity needed; eligibility criteria too restrictive
NLHydrogen	Hydrogen Industry Association	Supportive, but cautious	Tariffs negatively impacting hydrogen projects	Need tailored regulatory treatment for electrolysis
Energy Storage NL	Storage Industry Association	Supportive with reservations	Current tariff structure undermines storage viability	Restrictive tariff design; regulatory uncertainty
Batterijencoalitie	Battery Industry Coalition	Supportive with critical economic concerns	Tariffs damaging battery business cases	Regulatory delays affecting investment climate
Essent	Energy Supplier	Supportive but cautious	Tariff complexity creating entry barriers	Implementation complexity; regulatory clarity needed
Corre Energy	Energy Storage Company (Long-duration)	Supportive, demands tailored treatment	Current ATR economics unfavorable for long-duration storage	Uncertainty about curtailment risks and contract reliability
Nobian	Industrial User (Chemicals)	Supportive with clarity concerns	Unclear contract terms posing business risks	Regulatory uncertainty problematic for large-scale industrial investments
Equans	Energy Services Provider	Supportive but concerned about implementation delays	Delays affecting economic viability of projects	Grid operator readiness (IT, forecasting capabilities) insufficient
Vattenfall	Energy Producer	Strongly supportive; urges faster implementation	Delays causing investment bottlenecks	Regulatory timelines too slow for renewable energy expansion
Applied Medical	Industrial User (Medium-sized)	Supportive but calls for inclusivity	Limited eligibility criteria restricting benefits	Regulatory scope too narrow for mid-sized industrial users
CIP	Renewable Infrastructure Investor	Strongly supportive	Financial uncertainty from limited market integration	Regulatory clarity needed on dual-market participation (FCR, balancing markets)

The modeling results indicate that Time of Use (TOU) tariffs improve congestion management, suggesting that extending them to the Dutch distribution grid could help alleviate local congestion. However, the analysis also reveals that TOU tariffs are not currently economically viable for battery storage, with investment payback periods exceeding acceptable thresholds. This raises an important policy question: Should TOU tariffs be extended to the distribution grid, and if so, under what conditions?

Some stakeholders advocate for TOU expansion, believing it could improve investment certainty, market integration, and grid efficiency. Vattenfall has pushed for faster tariff implementation, suggesting that applying TOU at the distribution level could accelerate renewable energy integration while reducing curtailment risks (Vattenfall, 2023). Similarly, CIP has expressed concerns over limited market integration, implying that a more localized TOU tariff structure could better align investment incentives with congestion price signals (Copenhagen Infrastructure Partners, 2023). Industrial consumers, represented by Vereniging voor Energie, Milieu en Water (VEMW), emphasize the need for tariff predictability, arguing that TOU at the distribution level could provide better cost management opportunities for large consumers (VEMW, 2023). Meanwhile, the Batterijencoalitie does not explicitly call for TOU expansion but acknowledges that TOU could benefit battery storage if accompanied by financial incentives such as subsidies or deeper tariff reductions (Batterijencoalitie, 2023).

Despite this support, other stakeholders raise concerns about feasibility, complexity, and financial sustainability. Netbeheer Nederland remains cautious, arguing that DSOs lack the operational readiness and control systems necessary to implement TOU effectively at the distribution level (Netbeheer Nederland, 2023). The organization highlights the risk of introducing dynamic congestion pricing before DSOs have the forecasting tools needed to manage it efficiently. Essent also expresses skepticism, warning that expanding TOU tariffs could lead to greater tariff complexity, distort competition, and create new market entry barriers (Essent, 2023).

Power-Interest Grid

To gain a better understanding of which stakeholders must be prioritized in the potential extension of TOU tariffs to the distribution grid, a Power-Interest Grid is created (Figure 5.1). This framework helps determine how different actors should be managed throughout this policy change. On the x-axis the extent in which the actor has power to make change is shown, on the y-axis their interest, or how much the stakeholder is affected or engaged in the issue. Stakeholders with high power must be engaged carefully, as they can directly influence regulatory outcomes, while high-interest stakeholders must be informed and included in discussions, as they are significantly impacted by TOU expansion (Reddi, 2023).

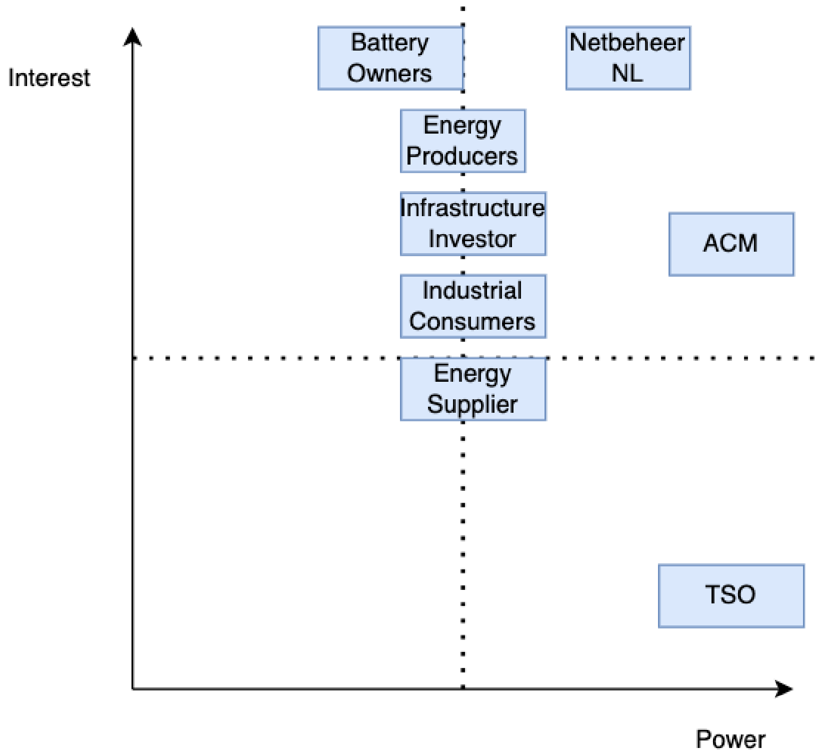

Figure 5.1: Power Interest Grid

The implementation of TOU tariffs at the distribution level is shaped by complex stakeholder interactions. Some actors, such as regulators and grid operators, hold direct authority over tariff implementation, while others, such as renewable energy producers, battery operators, and industrial consumers, are more affected by its consequences. These dynamics create a decision-making environment where power and interest are unevenly distributed, influencing the feasibility of TOU expansion.

The Power-Interest Grid (Figure 5.1) provides a structured way to analyze these relationships. It categorizes stakeholders based on their ability to influence policy (power) and their level of engagement or concern over TOU expansion (interest).

Two key insights emerge from this analysis:

1. The most powerful stakeholders (ACM and DSOs) are hesitant about TOU expansion:
    - ACM (Regulator) holds high power and moderate-high interest. While ACM has final authority over tariff design, it remains neutral and will not support TOU expansion unless economic justifications are strong.
    - Netbeheer Nederland (DSOs) holds power and high interest because TOU directly affects their grid operations and financial stability. They have less power than ACM because ACM has the final say in policy and can force system operators to use their suggested tariff systems (Autoriteit Consument en Markt, 2024). DSOs have raised concerns about feasibility, forecasting tools, and financial risks, making them cautious about expansion.
2. The stakeholders most interested in TOU expansion (batteries, renewables, and industrial consumers) lack direct influence.

- Battery operators and renewable investors (CIP, Vattenfall, Energy Storage NL) have high interest but low power, as they cannot directly implement TOU but would benefit from it.
- Industrial consumers (VEMW) also care deeply about TOU as it impacts their cost structures, but they lack regulatory authority.

The Power-Interest Grid (Figure 5.1) reveals a critical challenge in extending TOU tariffs to the distribution grid: the stakeholders with the power to implement TOU (DSOs and ACM) are hesitant, while the stakeholders who most need TOU (batteries, renewables, and industrial consumers) lack direct influence.

This power-interest imbalance is further complicated by the economic viability gap identified in the previous section. Without financial mechanisms such as subsidies, tariff adjustments, or additional revenue streams, TOU tariffs alone may not generate sufficient investment in flexibility assets like batteries. This creates a policy dilemma—TOU has the potential to improve congestion management, but if it remains economically unviable, even high-interest stakeholders will struggle to justify investments.

