Optimizing Grid Flexibility

An Agent-Based Analysis of Alternative Transport Rights for Large Energy Consumers in the Dutch Electricity Grid

CoSEM Master Thesis

Jard P. Zwaan

Delft University of Technology

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by

Jard P. Zwaan

TU Delft First Supervisor:	Dr. ir. Ö. Okur
TU Delft Second Supervisor & Chair:	Dr. A. F. Correljé
Deloitte First Supervisor:	C. Jacobs
Deloitte Second Supervisor:	Y. Sun
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Faculty:	Faculty of Technology, Policy and Management, Delft

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TU Delft

Preface

Before you lies the thesis: *”Optimizing Grid Flexibility: An Agent-Based Analysis of Alternative Transport Rights for Large Energy Consumers in the Dutch Electricity Grid”*. This thesis marks the completion of my Master’s in Complex Systems Engineering & Management at TU Delft and represents the closing chapter of my academic journey.

Throughout this program, I have greatly enjoyed studying socio-technical systems, particularly exploring how technical, societal, and economic factors dynamically interact. For my thesis, I chose to investigate potential solutions to grid congestion, an essential piece of one of society’s most pressing challenges today: the energy transition. During the process of writing this thesis, I have learned a lot about this subject, which I am eager to share through this work.

I had the opportunity to write my thesis at Deloitte, which allowed me to engage with industry experts and connect with large energy consumers, gathering valuable insights that shaped this thesis. In particular, I would like to express my sincere gratitude to my supervisors at Deloitte, Cas Jacobs and Yuxin Sun, whose feedback, guidance, and the positive energy during our meetings significantly enhanced the research process.

I would also like to thank my TU Delft supervisors, Aad Correljé and Özge Okur. I am especially grateful to Özge for our regular meetings, whose guidance and thoughtful insights made the research experience both rewarding and helped turn the process into a truly positive experience.

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I wish you a pleasant reading experience.

Jard P. Zwaan
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Summary

The transition towards renewable energy in the Netherlands has significantly increased the share of intermittent energy sources such as wind and solar power, amplifying electricity grid congestion. Grid congestion occurs when energy generation and demand exceed network capacity, causing reliability issues, renewable energy curtailment, and delays in connecting new consumers. To alleviate this, the Dutch Authority for Consumers and Markets (ACM) introduced Alternative Transport Rights (ATR), offering conditional grid access through Time-Duration-Based Transport Rights (TDTR) and Time-Block-Based Transport Rights (TBTR). These mechanisms incentivize large energy consumers (LECs) to shift their electricity consumption from peak to off-peak times, thereby optimizing grid capacity utilization.

Despite the promising nature of ATR, limited practical guidance exists on how large energy consumers can adapt operational practices and integrate technological solutions to comply effectively with these new regulatory instruments. This thesis aims to bridge this gap by exploring how LECs can optimize operational and data-driven practices for ATR compliance and assessing the subsequent impacts on grid congestion and the Dutch electricity system. The central research question guiding the thesis is:

> ”How can large energy consumers in the Dutch electricity market adapt their operational and data-driven practices to effectively utilize new alternative transport rights, and what impact will these adaptations have on grid congestion?”

To address this question, the research employed a mixed-methods approach. Initially, a qualitative analysis comprising a systematic literature review and stakeholder interviews identified regulatory requirements, flexibility potentials, and operational strategies. These insights informed scenario development, defining sector-specific flexibility potentials under different ATR adoption levels. Subsequently, an agent-based modeling (ABM) simulation using the ASSUME framework assessed the impact of these scenarios on the Dutch national and regional electricity grids.

The qualitative analysis identified significant challenges facing ATR adoption, including upfront investment requirements for advanced metering and control technologies, organizational inertia, compliance risks, and limited awareness of ATR benefits. A particularly critical barrier is the misalignment between existing tariff structures and the goals of demand flexibility; for instance, peak-based pricing components can inadvertently penalize load-shifting behavior that supports grid stability. Interviews highlighted the critical role of Enterprise Data Management (EDM) and digital infrastructure in operationalizing flexibility. High-resolution sub-metering, Energy Management Systems (EMS), automation, and behavioral strategies emerged as key enablers of effective ATR compliance.

In the quantitative analysis, simulation results demonstrated that TDTR significantly reduced peak electricity loads at the national level, improving overall demand stability and grid congestion management. However, shifting demand under TDTR also led to higher reliance on fossil-based generation during off-peak hours, resulting in modest electricity price increases. At the regional level, TBTR effectively redistributed peak demand into predetermined off-peak nighttime periods, substantially improving grid congestion under partial adoption (Hybrid scenario). Nonetheless, rigid load-shifting in the Full TBTR scenario led to unintended secondary peaks, suggesting a need for more adaptive implementation strategies.

The thesis concludes by offering practical recommendations to support the effective implementation of Alternative Transport Rights across the electricity system. For large energy consumers, it emphasizes the importance of investing in detailed sub-metering, automation technologies, and EDM systems. These tools are essential for unlocking operational flexibility and ensuring compliance with ATR requirements.

System operators are advised to carefully monitor the impact of ATR-induced demand shifts, particularly under full adoption of TBTR, where inflexible scheduling can lead to unintended secondary congestion

peaks. Furthermore, improving communication with large energy consumers about the structure, availability, and potential benefits of ATR contracts is essential to raise awareness and support effective adoption.

For policy makers, the study highlights the need to revise existing tariff structures to better align with the objectives of flexibility and congestion management. It also recommends providing financial incentives to support investments in the necessary digital infrastructure and launching targeted awareness campaigns to encourage wider adoption and understanding of ATR among potential participants.

Finally, the thesis emphasizes the need for ongoing research into dynamic market and behavioral adaptations, the inclusion of redispatch costs in economic evaluations, and further exploration of complementary technologies such as battery storage and demand-side resources. The thesis underscores ATR's potential to contribute significantly to grid stability and economic efficiency in the context of the Dutch energy transition, provided that technical, organizational, and regulatory barriers are adequately addressed.

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Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-Based Modeling
ACM	Autoriteit Consument en Markt (Dutch Authority for Consumers and Markets)
ATR	Alternative Transport Rights
API	Application Programming Interface
AI	Artificial Intelligence
CHP	Combined Heat and Power
CSV	Comma-Separated Values
DC	Direct Current
DER	Distributed Energy Resources
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EDM	Enterprise Data Management
EMS	Energy Management System
EOM	Economic Order of Merit
ETS	Emissions Trading System
EV	Electric Vehicle
HV	High Voltage
HVDC	High Voltage Direct Current
K&O	Kennis & Ontwikkeling (Knowledge & Development)
kV	Kilovolt
LEC	Large Energy Consumer
LMP	Locational Marginal Pricing
PV	Photovoltaics
RES	Renewable Energy Sources
TBTR	Time-Block-Based Transport Right
TDTR	Time-Duration-Based Transport Right
TSO	Transmission System Operator
V2G	Vehicle-to-Grid

1

Introduction and Research Design

1.1. Introduction

The transition to renewable energy is a critical global priority, and the Netherlands is no exception. As the country integrates sustainable energy sources like wind and solar power, the strain on the existing electricity grid has intensified, revealing a critical issue: grid congestion. Grid congestion occurs when the electricity grid is unable to accommodate all the energy generated or consumed at a given time. This problem has become particularly acute in the Netherlands, where the rapid increase in renewable energy production has created significant bottlenecks within the distribution network [1, 2]. As a result, energy suppliers and consumers face challenges that include curtailment of renewable energy production, inefficient energy utilization, and substantial delays in connecting new housing developments and businesses to the grid. Currently, nearly 10,000 companies face grid connection delays ranging from 7 to 10 years [3, 4, 5], highlighting the need for scalable, short-term interventions.

Although long-term grid reinforcement remains essential, it is both capital-intensive and time-consuming, often requiring multi-year permitting and construction timelines [6]. This makes it increasingly important to pursue demand-side solutions, particularly flexible electricity use, that can be implemented more rapidly. These interventions are not only crucial for relieving immediate congestion, but also for achieving broader policy objectives: reducing carbon emissions, phasing out fossil fuels by 2050 [7], and promoting equitable access to clean energy across regions [8]. Enhanced grid reliability also underpins the electrification of transport and heating, thereby accelerating cross-sectoral decarbonization.

In response to these challenges, the Dutch regulatory authority (*Autoriteit Consument & Markt*, ACM) introduced Alternative Transport Rights (ATR), comprising Time-Duration-Based Transport Rights (TDTR) and Time-Block-Based Transport Rights (TBTR). These mechanisms offer reduced tariffs to large energy consumers (LECs), defined as organizations with a connection exceeding 3x80 ampère [9, 10], in exchange for flexible electricity usage aligned with grid capacity constraints [9]. Despite this regulatory innovation, practical questions remain about their effectiveness and the operational adaptations required by large energy consumers.