Stakeholder concerns over TOU expansion reflect deeper operational and financial challenges. While grid operators and regulators control TOU implementation, their caution stems from uncertainties about forecasting capabilities, system automation, and cost recovery mechanisms. Understanding these technical and financial barriers is crucial to assessing whether TOU is a viable congestion management tool at the distribution level. The next section examines these challenges in detail, focusing on the feasibility of TOU implementation within the current grid infrastructure.

5.3.2. Implementation Feasibility

The practical feasibility of implementing Time of Use (TOU) tariffs at the distribution level depends on operational, technological, and financial constraints. While discussions between ACM and stakeholders (in Dutch: "zienswijzen") have focused on the current introduction of ATTs (TOU at the transmission level and Time Block at the distribution level), the challenges raised by stakeholders suggest that similar concerns would arise if TOU were extended further down to the distribution grid (Autoriteit Consument en Markt, 2024).

One of the most significant barriers is the current lack of advanced forecasting and grid control systems within DSOs. Reliable forecasting tools are critical to predicting when and where congestion occurs, allowing for real-time curtailment and battery dispatch under TOU pricing. However, stakeholder feedback on the implementation of existing ATTs has already indicated a readiness gap, with full operational capability for automated congestion forecasting and control not expected until at least 2026 (Netbeheer Nederland, 2023). If TOU were extended to the distribution level, these challenges would likely become even more complex, requiring more granular grid management at lower voltage levels.

Beyond forecasting capabilities, DSOs also require enhanced IT infrastructure and real-time data exchange systems to support TOU implementation. The successful operation of TOU tariffs at the distribution level would require seamless coordination between DSOs, TSOs, and market participants. This is because timely and flawless communication needs to take place between DSOs and the contracted party to ensure that parties know when they can and cannot participate on the market. Stakeholders such as Essent and Batterijencoalitie have emphasized that without sufficient IT integration, TOU expansion could create market inefficiencies rather than improve congestion management.

Although DSOs do not have regulatory authority to block ATT implementation, their technical and financial concerns significantly shape how effectively TOU could be extended. Stakeholders have already raised concerns about the financial aspects of managing new tariff structures, particularly if additional infrastructure investments are required.

Overcoming these feasibility challenges requires:

- Accelerating investments in advanced forecasting and control infrastructure, ensuring that DSOs have the necessary tools to manage TOU effectively.
- Developing clear contract terms and eligibility frameworks to ensure industrial consumers and battery operators have predictable participation rules.

Without addressing these technical and organizational barriers, DSOs may struggle to expand TOU beyond their minimum regulatory obligations, limiting its effectiveness as a congestion management tool. However, operational readiness is not the only concern. Even if DSOs had the necessary forecasting and control systems in place, the financial viability of TOU expansion remains a key challenge. The current tariff structure does not necessarily provide clear cost recovery mechanisms for DSOs, meaning they may lack financial incentives to proactively support TOU implementation at the distribution level. Similarly, battery operators and industrial consumers have raised concerns that under current conditions, TOU does not yet provide a strong investment case for flexibility assets.

These financial uncertainties must be addressed if TOU is to function as an effective congestion management tool at the distribution level. The next section explores whether subsidies, adjusted tariff structures, or alternative financial mechanisms are necessary to ensure the economic viability of TOU expansion.

5.3.3. Financial Implications

The economic viability of TOU expansion at the distribution level remains uncertain, as both distribution system operators (DSOs) and flexibility providers (battery storage and industrial consumers) have raised concerns about financial risks. While the TOU model results have demonstrated potential for congestion management, the current tariff structure does not provide sufficient incentives for key stakeholders to fully support its implementation at the distribution level.

Financial Barriers for DSO's

As became clear from the previous section, the DSO faces feasibility challenges. Implementing TOU at the distribution level would require investments in forecasting tools, real-time grid control systems, and IT infrastructure. However, DSOs do not currently have a guaranteed revenue stream to fund these upgrades. Since TOU encourages dynamic congestion pricing rather than fixed capacity payments, DSOs may face short-term revenue fluctuations that could impact their ability to invest in long-term grid improvements. At the same time, the alternative for DSOs, refusing new grid connections due to congestion, also presents financial risks. If grid constraints prevent DSOs from connecting new assets, they forgo potential revenue from new grid users and reduce overall network utilization. By extending TOU to the distribution level, DSOs could enable more asset connections, allowing them to increase grid utilization while maintaining system reliability.

Additionally, modeling results indicate that TOU at the distribution level can effectively reduce congestion. This suggests that by implementing TOU, DSOs could delay or even reduce the need for costly grid reinforcements. Grid expansion projects require significant capital investment and often face long permitting and construction timelines. If TOU provides a cost-effective congestion management tool, DSOs may be able to optimize existing grid capacity rather than immediately investing in physical upgrades.

This introduces a trade-off: while TOU expansion presents short-term financial uncertainties, it may offer long-term financial benefits by reducing grid congestion, deferring reinforcement costs, and increasing grid utilization. However, these long-term benefits are unlikely to materialize if private sector investors do not find TOU tariffs financially viable.

Financial Barriers for Flexibility Providers

With an IRR of 7.42%, TOU-driven storage investments remain below the 10-12% benchmark for OECD markets. Without targeted subsidies TOU participation will likely remain unattractive to private investors.

This aligns with concerns raised by Energy Storage NL, Batterijencoalitie, and Corre Energy, who emphasize that the existing tariff structure undermines the financial viability of large-scale storage investments (Batterijencoalitie, 2023; Corre Energy, 2023; Energy Storage NL, 2023). Without additional financial incentives—such as subsidies, regulatory credits for congestion management, or improved market access—battery investors are unlikely to deploy significant flexibility assets in response to TOU signals alone. European countries are increasingly recognizing the need for financial support in battery storage deployment. For example, Poland offers subsidies covering up to 45% of eligible costs for large enterprises and even higher rates (up to 65%) for SMEs (Dentons, 2025). These subsidies ensure that battery projects remain financially viable and attractive for private investors. Our analysis finds that for TOU-based battery storage in the Netherlands to reach a 10% IRR, a subsidy of 18% of investment costs is required. Given that other countries in the EU are subsidizing above this percentage, then similar policies in the Netherlands can be considered, enabling TOU-driven flexibility investments. Otherwise, additional market-based incentives or regulatory adjustments will be necessary.

Similarly, industrial consumers have expressed concerns that TOU expansion could introduce financial uncertainty without clear eligibility criteria or cost protections. If TOU pricing leads to unpredictable curtailment risks or volatile electricity costs, industrial users may hesitate to participate. Corre Energy and Nobian have stressed that unclear contract terms create operational risks for large-scale industrial investments in flexibility (Corre Energy, 2023; Nobian, 2023). However, for some industrial consumers with flexible electricity demand, TOU could present an opportunity rather than a risk. If industries can adjust their electricity usage in response to TOU price signals, they could optimize their energy costs by shifting consumption to low-tariff periods while avoiding peak congestion pricing. This could be particularly beneficial for industries with batch processes, thermal storage, or non-continuous production cycles, as they may have more flexibility to adapt to time-dependent tariffs. This creates a divide in the industrial sector. Industries with rigid electricity needs (e.g., energy-intensive chemical processes) see TOU as a risk due to potential curtailments and cost unpredictability. Meanwhile, industries with flexible demand (e.g., those that can adjust production schedules) could benefit from TOU expansion by lowering energy costs through strategic demand shifting.

Ultimately, the financial viability of TOU for industrial consumers will depend on how the tariff structure accommodates different levels of flexibility. If contract terms remain uncertain or overly restrictive, industries may hesitate to engage. However, if TOU design allows for strategic demand shifting, some industrial consumers could see TOU as an attractive grid access option.

While financial constraints limit TOU's attractiveness for both DSOs and private investors, the ultimate decision to expand TOU rests with regulatory authorities. ACM's approach to market neutrality and tariff design will determine whether financial support mechanisms—such as cost recovery models for DSOs or incentives for flexibility providers—can be introduced. The next section examines the role of ACM in shaping TOU expansion and how power dynamics influence regulatory decision-making.