This thesis therefore explores how large energy consumers can redesign their energy management processes to effectively leverage ATR, thereby alleviating grid congestion and contributing to the Dutch energy transition goals.

1.2. Problem Statement

Existing research highlights various technical and regulatory approaches for managing grid congestion, such as demand flexibility, energy storage, and demand response techniques [11, 12, 13]. While technological solutions such as model predictive control [14, 15] and reinforcement learning [16] offer promising results, these studies typically focus on technical innovations or market mechanisms in isolation. They rarely provide integrated insights on how organizations can holistically redesign their operational processes to comply effectively with regulatory instruments such as the newly introduced

ATR [17, 18, 19].

The introduction of ATR by the ACM represents a significant advancement in congestion management, yet current literature provides limited practical guidance for large-scale industrial and commercial consumers on adapting their operations to these specific contractual obligations. While studies have addressed consumer engagement at the residential scale [20, 21], comprehensive approaches tailored to large-scale energy consumers remain largely underexplored.

Moreover, while agent-based modeling (ABM) has been increasingly used to analyze decentralized electricity markets, most prior studies have focused on wholesale market behavior, demand response aggregation, and distributed energy resource (DER) adoption [22]. ABM has proven to be an effective tool for analyzing smart grids, dynamic market interactions, and prosumer behavior, but limited applications exist for evaluating the compliance of large-scale consumers with newly introduced regulatory instruments. Existing ABM studies predominantly focus on price-based market responses, such as wholesale market dynamics [22]. While these models offer valuable insights, they often overlook the operational complexities of complying with regulatory instruments like ATR, which combine financial incentives with contractual and temporal constraints. Consequently, there is limited research on how such compliance strategies affect not only firm-level operations but also system-wide outcomes, particularly their impact on grid congestion patterns and transmission line utilization.

Thus, the central challenge addressed in this thesis involves bridging the gap between regulatory frameworks, technical energy management strategies, and organizational process adaptations necessary for large energy consumers to effectively utilize ATR, thereby reducing grid congestion.

1.3. Research Objectives and Questions

Based on the problem formulation and identified knowledge gaps, this thesis aims to answer the following research question:

> **How can large energy consumers in the Dutch electricity market adapt their operational and data-driven practices to effectively utilize new alternative transport rights, and what impact will these adaptations have on grid congestion?**

To systematically address this central question, four sub-questions were formulated:

1. What are the regulatory requirements of Alternative Transport Rights, and how do they impact the economic costs and benefits for large energy consumers?
2. How can large energy consumers leverage data and technology to optimize their operational processes for Alternative Transport Rights compliance?
3. What are the impacts of adopting Time-Duration-Based Transport Rights by large energy consumers on congestion management effectiveness and the overall stability of the Dutch national grid?
4. What are the impacts of adopting Time-Block-Based Transport Rights by large energy consumers on congestion management effectiveness and the overall stability of the regional grid?

These sub-questions structure the research by linking qualitative insights to quantitative modeling, allowing comprehensive analysis and practical recommendations.

1.4. Research Design

In this research, a mixed-methods approach was employed, combining qualitative stakeholder insights with quantitative simulations through agent-based modeling. Given the socio-technical complexity of the Dutch electricity market, especially in the context of newly introduced ATR, this approach provides a robust framework for capturing both organizational behavior and system-level dynamics.

The research is structured around four sub-questions, deliberately divided across the two methodological components. The qualitative component addresses Sub-Questions 1 and 2, which examine the regulatory design of ATR and the operational strategies large energy consumers may adopt in response. These were investigated through a systematic literature review and semi-structured stakeholder interviews. The quantitative component focuses on Sub-Questions 3 and 4, which evaluate the grid-level impacts of these adaptations under different ATR configurations. These were explored through the development and simulation of an agent-based model using the ASSUME framework.

This dual approach enabled methodological triangulation [23], allowing qualitative insights to inform scenario construction while simulation results validated and enriched the qualitative findings. The integration of these components strengthened the reliability and applicability of the research, offering both depth and breadth in addressing the central research question.

The detailed implementation of this research methodology, including data sources, interview protocols, scenario development, and the structure of the agent-based model, is presented in the next chapter.