5.3.4. Regulatory and Decision-Making Power

Successfully implementing alternative transport tariffs (ATTs) and expanding Time-of-Use (TOU) tariffs at the distribution level depends on regulatory approval, economic feasibility, and the willingness of decision-makers to adapt market rules. While stakeholders acknowledge TOU's potential benefits, regulatory uncertainty, restrictive eligibility criteria, and slow approval processes remain major obstacles. Compliance with European Union regulations on transparency, non-discrimination, and cost-reflectivity further complicates the process, as unclear tariff structures could trigger disputes and limit stakeholder acceptance. Energie-Nederland and Energy Storage NL have raised concerns about the lack of transparent justifications for tariff levels and curtailment rules, emphasizing the need for clear, evidence-based decisions to ensure regulatory alignment.

ACM plays a decisive role in determining whether TOU expansion is viable. As the key regulatory authority, it assesses tariff structures based on market efficiency and fairness, making its approval essential. Although ACM has permitted TOU at the transmission level and the Time Block model at the distribution level, further expansion raises new questions. If ACM insists on strict market neutrality, it may resist financial mechanisms that support TOU participation, such as cost-recovery models for DSOs or flexibility providers. However, if it recognizes that financial support is necessary for TOU to function effectively at the distribution level, it could consider regulatory adjustments that facilitate broader participation. This decision will determine whether TOU remains an abstract policy concept or evolves into a viable congestion management tool.

The imbalance of power and interest among stakeholders complicates this regulatory landscape. ACM and DSOs, who hold the most influence, remain cautious about TOU expansion, prioritizing operational feasibility and financial stability. Meanwhile, the stakeholders who stand to gain the most—battery storage operators, renewable energy producers, and industrial consumers—lack direct control over regulatory decisions. This dynamic creates a significant barrier to TOU implementation, as those with the strongest business case for TOU must rely on influencing decision-makers rather than driving policy themselves.

For TOU to gain regulatory traction, lower-power stakeholders must actively coordinate their efforts. Battery storage providers, renewable energy investors, and industrial consumers need to form strategic alliances that amplify their collective influence. By aligning their advocacy efforts, presenting a unified economic case, and engaging in structured dialogues with regulators and DSOs, they can push for the regulatory adjustments necessary to make TOU financially and operationally viable. Without this coordinated effort, TOU risks remaining an underutilized tool, unable to bridge the gap between congestion relief potential and regulatory approval.

The analysis of stakeholder power and regulatory authority underscores the complexity of TOU expansion. While ACM and DSOs remain cautious, flexibility providers and industrial consumers advocate for regulatory adjustments that would make TOU financially viable. Given that the current market structure does not provide sufficient incentives for private investment, financial and regulatory adjustments will be necessary to ensure TOU expansion succeeds. The following section synthesizes these findings, evaluating the required financial mechanisms, technical feasibility constraints, and policy trade-offs involved in TOU implementation.

5.4. Summary of Findings and Policy Trade-offs

This discussion has evaluated the feasibility, economic viability, and system-wide implications of implementing Time of Use (TOU) tariffs at the distribution grid level. The findings highlight a key trade-off: while TOU tariffs effectively reduce congestion, their implementation requires financial support for both battery operators and Distribution System Operators (DSOs). The central question remains: do the system-wide benefits justify these costs?

The results demonstrate that TOU tariffs reduce congestion, decreasing both the number of congested lines and total congestion hours. This congestion relief enhances grid efficiency and could delay or reduce the need for costly grid reinforcements. However, the financial feasibility of TOU implementation depends on whether the cost of supporting flexibility providers and DSOs remains lower than the total system costs of congestion that would be solved with this tariff. Given that congestion and curtailment impose substantial annual costs on the Dutch electricity system—estimated between €10 and €35 billion per year in lost economic value, there is evidence that the system can afford to provide targeted incentives for TOU participation (Venema et al., 2024). If subsidies for battery operators and compensation mechanisms for DSOs amount to just a fraction of these system-wide losses, extending TOU tariffs to the distribution grid would be an economically justified intervention. However, the modeled Internal Rate of Return (IRR) of 7.42% for battery storage remains below the OECD benchmark of 10-12%, indicating that private-sector participation will not materialize without additional financial support. Other EU nations, such as Poland, already provide subsidies of up to 45% for battery storage investments, recognizing their critical role in grid flexibility and congestion management (Dentons, 2025). The Netherlands should consider adopting similar subsidy structures to maintain competitiveness and incentivize private investment in TOU-based flexibility solutions. In the case of a 40 MWh battery under TOU tariffs, they need to be subsidized 18% to achieve the OECD benchmark of 10%. Without such support, investment in battery storage under TOU tariffs may remain unattractive, delaying the potential grid benefits of dynamic congestion pricing. This reinforces the need for targeted incentives to ensure participation from flexibility providers.

While the technical and financial findings suggest TOU expansion is beneficial, regulatory barriers and power dynamics complicate implementation. The Dutch Authority for Consumers and Markets (ACM) and DSOs hold the most decision-making power, yet remain hesitant about TOU expansion due to operational feasibility, cost recovery concerns, and the need for forecasting tools. Meanwhile, the stakeholders that would benefit most from TOU—battery operators, renewable investors, and industrial consumers—lack direct influence over implementation. ACM's cautious regulatory stance, focused on market neutrality and fairness, suggests that TOU expansion will not occur unless a clear economic case is made. Without a structured framework to align stakeholder incentives, TOU expansion may remain stalled despite its congestion-reducing potential.

These findings reveal that while TOU expansion offers clear congestion-relief benefits, it remains an incomplete solution. Without decisive regulatory and financial interventions, TOU expansion will remain stalled, limiting its potential to alleviate congestion and improve grid efficiency. In chapter 6, in the recommendations, policy actions are outlined that can bridge this feasibility gap, ensuring TOU delivers benefits for the Dutch electricity system.

5.5. Limitations

This section describes the limitations of the study. These are split into the three methods used.

5.5.1. Literature Review

A literature review was conducted in two key aspects of this study: identifying the existing knowledge gap and determining key performance indicators (KPIs) for congestion management. In the process of identifying KPIs, a vote-counting approach was employed to determine the most frequently used indicators in the literature. The underlying rationale was that the more frequently an indicator appeared in academic studies, the more it had been subjected to peer review, thereby enhancing its legitimacy as a performance measure. However, vote counting inherently assigns equal weight to all studies, regardless of research quality. As a result, this approach may lead to biased or misleading conclusions, as it does not account for variations in study reliability, methodology, or context-specific applicability.

Beyond the selected KPIs, additional indicators such as congestion hours and total profit were also coded into the model as exploratory variables. These parameters provided insights beyond the primary framework, revealing important dynamics in congestion management that were not fully captured by the most frequently cited indicators in the literature. This suggests that rigid adherence to predefined KPIs may limit the analytical depth of the study, as it risks overlooking insights that arise from the modeling process itself.

A similar limitation was encountered in the use of financial KPIs. While cost recovery period was included as a standard investment metric, additional financial feasibility indicators, such as the Internal Rate of Return (IRR), were not commonly emphasized in congestion management literature. However, the IRR analysis in this study revealed that economic feasibility extends beyond simple break-even calculations. The findings showed that even when cost recovery was achieved within a reasonable time frame, the projected IRR remained below the typical investment thresholds required for battery storage deployment. This suggests that had the study relied solely on cost recovery period as the primary financial KPI, it would have failed to capture the broader investment challenges that ultimately determine whether market participants adopt congestion solutions.

5.5.2. Optimization

One of the limitations of this study is the assumption that the battery's performance remains constant throughout its entire 25-year operational lifetime. While extensive research was conducted to identify optimal operational strategies that minimize battery degradation, the model does not account for the effects of aging, capacity fade, or increased efficiency losses over time. In reality, battery degradation could significantly influence both its operational behavior and economic viability, which may alter the findings of this study.

The study assumes that two representative summer weeks and two representative winter weeks accurately reflect a full year's operational conditions. These weeks were constructed using averaged data from a three-year period, likely reducing the impact of extreme market or weather conditions. However, averages inherently smooth out volatility, which may underestimate or misrepresent the frequency and severity of high-price events, congestion peaks, or unexpected operational challenges that could affect battery profitability and grid conditions over a longer time horizon. The cost recovery analysis, which extrapolates results over the entire battery lifetime based on these representative weeks, is thus subject to potential inaccuracies arising from the exclusion of market and system outliers.

5.5.3. Electricity Market

Furthermore, this study exclusively models battery participation in the wholesale electricity market, excluding other relevant congestion management mechanisms, such as the GOPACS market. This decision was primarily due to data availability constraints, particularly the lack of publicly accessible GOPACS market data with sufficient temporal granularity. However, in practice, battery owners would likely engage with multiple revenue streams, and participation in GOPACS could significantly alter battery dispatch behavior and financial returns. Future research incorporating GOPACS or similar localized congestion markets could provide a more comprehensive understanding of battery participation in congestion management.