1.5. Scientific and Societal Relevance

1.5.1. Scientific Relevance

This research contributes to the academic literature by addressing a notable gap concerning how large energy consumers operationally adapt to newly introduced regulatory mechanisms, such as alternative transport rights. By integrating qualitative stakeholder insights with an ABM framework, this thesis extends the scope of ABM toward evaluating the system-wide impact of contract-driven flexibility, particularly its effects on grid congestion. This interdisciplinary approach offers novel insights into how regulatory instruments can be operationalized by firms and how such adaptations influence electricity system performance.

1.5.2. Societal Relevance

The societal relevance of this research is significant, given the urgent need to alleviate grid congestion in support of the Netherlands' energy transition. As renewable energy integration accelerates, effective use of existing grid infrastructure becomes essential for avoiding costly delays in new housing, business development, and decarbonization initiatives. By demonstrating how large energy consumers can operationalize flexibility under ATR frameworks, this study provides concrete strategies to reduce peak demand and improve load distribution without requiring immediate grid expansion. In doing so, it supports the broader public interest: increasing the reliability and affordability of electricity, enabling cleaner production and electrified transport, and lowering the societal cost of energy infrastructure bottlenecks.

Moreover, by translating policy design into practical adaptation strategies, this work empowers companies, grid operators, and policymakers to co-develop more effective and socially responsible congestion management solutions.

1.5.3. Relevance to Master's Program

This thesis aligns closely with the aims of the MSc Complex Systems Engineering and Management (CoSEM) program, which focuses on addressing complex, multi-actor challenges in socio-technical systems (STS), defined as interconnected elements fulfilling societal functions [24]. The Dutch electricity grid exemplifies such a system, where technical constraints, regulatory policies, market forces, and organizational behavior are deeply intertwined.

By applying systems thinking, regulatory analysis, and simulation modeling to a real-world congestion issue, this research exemplifies CoSEM's core competencies. It demonstrates the ability to diagnose system complexity, evaluate stakeholder behavior, and assess policy interventions using both qualitative and computational tools. Ultimately, the thesis contributes to a deeper understanding of how systemic interventions, like ATR, can be embedded within organizational and infrastructural realities to guide sustainable transitions, reflecting the interdisciplinary ambition and societal mission of the CoSEM program.

2

Research Approach

This chapter provides a detailed explanation about the approach and methodology that guided this thesis. The chapter begins by outlining the qualitative research component (Section 2.1), which includes a systematic literature review and stakeholder interviews. Next, the quantitative research component is described (Section 2.2). Section 2.3 then explains how insights from both components were integrated. Finally, Section 2.4 provides a visual summary of the research process and its contribution to the thesis objectives.

2.1. Qualitative Research Component

The qualitative research component was structured around two complementary methodologies: a systematic literature review and stakeholder interviews. These methods provided robust qualitative insights to answer Sub-Questions 1 and 2. Specifically, this qualitative phase aimed to understand regulatory contexts, technological adaptation strategies, and practical challenges faced by large energy consumers regarding the newly introduced alternative transport rights.

2.1.1. Systematic Literature Review

The systematic literature review was conducted in two distinct phases. The first phase focused on identifying academic research relevant to defining the research gap, while the second phase supplemented these findings with targeted grey literature and technical documentation to inform stakeholder analysis and scenario development.

Phase 1: Academic Literature Review for Problem Framing

An initial systematic literature review was conducted to establish a solid theoretical and empirical foundation for the research. This review focused explicitly on identifying existing academic studies related to congestion management, demand response, and energy management practices of large energy consumers. The primary aim was to uncover insights into organizational process redesign, and to assess how flexible energy contracts could contribute to alleviating grid congestion and enhancing grid stability. Relevant academic studies were retrieved from established scientific databases, specifically Scopus and ScienceDirect. Structured search terms were formulated based on terms such as grid congestion, alternative transport rights, demand flexibility, and energy management. The complete list of search terms is provided in Table A.1. Articles were screened by reviewing abstracts and conclusions. Inclusion criteria emphasized publication recency, citation count, and contextual relevance, with a focus on the Dutch and European regulatory landscape.

This initial review revealed a strong body of work on technical solutions such as energy storage [11], predictive power flow control [12], demand response with DERs [13], model predictive control [14, 15], and reinforcement learning for energy optimization [16]. However, gaps were identified in the literature regarding how regulatory frameworks like ATR could be operationalized by large-scale energy users. In particular, few studies addressed how such users could redesign internal processes or leverage technology to comply with new contractual requirements [20, 21]. An overview of the reviewed academic literature, including the technical and regulatory focus of each study and its relevance to large consumer adaptation, is provided in Table A.2. These insights informed the research problem, justified the need for qualitative stakeholder engagement, and shaped the initial formulation of the research questions.