5.5.4. Grid Dynamics and Network Topology

A significant limitation of this study is the use of a synthetic network model rather than an exact replica of the Dutch distribution grid. Due to privacy restrictions, real-world Dutch distribution grid data is not publicly available. Consequently, the network model was designed to resemble Dutch distribution grid characteristics as closely as possible using available sources on renewable integration, load profiles, and typical line voltages per connection type. While this approximation enhances the study's relevance, it does not fully capture the complex spatial and operational constraints of the actual distribution grid. The absence of real-time congestion effects, voltage fluctuations, and grid reinforcement decisions may introduce deviations between modeled and real-world congestion outcomes.

The model is sensitive to the network topology chosen, including the number of buses, generator distribution, and overall structure. These factors influence power flow and, consequently, the congestion impact of introducing new loads with batteries. A key limitation is whether the chosen network topology accurately represents the Dutch distribution grid. The Netherlands has a meshed transmission network but a more radial structure in distribution grids, and deviations in network configuration can lead to different congestion patterns. If the topology were different—e.g., with more decentralized generation, fewer interconnections, or higher network redundancy—the results might shift, affecting the feasibility and grid impact of alternative transport tariffs.

5.5.5. Financial Uncertainties

A key financial limitation of this study is the assumption of fixed grid connection and transport tariffs over a 25-year period. Given the increasing electrification of heating and industry, and the integration of more variable renewable energy sources, it is unlikely that current tariff structures will remain unchanged in the long term. However, due to the uncertainty surrounding future pricing regulations, any attempt to forecast tariff changes would introduce additional layers of speculation, potentially reducing the reliability of the results.

Additionally, the model assumes that battery operators allocate 100% of their profits toward debt repayment, which simplifies the economic analysis but does not fully reflect real-world financial decision-making. In practice, battery owners may diversify their revenue allocation, reinvest in system upgrades, or face external financing constraints that could influence payback periods and overall investment feasibility. Nevertheless, since this assumption is applied consistently across all tariff scenarios, its impact on the comparative analysis is expected to be minimal.

5.5.6. General Limitations

Lastly, the optimization doesn't have any stochastic parameters embedded in the model. This then assumes that all parameters are certain, while wind, load and pricing data are in real-life very uncertain. However, due to the scale of the two models, adding randomness to these parameters would have made the model infeasible to run within a manageable time frame.

Despite these limitations, the study provides insights into the interplay between market-based and non-market-based congestion management measures. While real-world uncertainties, grid model approximations, and the exclusion of alternative flexibility markets (e.g., GOPACS) may introduce some deviations from actual system behavior, the findings remain relevant for policymakers and system operators seeking interim congestion relief strategies.

6
Conclusion

This chapter aims to answer the main research question posed in the introduction. It does this by first answering the sub-research questions and finally, by combining those insights, answer the main research question.

6.1. Addressing the Research Questions

This study set out to evaluate the impact of alternative transport tariffs on battery performance and grid stability in the Dutch electricity distribution network. Among the alternatives examined, Time-of-Use (TOU) tariffs emerged as the most effective option, balancing congestion reduction and investment feasibility, while Time Block (TB) tariffs imposed excessive constraints that hindered both battery profitability and grid benefits.

This conclusion is reached by answering the following sub-research questions:

Sub-Research Question 1 The first research question, *how is performance of congestion management alternatives in distribution grids measured in the literature*, establishes how the battery's behavior in different tariff circumstances will be compared. To answer this sub research-question, a literature review was conducted on congestion management. Literature commonly relies on KPIs to quantify congestion management effectiveness and helps compare the different alternatives. From this review, it became clear that there are many different KPIs across different themes: economic, operational and environment KPIs. However, measuring trade-offs remains a challenge, as certain KPIs may conflict with each other. For instance, reducing congestion costs through demand-side management might increase costs for certain consumers, while increased battery participation in congestion management could enhance financial efficiency but introduce new uncertainties in demand forecasting. This highlights the complexity of congestion management, where policymakers navigate the balance between economic efficiency, technical feasibility, and equity to develop strategies that are both effective and socially acceptable. To achieve a balanced set of KPIs that covered effectiveness and social contribution, the KPIs with the highest tally count per category were extracted and used to measure performance of the battery under different tariff situations. This way economic, technical and environmental aspects were taken into consideration. The chosen KPIs were:

- Cost Recovery (years)
- Renewable Energy Curtailment (MWh)
- Line Overloading (Number of overloaded lines)

These three KPIs then formed the basis of the rest of the analysis, measuring the effectiveness of the different tariff systems.

6.1.1. Sub-Research Question 2

The second research question states: *"How well does a battery perform based on the identified KPIs?"* To evaluate this, the study applies a Mixed Integer Linear Programming (MILP) model and a PyPSA network model, using economic, operational, and social KPIs to quantify battery performance in managing grid congestion.

The results demonstrate that in the absence of an Alternative Transport Tariff (No ATT), market-based mechanisms alone fail to effectively alleviate grid stress. In this scenario, congestion hours increase to 988 per year, highlighting the limitations of relying solely on market incentives for congestion management. However, the amount of lines with improved congestion is very high at 221, the same as under TOU tariffs.

From a financial perspective, the battery generates €1,37 million per year under the No ATT scenario, primarily from arbitrage opportunities in the Day-Ahead and Intraday markets. The cost recovery period is 18,45 years, making the investment about as attractive as in the TOU tariff scenario. The primary issue is that while the battery can technically operate in this market structure, its access to the grid is highly restricted due to long waiting lists and grid connection constraints.

Overall, the findings indicate that a system without TOU tariffs is not a viable long-term option, despite the battery's ability to generate revenue under No ATT. Without tariff structures that enable flexibility and facilitate connections, the battery cannot be deployed within a reasonable time frame, making this scenario impractical for congestion management. This reinforces the argument that policy-driven measures such as TOU tariffs are essential for integrating flexibility resources like batteries into congestion management strategies.

By analyzing the battery's behavior under no tariff circumstances we do gain understanding in how well battery, without non-market based interventions operates. Because it was able to participate in the market during high load periods (when TOU was restricted) it increased the hours of congestion over the period of a year and made slightly more profits. It showed that when fully optimized for profit, under no constraints it is difficult for a battery to provide the same grid stability than when subject to tariff constraints.

6.1.2. Sub-Research Question 3

The third research question, *"How well does a battery perform after the introduction of the new Dutch transport time-of-use tariff?"*, uses the KPIs identified in the first sub-research question to assess battery performance under the TOU tariff compared to a system without the battery. The TOU tariff allows consumers to reduce contracted transport costs by limiting grid participation for up to 15% of the time, incentivizing demand shifts away from congestion-heavy periods. To evaluate its impact, battery operation was simulated in Day-Ahead (DA) and Intraday (ID) markets across summer and winter periods, and its effects on grid congestion, renewable integration, and financial feasibility were compared to a scenario where no battery was present.

Results indicate that in a system without a battery, congestion persists, with high reliance on redispatch and curtailment measures to stabilize the grid. The introduction of a battery under the TOU tariff reduces congestion by 14.5%, lowering congestion hours by 845, demonstrating that batteries actively shift energy use to off-peak times, thereby improving grid stability.

From an economic standpoint, a system without a battery results in higher curtailment and congestion costs, as grid operators rely on redispatch measures and network reinforcements to manage congestion. With a battery under TOU, total market revenue is slightly lower (€1,231,734 vs. €1,372,549 in the no-tariff battery case), as restricted operational windows limit profit opportunities. However, despite lower revenue, the cost recovery period remains nearly the same, at 18.63 years under TOU vs. 18.45 years under no tariff, indicating that investment viability is not greatly impacted. Ultimately, the results show that a battery under TOU improves congestion hours compared to a system without a battery, while maintaining economic feasibility. Compared to a no-battery system, TOU tariffs offer a more structured and market-aligned congestion management strategy

6.1.3. Sub-Research Question 4

The final sub-question states: *How well does a battery perform after the introduction of the new Dutch transport Time Block tariff based on the identified KPI's?*. This question aims to compare battery performance under the Time Block (TB) tariff to a system without a battery, using the KPIs established earlier. The TB tariff restricts battery operation during predefined hours, limiting market participation and reducing its flexibility to respond to grid needs. To assess its impact, battery operation was modeled in summer and winter periods, comparing it against the No Alternative Transport Tariff (No ATT) scenario in which the battery operates without external constraints.