Phase 2: Supplementary Literature Review

In the second phase of the review, the findings from academic sources were substantiated and extended through the inclusion of grey literature and additional studies identified via snowballing. This phase aimed to deepen the contextual understanding of regulatory developments and industry-specific challenges relevant to ATR implementation. Grey literature sources included government policy documents, regulatory guidelines, consultation reports, technical studies from energy agencies, and publications by consultancies active in the Dutch energy sector. These sources offered up-to-date and practical perspectives on ongoing ATR pilot programs, expected implementation timelines, stakeholder reactions, and anticipated barriers. Snowballing techniques were used to trace references cited in core academic papers and to identify complementary studies that addressed emerging themes. This approach allowed for the integration of niche or recently published materials not yet indexed in major academic databases, ensuring the review remained current and practically grounded.

Together, the two phases of the systematic review provided both a theoretical framework and a practical evidence base for the qualitative analysis and scenario construction. While Phase 1 focused on identifying conceptual and technical gaps in the academic literature, Phase 2 enriched the research with real-world insights, policy context, and implementation details from grey literature. These combined findings formed the foundation for addressing Sub-Questions 1 and 2, by clarifying the regulatory requirements of alternative transport rights and identifying the technological and organizational strategies large energy consumers could adopt for compliance. They were also essential for guiding the stakeholder interviews and for designing realistic, context-informed scenario configurations used in the agent-based simulations presented in the following sections.

2.1.2. Stakeholder Interviews

To supplement and validate findings from the literature review, semi-structured stakeholder interviews were conducted as part of a thesis internship at Deloitte. These interviews provided context-specific insights into the operational realities, organizational barriers, and adaptation strategies relevant to ATR. The primary objective of these interviews was to address Sub-Questions 1 and 2, which concern the regulatory design of ATR and the ways in which large energy consumers can adapt their operations to comply with these new requirements.

Interviews were conducted with three industry professionals directly responsible for energy management in large-scale energy-consuming organizations. The first interview (I1) engaged the Deputy Energy Director of a major greenhouse farming enterprise; the second (I2) involved the Energy Manager at a large flower auctioning company; and the third (I3) was conducted with a Product Manager specializing in energy management solutions at a firm in electrification and automation technologies. Interviewees were selected to ensure sectoral diversity across key energy-intensive domains, agriculture, commercial buildings, and industry, each with distinct operational constraints and flexibility potential. Selection criteria included the relevance of their organization to ATR implementation, the interviewee's direct responsibility for energy-related decision-making, and their willingness to participate. This cross-sectoral lens enabled a comprehensive exploration of how organizational context influences ATR compliance feasibility.

All interviews were conducted via video call, lasting approximately 45–60 minutes each. This medium facilitated convenience and flexibility for the interviewees, enabling detailed and thoughtful responses. Each interview followed a structured yet flexible format divided into four distinct parts:

First, general introductory questions were posed to understand the business context and energy consumption profile of each organization. This initial phase helped establish a baseline of operational characteristics and provided context for interpreting subsequent responses.

Second, interviewees were asked questions regarding their awareness and perception of ATR, aimed specifically at gaining insights into Sub-Question 1. These questions explored respondents' understanding of the regulatory framework, perceived challenges, and anticipated impacts of ATR on their operations.

Third, questions related to energy management strategies were presented to inform Sub-Question 2. This part focused on practical approaches to operational flexibility, demand response strategies, and specific actions taken or planned to comply with ATR.

Finally, discussions centered around technology implementation and enterprise data management were conducted. These questions aimed to provide further insights into Sub-Question 2, particularly regarding technological readiness, the role of digital infrastructure, and the integration of advanced data analytics in energy management practices. The complete list of interview questions used to guide these conversations is provided in Appendix B.

All interviews were conducted in Dutch to enhance participant comfort and encourage detailed responses. Subsequently, interviews were transcribed for consistency and analytical clarity. A manual thematic analysis was performed on the qualitative data, involving iterative reviews of transcripts to identify recurring themes related to operational flexibility, technological readiness, regulatory interpretation, and internal coordination. This inductive approach ensured a systematic yet open-ended interpretation of stakeholder perspectives. English summaries of each interview are included in Appendix C.

Insights gained from these interviews were instrumental in formulating realistic and contextually grounded operational scenarios, which are described in Chapter 5. These scenarios were subsequently used to assess the system-level impact of ATR implementation in the quantitative agent-based modeling phase.

In summary, the combination of the systematic literature review and detailed stakeholder interviews provided a robust qualitative foundation, instrumental for scenario design and the overall analytical structure guiding this research, as visualized in Figure 2.1.

2.2. Quantitative Research Component

The quantitative component of this research employs an agent-based modeling approach using ASSUME [25], an open-source agent-based electricity markets simulation toolbox. ABM was chosen for its ability to simulate system-level change emerging from the interactions of individual agents whose behavior is shaped by external interventions. In this case, the introduction of ATR alters the economic incentives and operational constraints faced by large energy consumers, prompting changes in their energy management strategies. These behavioral responses, derived from qualitative stakeholder insights, were implemented in the model to assess their aggregated impact on grid congestion and system performance. This modeling approach is well-suited to analyzing complex socio-technical systems such as electricity markets [26, 22], where multiple heterogeneous actors interact dynamically over time.

To ensure a systematic and transparent development of the agent-based model, this thesis adopted the ten-step methodology for agent-based modeling in socio-technical systems as proposed by van Dam et al. (2013) [27]:

1. Problem formulation and actor identification
2. System identification and decomposition
3. Concept formalization
4. Model formalization
5. Software implementation
6. Model verification
7. Experimentation
8. Data analysis
9. Model validation
10. Model use

Each step supported the transition from problem framing to simulation and application, ensuring scientific rigor and traceability. The steps were executed as follows:

Step 1: Problem Formulation and Actor Identification
The modeling process began by clearly defining the central research problem and identifying the key actors involved in the system. The focus was on grid congestion in the Dutch electricity network and the roles of large energy consumers, grid operators, and regulators. Understanding stakeholder objectives and constraints was essential for developing a realistic and policy-relevant model.

Step 2: System Identification and Decomposition
The system boundaries were defined, relevant subsystems identified, and the model was decomposed into key components. This included high-voltage transmission infrastructure, market mechanisms, demand agents, generation units, and network tariffs. The model distinguished between regional and national grid levels and incorporated spatial and temporal heterogeneity.

Step 3: Concept Formalization
A conceptual model was developed that specified the agents, their attributes, and their interaction rules in qualitative terms. This included the roles of generation and demand agents, the structure of market interactions, and behavioral responses to ATR incentives. This step laid the foundation for the abstraction of real-world behavior.

Step 4: Model Formalization
The conceptual model was translated into mathematical and algorithmic form. Bidding strategies, grid flow calculations, operational constraints, and pricing mechanisms were defined. Behavioral rules and technical parameters were formalized for computational implementation.

Step 5: Software Implementation
The model was implemented using the ASSUME framework, an open-source simulation environment for electricity market dynamics. Python was used for scenario configuration and simulation control, while PostgreSQL and Docker facilitated structured data handling. This ensured the model was operational and reproducible for scenario testing.

Step 6: Model Verification
Verification activities ensured the model functioned as intended and was free of coding or logical errors. This involved running test cases, checking output consistency, and validating internal relationships such as power flow conservation. Upon successful verification, the model proceeded to full-scale experimentation.

Step 7: Experimentation
Multiple scenarios were designed and simulated to explore the effects of different ATR configurations. Each scenario incorporated specific assumptions regarding demand flexibility and tariff design. The model was executed iteratively over a one-year load profile to produce quantitative outputs for each configuration.

Step 8: Data Analysis
Simulation results were analyzed to evaluate market behavior, grid loading, congestion incidence, and agent performance. The output data were interpreted using descriptive statistics and visual tools to extract meaningful insights into system behavior under various conditions.

Step 9: Model Validation
The model's behavior was validated against historical data from the Dutch electricity system, enhancing the credibility of the results.

Step 10: Model Use
The final model was used to derive actionable insights for both industry and policy. It informed recommendations for large energy consumers on adapting to ATR and provided evidence-based guidance for regulators on the broader system-level impacts of ATR implementation.

These ten steps were not followed in a strictly linear sequence; instead, iterative refinements were made as necessary throughout the modeling process. The integration of these steps across the thesis chapters is further detailed in Table 2.1. A detailed description of the agent-based model development process, including data collection, model structure, and scenario implementation, and agent interaction is provided in Chapter 6.