The results show that, without a battery, the system experiences 988 congestion hours. The introduction of a battery under the TB tariff reduces congestion by 429 hours, which is less effective than the TOU tariff (845 hours reduction). This suggests that the rigid TB-imposed constraints prevent the battery from responding well to congestion events, making it a less efficient congestion management tool. Similarly, renewable curtailment is barely improved under TB (-2 MWh reduction), however, improvements in curtailment were limited in every tariff situation. From an economic perspective, the TB tariff significantly reduces battery revenue. The initial investment of the battery is just above 10 million euros. Under No ATT, the battery earns €1,372,549 revenue annually, whereas under TB, total market revenue drops by nearly 64% to only €439,666. This limits the battery's profitability, making cost recovery impossible under TB. In contrast, under TOU and No ATT, cost recovery is feasible within 18.5 years (including interest, yearly maintenance and grid costs etc.).

Overall, the TB tariff imposes many operational and financial constraints on battery participation. Compared to No ATT, TB underperforms across all KPIs, with minimal congestion reduction and poor investment returns. Compared to TOU, TB is both technically and financially weaker, highlighting the importance of tariff flexibility. The results indicate that the TB tariff does not provide a viable business case for battery storage, as its rigid constraints limit its potential role in congestion management and grid optimization.

6.1.4. Main Research Question

Now that all the individual conclusions per research question are established, the final research question, *how do alternative transport tariffs impact battery performance and grid stability in the Dutch electricity distribution network?*, can be discussed.

This study set out to determine how alternative transport tariffs impact battery performance and grid stability in the Dutch electricity distribution network. The results demonstrate that tariff design is a decisive factor in determining whether batteries can effectively alleviate congestion while remaining financially viable. Among the alternatives analyzed, Time-of-Use (TOU) tariffs emerged as the strongest congestion management tool, striking a balance between grid efficiency and economic sustainability. Time Block (TB) tariffs, by contrast, imposed rigid constraints that severely limited both the operational effectiveness of batteries and their financial viability, making them an unattractive solution. A system without alternative transport tariffs (No ATT) allowed for higher financial returns but failed to address congestion, underscoring the fact that market-based mechanisms alone are insufficient to ensure effective grid management.

Beyond these direct findings on battery operations and tariff performance, the broader system-wide implications of congestion and curtailment costs cannot be ignored. The discussion revealed that grid congestion imposes an annual economic burden of €10 to €35 billion on the Netherlands, stemming from unserved electricity demand, rising redispatch costs, and delayed renewable energy integration. Without an effective congestion management strategy, these costs will only continue to grow, threatening the financial and operational stability of the electricity system. The core question is no longer whether congestion needs to be addressed, but rather whether TOU tariffs provide a cost-effective mechanism to do so.

The findings suggest that TOU tariffs, through reducing congestion, can defer the need for costly grid reinforcements, providing a possible solution to optimize existing infrastructure before large-scale investments become necessary. However, the long-term viability of TOU tariffs depends on whether the financial support required for battery operators and Distribution System Operators (DSOs) remains lower than the total economic burden of unmanaged congestion. Given the scale of congestion-related economic losses, the evidence suggests that the financial support required for TOU implementation would be a fraction of the economic burden imposed by an unmanaged grid. In other words, failing to implement TOU tariffs could result in far greater long-term costs than the subsidies or regulatory adjustments required to support them.

Despite their advantages, TOU tariffs alone are not perfect. Their successful deployment will require a financial and regulatory framework that ensures DSOs and battery operators are adequately incentivized to participate. Without financial support, private investors will not deploy batteries at the scale needed to meaningfully impact congestion, and DSOs may resist implementation due to cost recovery concerns. However, if policymakers introduce targeted incentives that align private investment opportunities with system-wide benefits, TOU tariffs can evolve into a scalable, self-sustaining congestion management tool that enhances grid reliability without distorting market conditions.

These findings are particularly relevant in the context of the Netherlands, which is at the forefront of renewable energy integration and one of the first countries to experience widespread congestion in the electricity grid due to the rapid deployment of solar and wind power. As the Dutch electricity system transitions towards a low-carbon future, managing congestion at the distribution level has become an urgent challenge, making it an ideal testbed for evaluating market-based congestion management strategies.

With renewable penetration increasing rapidly, congestion threatens to slow down the energy transition, increase redispatch costs, and create inefficiencies in grid operation. This research provides insights into how transport tariffs influence the role of batteries as flexibility assets, demonstrating that TOU pricing mechanisms can offer a viable solution for congestion relief. By designing adaptive tariff structures, policymakers and grid operators can leverage battery storage as an effective tool to mitigate congestion while maintaining economic feasibility for investors.

While TOU tariffs present a viable pathway to managing congestion, their success is not guaranteed without further policy refinement. The incentives provided to battery operators and DSOs must be carefully calibrated to ensure that private investment in flexibility is financially sustainable without imposing undue burdens on consumers or distorting market competition. Additionally, integrating TOU pricing into existing regulatory frameworks will require close coordination between policymakers, grid operators, and market participants to avoid unintended consequences such as cost shifting or access inequities.

Despite these challenges, the evidence suggests that if designed and implemented effectively, TOU tariffs could play an important role in congestion management, offering a scalable approach to filling grid capacity that is left and lowering congestion hours. Realizing this potential will depend on how effectively policymakers align financial incentives, market design, and regulatory structures to create a system that is both economically viable and technically robust.

6.2. Recommendations

The findings of this study demonstrate that TOU tariffs can significantly enhance congestion management by aligning battery operation with system needs. However, their successful implementation at the distribution level faces three major challenges: the financial viability of battery investments, the need for a transparent regulatory framework, and the requirement for DSOs to enhance their forecasting and grid management capabilities. Addressing these challenges is essential to ensure that TOU tariffs become a viable congestion management tool rather than an underutilized policy mechanism.

This chapter presents three targeted recommendations to overcome these barriers. First, a market-based subsidy allocation mechanism is proposed to ensure cost-efficient battery deployment. Second, a standardized and transparent regulatory framework is needed to provide clarity for market participants. Finally, financial support for DSOs is essential to improve forecasting tools and real-time grid monitoring, enabling effective TOU implementation.

6.2.1. Market-Based Subsidy Allocation for Battery Deployment

The study finds that for battery investments to be financially viable under TOU tariffs, they require an 18% subsidy to meet the OECD benchmark IRR of 10%. However, instead of implementing a fixed subsidy, policymakers should establish a competitive bidding system where energy providers, large-scale battery owners, and flexibility service providers bid for the lowest possible subsidy required to deploy storage solutions.

In this system, companies would submit bids detailing the minimum subsidy they need to make battery deployment financially viable. The government would allocate subsidies to those requiring the least financial support per MWh of deployed storage capacity. This approach incentivizes market participants to optimize costs while ensuring public funds are used efficiently. By fostering competition, the subsidy level could fall below the estimated 18%, reducing the overall cost to taxpayers. Large-scale projects may choose to operate at a lower IRR benchmark, such as 9% instead of 10%, benefiting from economies of scale and further decreasing the required subsidy. This structure ensures that battery deployment occurs as cost-effectively as possible while still delivering the necessary flexibility for congestion management.

By introducing this mechanism, the Dutch government can maximize the impact of TOU-based flexibility solutions, ensuring rapid deployment of storage assets while minimizing financial burdens.

6.2.2. Establishing a Transparent and Standardized Regulatory Framework

A well-structured regulatory framework is essential for TOU tariffs to function effectively at the distribution level. The current lack of cost transparency, tariff standardization, and participation clarity creates uncertainty for market participants, which discourages investment in flexibility solutions. To address this, the Autoriteit Consument & Markt (ACM) should introduce a nationally uniform TOU tariff structure that aligns with existing congestion management mechanisms.

First, ACM must conduct a comprehensive cost-benefit assessment of TOU pricing at the distribution level, evaluating its financial impact on different market participants, including industrial consumers, battery operators, and DSOs. This assessment should inform the creation of a clear and predictable TOU tariff framework applicable across all DSOs, ensuring that flexibility providers operate under consistent financial and operational conditions.

To maintain fairness and prevent excessive cost shifts, protective mechanisms for non-flexible consumers should be introduced. TOU tariffs must not disproportionately burden users who cannot adjust their electricity demand, as this could lead to public resistance and undermine long-term policy support. ACM should implement cost-balancing mechanisms to ensure equitable participation while preserving the efficiency benefits of TOU pricing.