Table 2.1: Integration of ABM Development Steps into thesis structure [27]

Step	ABM Development Step	Corresponding Section in Thesis
1	Problem formulation and actor identification	Chapter 1 Problem Introduction, Section 1.2
2	System identification and decomposition	Section 6.3 Grid Representation, Section 6.4 Spatial Mapping of Generation and Demand
3	Concept formalization	Section 6.1 Framework Overview, Development ABM
4	Model formalization	Section 6.6 Agent Behavior and Market Interaction
5	Software implementation	Sections 6.1 and 6.2 (ASSUME Implementation and Data Collection)
6	Model verification	Section 6.7 Model Verification
7	Experimentation	Section 5.6 Scenario Justification and Development, Section 6.8.1 TDTR Implementation and Section 6.8.2 TBTR Implementation
8	Data analysis	Chapter 7 Results and Chapter 8 Discussion
9	Model validation	Section 7.1 Model Validation
10	Model use	Chapter 9

The developed agent-based model generated several key outputs to evaluate the effects of alternative transport rights on the electricity market, grid congestion, and energy management strategies. These outputs provided a quantitative foundation for analyzing how large energy consumers adapted under different ATR scenarios., which were developed based on stakeholder insights and literature findings (see Section 5.6). Each scenario was simulated over a one-year horizon and systematically compared to evaluate system-level effects. The results of this analysis are presented in Chapter 8.

2.3. Integration of Mixed-Methods

The final phase of this research synthesized findings from both the qualitative component and the quantitative scenario simulations conducted using the agent-based model. Stakeholder interviews provided contextual understanding of regulatory barriers, operational constraints, and technological readiness, which informed the development of realistic scenario assumptions. Conversely, the simulation results validated and enriched the qualitative insights by demonstrating the system-level effects of ATR adoption on load profiles, electricity prices, and grid congestion.

This methodological integration ensured that the proposed adaptation strategies were both technically feasible and operationally grounded. It also enabled the formulation of actionable recommendations for large energy consumers seeking to comply with ATR, as well as targeted policy suggestions for grid operators and regulators aiming to enhance the effectiveness of congestion management. Ultimately, this combined approach contributes to advancing a more flexible and resilient Dutch electricity system.

2.4. Research Flow Diagram

Having described the methodological choices and their implementation, a flow diagram which visually illustrates the structured progression of these phases and how they collectively contributed to achieving the research objectives is shown in Figure 2.1.

The next chapters build on this structure by first providing contextual background on the Dutch electricity grid (Chapter 3), then presenting the qualitative findings from the literature review and stakeholder interviews (Chapters 4–5). Subsequently, the thesis details the development, validation, and outcomes of the agent-based model (Chapters 6–7). The findings are then interpreted in the discussion (Chapter 8) and synthesized into final conclusions and recommendations (Chapter 9).