By establishing a transparent, standardized regulatory structure, ACM can provide certainty and predictability for all market participants. This will unlock investment in flexibility assets, encourage widespread adoption of TOU-based congestion management, and ensure that TOU pricing aligns with broader electricity market goals.

6.2.3. Financial Support for DSOs to Improve Forecasting and Grid Monitoring

The effectiveness of TOU tariffs depends on accurate congestion forecasting and real-time grid monitoring. Currently, many DSOs lack the technological infrastructure to manage congestion dynamically, making TOU implementation technically challenging and financially risky. Without advanced forecasting tools, TOU pricing may lead to suboptimal flexibility deployment, reducing its overall effectiveness.

To address this, targeted financial support for DSOs is necessary to fund investments in state-of-the-art forecasting models, AI-driven congestion prediction tools, and real-time data collection systems. A grid intelligence investment fund should be established to finance these technological upgrades, ensuring that DSOs have the necessary capabilities to manage TOU pricing effectively. It is vital that DSOs work on these technologies together so that the capabilities in each DSO region are the same and that the technologies are compatible for parties with connections across DSO regions. This collaboration could be coordinated by Netbeheer Nederland.

The Dutch government or ACM could introduce a temporary cost-recovery mechanism, allowing DSOs to recover part of their investment costs over time. This approach ensures that DSOs are not financially penalized for making infrastructure improvements that ultimately benefit the entire energy system.

Additionally, regulatory mandates should require DSOs to demonstrate improved forecasting capabilities before TOU tariffs are expanded. A phased rollout strategy could be implemented, where DSOs receive funding in exchange for meeting specific technological milestones. This would ensure that investments in forecasting and monitoring occur in parallel with TOU implementation, preventing operational inefficiencies.

By equipping DSOs with the necessary forecasting and monitoring tools, TOU tariffs can function as intended, enhancing grid efficiency, improving price signals for flexibility providers, and preventing congestion before it occurs. Without this investment, DSOs may continue to resist TOU expansion, limiting its potential as a long-term congestion management solution.

6.2.4. Conclusion

The successful implementation of TOU tariffs at the distribution level requires a coordinated strategy that integrates financial, regulatory, and technological reforms. Failing to implement these reforms risks leaving TOU tariffs as an incomplete solution—technically promising but financially and operationally impractical. Only with a coordinated financial, regulatory, and technological strategy can TOU evolve into a scalable congestion management tool.

Introducing a market-based subsidy allocation process will ensure the cost-efficient deployment of battery storage, accelerating investment while minimizing public expenditure. Establishing a standardized regulatory framework will provide certainty for market participants, encouraging wider participation in TOU-based congestion management. Finally, targeted financial support for DSOs will enable the necessary technological upgrades to manage congestion dynamically, ensuring that TOU pricing is both effective and scalable.

By implementing these three recommendations, policymakers can bridge the feasibility gap, transforming TOU tariffs from a theoretical congestion management tool into a solution that enhances grid stability and supports the energy transition in the Netherlands.

6.3. Future Research

While this study provides insights into the impact of TOU tariffs on battery behavior, further research is needed to refine congestion management strategies and assess their long-term financial, regulatory, and technological implications. The findings and recommendations highlight key areas where additional research is necessary to ensure that TOU implementation is both effective and sustainable.

A critical area for future investigation is the financial viability of TOU tariffs at the system level, particularly in relation to the market-based subsidy allocation mechanism and grid management fund proposed in this study. While the research establishes that an 18% subsidy is needed for battery investments to meet the OECD benchmark IRR, the effectiveness of a competitive bidding process remains untested. Future studies should analyze how market participants would respond to a bidding system and whether it could drive subsidy levels below 18%, reducing overall government expenditure. Additionally, further research is needed to quantify the economic benefits of congestion reduction, such as deferred grid reinforcements and lower curtailment, to determine whether subsidy and DSO grid monitoring expenditures are justified by system-wide financial gains.

Beyond batteries, future research should investigate how TOU tariffs interact with other flexibility assets, such as demand response, industrial load shifting, and electric vehicle charging. This aligns with the recommendation to establish a transparent and standardized regulatory framework, as different flexibility providers may require distinct tariff structures to maximize participation. Investigating whether a single TOU design is sufficient or if a multi-tiered approach is necessary will be essential in refining congestion pricing mechanisms and ensuring an inclusive and efficient flexibility market.

Further research is also required to assess the long-term feasibility of TOU tariffs in the evolving electricity landscape. As grid reinforcements, electrification, and increasing renewables change system dynamics, it is unclear whether TOU will remain a necessary congestion management tool or if alternative mechanisms will emerge. Scenario modeling should explore whether TOU tariffs should be adjusted, phased out, or complemented by other market-based congestion solutions over time. This is particularly relevant for DSOs, as the recommendation to provide financial support for forecasting improvements assumes that real-time congestion management will remain critical—but further research is needed to confirm this assumption.

The social and equity implications of TOU tariffs also require deeper investigation. While TOU pricing improves market efficiency, it may disproportionately impact consumers who cannot adjust their electricity demand, such as households without access to battery storage or demand response options. Research should evaluate whether alternative transport tariffs create cost disparities and explore potential mitigation strategies, such as targeted consumer protections, differentiated tariff structures, or direct compensation for affected users. Ensuring that congestion pricing remains socially equitable is crucial for public acceptance and long-term policy success.

Optimizing battery participation under TB tariffs is another important area for further research. This study allowed battery participation from 22:00 to 06:00, but alternative participation windows or dynamic response models may yield better economic and technical outcomes.

By aligning future research with the recommendations of this study, policymakers and market participants can enhance congestion management. This approach fosters a more effective, flexible, and socially equitable framework. Addressing these questions will be essential for ensuring that TOU tariffs continue to support the transition to a cost-effective, resilient, and renewable-based electricity system in the Netherlands and beyond.

7 Reflection

Though my graduation internship began on September 1st, just a few months ago, it feels both like yesterday and a lifetime ago.

It feels as if a lifetime has passed because I have learned an incredible amount about a field I had some knowledge of, but have now explored at new levels. Gaining an understanding of the inner workings of the Dutch distribution grid, the challenges it faces in the coming years and the opportunities there are to fix it has fascinated me. Also, while I had some basic coding knowledge, I have been able to grow exponentially in structuring a larger model. I was used to building code for an exam or for a short project, but to, for weeks on end, puzzle my way through PyPsa, a package I had never worked with before, and finding a way to connect the optimization to the grid demanded a very steep learning curve.

At the same time, I cannot believe I am coming to the end of the thesis. Many people warned me that the process would be a lonely, but that has not been my experience. I felt supported through bi-weekly check-ins with Rudi, who was able to steer me on the right track. My weekly meetings with Duco and Marc helped me stay focused and understand the real-life and business implications of congestion, and helped me talk through the steps of my research. Because of the support of my thesis committee and my team at Accenture, it was never a lonely project and time flew by.

If I could go back in time, I would tell myself to be less frustrated with the starting process of the thesis and trust that the right scope and research direction would come my way. I am a competitive person, and felt that I was behind in a race I was the only one participating in. In the beginning I was too strict in wanting to do a certain type of analysis and finding literature to back why it was a valid research idea. When I started reading about what the current changes are in the socio-technical landscape, the idea for the thesis came together. My advice to people starting their thesis today would be to jump in without being held back by your own notions of the "best" or "coolest" method or idea, but to read and understand the problems in the system first and figure out a way to analyze that best. Take all the time you need in this process, because even though it is frustrating that you're not getting any words on paper, the things you learn during these steps will greatly help in the final stretches of writing.

For this paper, I used AI (specifically Grammarly) to help rephrase sections to maintain a consistent tone, improve clarity, and ensure consistency in tense. Additionally, Chat GPT was used as a support tool for debugging code, particularly for structuring data processing steps and suggesting alternative approaches when encountering errors. However, all model development, parameter selection, and final analysis were conducted independently, with AI assistance limited to improving code clarity and efficiency. Finally, ChatGPT was used to create the timeseries from input ENTSO-e transparency data to ensure representative data for 2 winter weeks and two summer weeks.

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A

Knowledge Gap Search Terms and Overview of Articles

Search Term	**Website**	**Used Articles**
Electricity markets flexibility energy retailers	Scopus	Chakraborty et al., 2023
Flexible capacity portfolio management electricity retailer	Google Scholar	Koltsaklis and Dagoumas, 2019, Lampropoulos et al., 2019
Flexible asset portfolio electricity retailer profit maximization	Google Scholar	Boroumand et al., 2015, Kettunen et al., 2010
Flexible AND asset AND electricity AND portfolio AND congestion AND management	Scopus	Yun et al., 2022, Brummund et al., 2022
Flexible AND asset AND electricity AND congestion AND management	Scopus	Junhua et al., 2017, Z. Wang et al., 2024b, Li et al., 2024
Roles AND in AND future AND electricity AND congestion AND management	Scopus	Safdarian, 2018, X. Wang et al., 2012
Policy AND approaches AND electricity AND grid AND congestion	Scopus	Dhabai and Tiwari, 2023, Buchmann, 2020, Gi and Xie, 2014, Singh et al., 2014 Hadush and Meeus, 2018
Congestion management transmission network	Google Scholar	Khanabadi and Ghasemi, 2011, Salkuti, 2018
Congestion management costs	Google Scholar	Singh and Bohre, 2022, Khan et al., 2023, Escudero–Sahuquillo et al., 2010
Risk congestion management distribution grids	Scopus	Hennig et al., 2023, Hennig et al., 2024a
Comparing congestion management techniques	Google scholar	Gumpu et al., 2019
Comparing congestion management alternatives	Scopus	Alavijeh et al., 2023

Table A.1: Search Method

Paper	Method	Goal
(Chakraborty et al., 2023)	Literature Review	Reviews different optimization techniques to improve load forecasting and maximizing profits for retailers and end-users, while minimizing cost for consumers
(Koltsaklis & Dagoumas, 2019)	Multi-Integer Linear Programming Model	Optimize portfolio management of vertically integrated utilities, focusing on risk minimization across both wholesale and retail power markets
(Lampropoulos et al., 2019)	Literature review, case study, historical market data	Propose a hierarchical control framework that facilitates the provision of flexibility services in power systems through aggregation entities (focus on wholesale trading for TSO/DSO)
(Boroumand et al., 2015)	Value at Risk and Conditional Value at Risk models	Define optimal hedging portfolios for electricity retailers in the context of intra-day markets, focusing on managing joint-price and quantity risk associated with demand uncertainty
(Kettunen et al., 2010)	Multi-stage stochastic optimization model	Develop an approach for managing an electricity contract portfolio that effectively addresses volume risk associated with meeting load.
(Yun et al., 2022)	Response Characteristic Model	Establish an optimal combination of resources within a VPP to manage congestion in the distribution network.
(Brummund et al., 2022)	Pilot demonstration	Study the integration of flex services from local and regional assets, establishing a flex value chain to manage congestion and facilitate procurement of flex through local market
(Junhua et al., 2017)	Power Flow Sensitivity Analysis	Investigate how a VPP that incorporates solar photovoltaic generation and energy storage can alleviate congestion in the system
(Khanabadi & Ghasemi, 2011)	Mixed Integer Programming	Achieve lower energy prices and higher market efficiency by altering the network topology through transmission switching.
(Z. Wang et al., 2024b)	Two-stage optimization model	Introduces a multi-energy system aimed at independent planning and real-time operation to minimize cost while balancing electricity

Table A.2: Overview of Articles Used for Review: Part 1

(Li et al., 2024)	Used computational framework	Determine the optimal allocation of wind and solar capacity and evaluate impact of network capacity constraints on cost and unserved energy.
(Hennig et al., 2024a)	Case Study	Explore congestion management mechanisms that utilize the flexibility of electrified end-uses to mitigate network congestion during peak load times
(Safdarian, 2018)	Mathematical modeling, simulation and coordination frameworks	Explore effective coordination frameworks for DR programs in smart grids
(X. Wang et al., 2012)	Literature review and feasibility tests	Design and implementation of the Southwest Power Pool's (SPP) Integrated Marketplace (DA and Real-time). The aim is to ensure reliable electricity supply and facilitate competitive wholesale pricing.
(Dhabai & Tiwari, 2023)	Developed algorithm to manage curtailment and applied to a test system	Provide a solution for managing curtailment minimising waste and improving economic viability of renewable energy projects
(Buchmann, 2020)	Analytical framework assessing implication of local congestion markets	Explore governance options for local congestion markets ensuring fairness and efficiency in integrating renewables
(Gi & Xie, 2014)	Analytical approach with iterative simulations	Offer a more efficient and effective tool for the impact of curtailment
(Singh et al., 2014)	Integrated approach combining multiple methods (numerical and physical	Provide a comprehensive framework for analyzing and optimizing large power transmission networks, aiding policymakers
(Hadush & Meeus, 2018)	Literature review	Explore effective DSO-TSO cooperation solutions to enhance congestion management
(Salkuti, 2018)	Multiobjective methodology that uses optimal transmission switching (OTS) strategies	Balance two conflicting objectives: minimizing total operating costs and maximizing probabilistic reliability within the power system.
(Escudero–Sahuquillo et al., 2010)	Algorithm development and simulation	To present an improved version of the FBICM (Feedback-Based Interconnect Congestion Management) technique, which is designed to eliminate Head of Line (HOL) blocking in distributed deterministic routing networks. The improvement focuses on reorganizing switch memory resources to significantly reduce the silicon area, complexity, and cost required for implementation
(Khan et al., 2023)	Develop a multi-objective optimization scheme that uses Demand Side Management	Alleviate potential congestion in distribution networks caused by the increased penetration of heavy loads. The proposed scheme aims to optimize the scheduling of flexible loads in a way that minimizes consumers' electricity costs while reducing the peak-to-average ratio of the load curve to a level that prevents congestion.
(Singh & Bohre, 2022)	Literature review on FACTS devices	Focusing on the use of Flexible AC Transmission Systems (FACTS) devices to relieve congestion in transmission networks. The paper aims to address the economic, operational, and optimal placement aspects of FACTS devices
(Gumpu et al., 2019)	Literature review	Review different congestion management methods over distribution and transmission grids
(Alavijeh et al., 2023)	Literature review and simulation	Comparing different congestion management solutions using different metrics (cultural, technical, complexity
(Hennig et al., 2023)	Present a design framework for congestion management alternatives	Discuss pros and cons of different mechanisms for different problem types.
(Chondrogiannis et al., 2022)	Literature review	Reviews some of the main projects on developing flexibility markets in Europe

Table A.3: Overview of Articles Used for Review: Part 2

B

Sensitivity Analysis

B.1. Parameter Variations

Table B.1: Parameter Variations for Battery, Operating, and Tariff Conditions with Uncertainty Justifications

Parameter	Value	Uncertainty	Reasoning
Battery Capacity (MWh)	20	Low	Small-scale batteries are common in pilot projects
Battery Capacity (MWh)	80	Medium-High	Large-scale batteries require significant investment and policy support
Charge Rate (MW)	5	Low	Conservative charge rates are typical for grid safety
Charge Rate (MW)	20	Medium-High	High charge rates require advanced grid infrastructure, more innovation and regulation
Battery Efficiency (%)	0.75	Medium	Older batteries have lower efficiency, well-documented performance. However unlikely that batteries will become less efficient over time.
Battery Efficiency (%)	0.98	High	Achieving near-perfect efficiency depends on future technological advances
Operating Costs (EUR)	0.6	High	Future cost uncertainties due to supply chain fluctuations and policy changes, however costs could decrease as more innovation takes place
Operating Costs (EUR)	2.6	Medium	Variability due to maintenance and operational changes
Wind Threshold (%)	0.70	Low	Dependent on battery bidding strategy so can be changed by battery owner
Wind Threshold (%)	0.90	Low	Dependent on battery bidding strategy so can be changed by battery owner
Solar Threshold (%)	0.70	Low	Dependent on battery bidding strategy so can be changed by battery owner
Solar Threshold (%)	0.90	Low	Dependent on battery bidding strategy so can be changed by battery owner
Load Threshold (%)	0.30	Low	Dependent on battery bidding strategy so can be changed by battery owner
Load Threshold (%)	0.50	Low	Dependent on battery bidding strategy so can be changed by battery owner
Min SOC (MWh)	0.05	Low	Dependent on battery depletion strategy so can be changed by battery owner
Min SOC (MWh)	0.20	Low	Dependent on battery depletion strategy so can be changed by battery owner
Max SOC (MWh)	0.85	Low	Dependent on battery bididng strategy so can be changed by battery owner
Max SOC (MWh)	1.00	Low	Dependent on battery bididng strategy so can be changed by battery owner

B.2. Sensitivity Analysis Seasonal Changes

Metric	No ATT	TOU	Time Block
Number of lines with overloading	330	335	590
Required Curtailment (MWh)	18	19	23
Cost Recovery Period (years)	19.2	19.5	inf.

Table B.2: Spring Sensitivity Analysis: Grid and Profitability Metrics

Metric	No ATT	TOU	Time Block
Number of lines with overloading	320	325	580
Required Curtailment (MWh)	17	18	22
Cost Recovery Period (years)	19.1	19.3	inf.

Table B.3: Fall Sensitivity Analysis: Grid and Profitability Metrics

C
Power Flow Calculations

The network model has the power flow calculations imbedded in the package. These are run by calling "network.pf(snapshots = network.snapshots). The analysis uses the following steps to complete the full power flow. The power flow analysis is governed by the AC power flow equations, which relate the complex power at each bus to the network voltages and admittances. The fundamental equation is:

$$S_n = P_n + jQ_n = V_n I_n^* \tag{C.1}$$

where S_n is the complex power (comprising active power P_n and reactive power Q_n), V_n is the complex voltage at bus n, and I_n^* is the complex conjugate of the current. The current I_n is related to the bus voltages through the bus admittance matrix Y_{nm}:

$$I_n = \sum_m Y_{nm} V_m \tag{C.2}$$

Combining these equations gives:

$$S_n = V_n \sum_m Y_{nm}^* V_m^* \tag{C.3}$$

This forms a non-linear system of equations that must be solved iteratively. The non-linear power flow equations are solved using the Newton-Raphson iterative method, which involves the following steps:

1. **Initial Guess:** Set initial values for voltage magnitudes (typically 1.0 per unit) and angles (0 degrees).
2. **Mismatch Calculation:** Compute the difference between specified and calculated power at each bus.
3. **Jacobian Matrix Formation:** Construct the Jacobian matrix, representing the sensitivity of power mismatches to changes in voltage magnitudes and angles.
4. **Linear System Solution:** Solve the linear system:

   $$J \cdot \Delta X = \Delta S \tag{C.4}$$

   where J is the Jacobian matrix, ΔX represents voltage corrections, and ΔS is the power mismatch vector.
5. **Update Variables:** Apply the corrections to the voltage magnitudes and angles.
6. **Convergence Check:** Repeat the process until the power mismatches are within a specified tolerance.

D
Model Variables

D.1. Model Parameters

Parameter	Value	Description	Reasoning	Source
battery_capacity	40 MWh	Maximum battery capacity	Chosen based on real-world efficient battery sizes	EKU Energy, 2024
battery_efficiency	90%	Roundtrip efficiency of battery	Typical efficiency for lithium-ion batteries	Lazard, 2020
max_charge_rate	10 MW	Maximum charge per hour	Common charge rate for 40MWh battery	Lazard, 2020
max_discharge_rate	10 MW	Maximum discharge per hour	Common discharge rate for 40MWh battery	Lazard, 2020
charging_cost	1.6 EUR / MWh	Variable cost per MWh charged	Derived from market rates	Yuan, 2022
discharging_cost	1.6 EUR / MWh	Variable cost per MWh discharged	Derived from market rates	Yuan, 2022
initial_soc	20 MWh	Initial battery charge	Starts at 50% for optimal behavior	
min_operating_soc	4 MWh	Minimum operating charge	Prevents full depletion	Gul, 2022
max_operating_soc	38 MWh	Maximum charge limit	Prevents overcharging	Wang, 2024a
wind_load	Timeseries	Wind generation data	Extracted from Entso-e	Entso-e platform
solar_load	Timeseries	Solar generation data	Extracted from Entso-e	Entso-e platform
total_load	Timeseries	Total system load	Extracted from Entso-e	Entso-e platform

Table D.1: List of Parameters Used in the Study: Part 1

Parameter	Value	Description	Reasoning	Source
day_ahead_prices	Timeseries [€/kWh]	Hourly day-ahead prices	Extracted from Entso-e	Entso-e platform
intraday_prices	Timeseries [€/kWh]	15-min intraday prices	Extracted from Entso-e	Entso-e platform
wind_threshold	80th percentile	Encourages charging at high wind	Higher renewables → lower prices	
solar_threshold	80th percentile	Encourages charging at high solar	Higher renewables → lower prices	
load_threshold	40th percentile	Encourages charging at low load	High load → lower prices	
TARIFF_TYPE	"No Alternative Transport Tariff", or, "TIME_OF_USE", or, "TIME_BLOCK"	Defines tariff system applied	Affects battery market participation	
TIME_BLOCK_START	22	Start of time block tariff	Battery allowed to bid from this hour	Netbeheer Nederland, 2024
TIME_BLOCK_END	6	End of time block tariff	Battery must stop participation	Netbeheer Nederland, 2024
congestion_threshold	90th percentile	Identifies congestion moments	Used for Time-of-Use tariffs	
max_blocked_periods	15%	Max restriction period	Limits market restrictions	
is_congested	True/False	Indicates congestion presence	Used in optimization	
day_ahead_soc	Decision Variable	Battery SOC in day-ahead	Gurobi optimization result	
day_ahead_charge	Decision Variable	Battery charging in day-ahead	Gurobi optimization result	
day_ahead_discharge	Decision Variable	Battery discharging in day-ahead	Gurobi optimization result	
intraday_soc	Decision Variable	Battery SOC in intraday	Gurobi optimization result	
intraday_charge	Decision Variable	Battery charging in intraday	Gurobi optimization result	
intraday_discharge	Decision Variable	Battery discharging in intraday	Gurobi optimization result	

Table D.2: List of Parameters Used in the Study: Part 2

Parameter	Value	Description	Reasoning	Source
day_ahead_profit	Calculated Value	Profit from day-ahead market	Revenue from DA bidding	
intraday_profit	Calculated Value	Profit from intraday market	Revenue from intraday bidding	
total_profit	Calculated Value	Total profit	Sum of DA and intraday profits	
transport_cost	Calculated Value	Fixed transport cost	Based on transport tariff	
net_profit	Calculated Value	Final profit after costs	Market profit minus transport cost	
network_buses	DataFrame	Power network bus data	Imported from external file	
network_lines	DataFrame	Power network line data	Imported from external file	
network_generators	DataFrame	Generator dataset	Imported from external file	
line_loading _no_battery	DataFrame	Line utilization without battery	Used for congestion analysis	
line_loading _with_battery	DataFrame	Line utilization with battery	Used for congestion analysis	
congested_lines _no_battery	Calculated Value	Number of congested lines (no battery)	Derived from line utilization	
congested_lines _with_battery	Calculated Value	Number of congested lines (with battery)	Derived from line utilization	

Table D.3: List of Parameters Used in the Study: Part 3

D.2. Prompt for Timeseries

Prompt: "Generate a synthetic time series dataset that represents two weeks of summer and two weeks of winter energy data for the Netherlands. The dataset should include the following variables:

Time: Timestamps in 15-minute intervals. Total Load: Simulated total electricity demand based on historical averages from ENTSO-E Transparency Platform data for the years 2022, 2023, and 2024. Wind Load: Simulated wind generation based on ENTSO-E data for those years, with seasonal variations (higher in winter). Solar Load: Simulated solar generation using ENTSO-E data, peaking at midday and reflecting differences between summer and winter. Day-Ahead Prices: Hourly price data from ENTSO-E for 2022, 2023, and 2024, interpolated to match the 15-minute time resolution by duplicating each hourly value across four intervals. Intraday Prices: Prices reflecting real-time market fluctuations. Additional instructions: Attached data: You can find ENTSO-E data for 2022, 2023, and 2024, which provides 15-minute resolution for wind load, solar load, total load, and day-ahead prices. Use this to generate a representative synthetic dataset. Intraday Prices: Before generating intraday prices, read the attached articles on intraday market behavior and create realistic prices that align with the load and renewable generation trends. Intraday prices should be more volatile than day-ahead prices and reflect supply-demand dynamics. Price variations: Ensure that day-ahead prices follow structured daily fluctuations, while intraday prices react more dynamically to short-term changes in generation and demand. The dataset should cover exactly two weeks for each season, with realistic daily and nightly demand patterns. Format the output as a pandas DataFrame and save it as a CSV file."