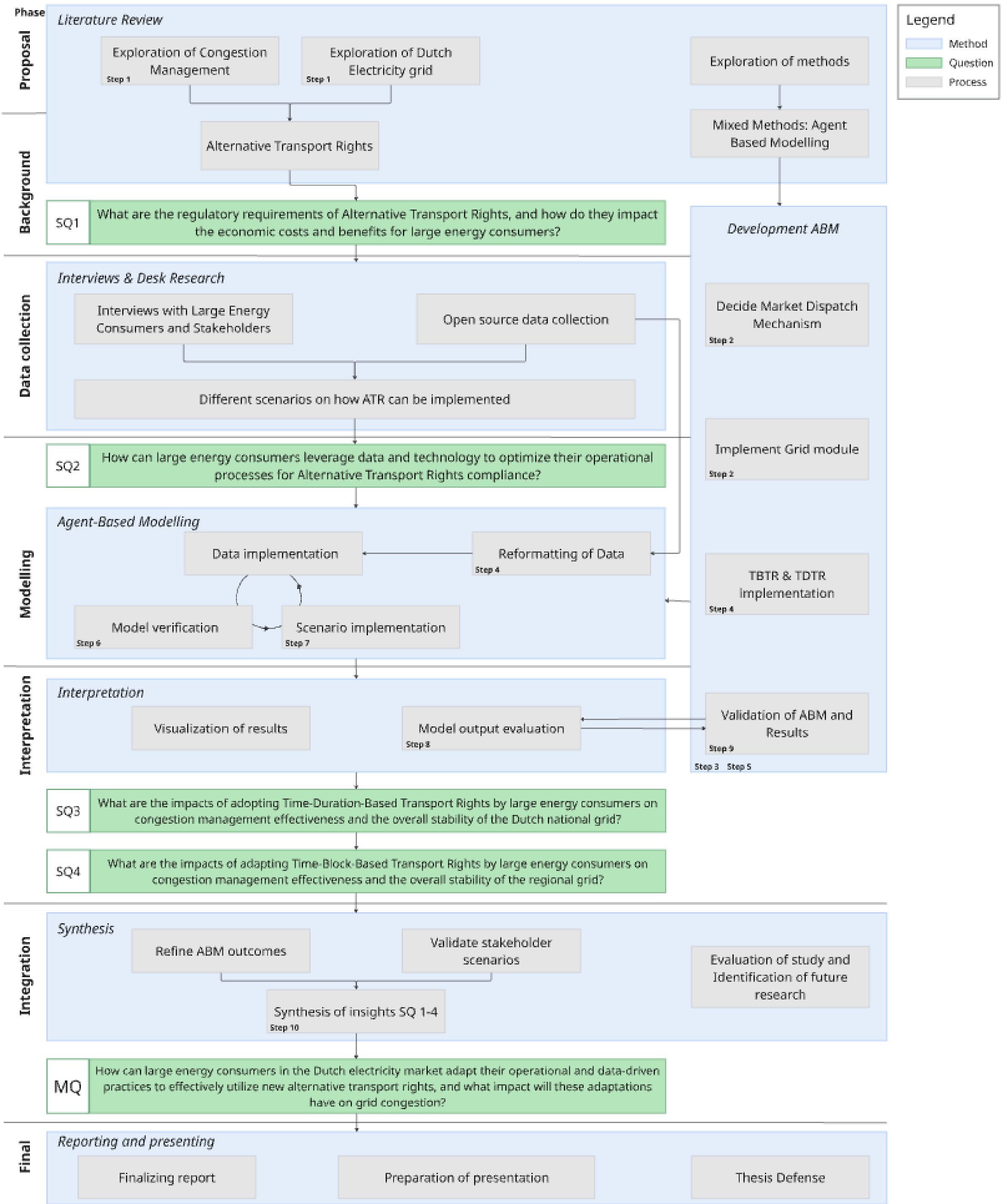

Figure 2.1: Research Flowchart with 10 steps of van Dam et al.(2013) [27]

3 Dutch Electricity Grid: Current State

This chapter outlines the structural and regulatory context of the Dutch electricity grid, focusing on the rise of congestion due to renewable integration and electrification. It begins by describing the roles of national and regional grid operators (Section 3.1), followed by an overview of current congestion management strategies (Section 3.2), including market-based methods, dynamic tariffs, and direct load control.

Section 3.3 then discusses the limitations of traditional tariff structures and introduces emerging approaches that incentivize flexible electricity use. This background provides the foundation for understanding alternative transport rights, explored in the next chapter.

3.1. Grid Structure and Operational Roles

The Dutch electricity grid operates through a two-tier system. The high-voltage transmission network is managed by TenneT, the national Transmission System Operator (TSO), which balances electricity supply and demand across voltage levels of 110, 150, 220, and 380 kV. TenneT ensures grid stability and oversees interconnections with regional grids and large-scale consumers [28]. Medium- and low-voltage networks (66 kV and below) are managed by seven regional Distribution System Operators (DSOs), which distribute electricity to residential, commercial, and industrial users. Within this structure, TenneT manages capacity allocation for high-voltage connections exceeding 100 MW, while DSOs oversee smaller-scale connections. Each operator integrates new users according to the technical and economic constraints of their respective networks, ensuring overall grid reliability.

Until April 1st, 2025, users were guaranteed continuous access to their contracted transport capacity, regardless of grid congestion levels [9]. This model, which is based on unrestricted access, was effective when electricity demand and generation were relatively stable and predictable. However, the rapid expansion of variable renewable energy sources, combined with rising electrification in transport and industry, has placed increasing pressure on the grid. Congestion has become a critical bottleneck, preventing new connections and occasionally forcing curtailment of renewable production to avoid overloads. The issue is particularly acute in areas with high solar PV concentrations or clustered industrial activity, where local generation regularly exceeds grid capacity during peak hours. To visualize the extent of congestion, Dutch grid operators publish a real-time capacity map (see Figure 3.1). Projections suggest that without corrective measures, more than 1.5 million users could face voltage or capacity constraints by 2030 [29].

Under the conventional access model, all users are treated equally, regardless of their ability to shift or reduce demand. This has led to inefficiencies: some users reserve excessive capacity without fully utilizing it, while others face long delays in gaining access, hindering grid efficiency and slowing down energy transition efforts.

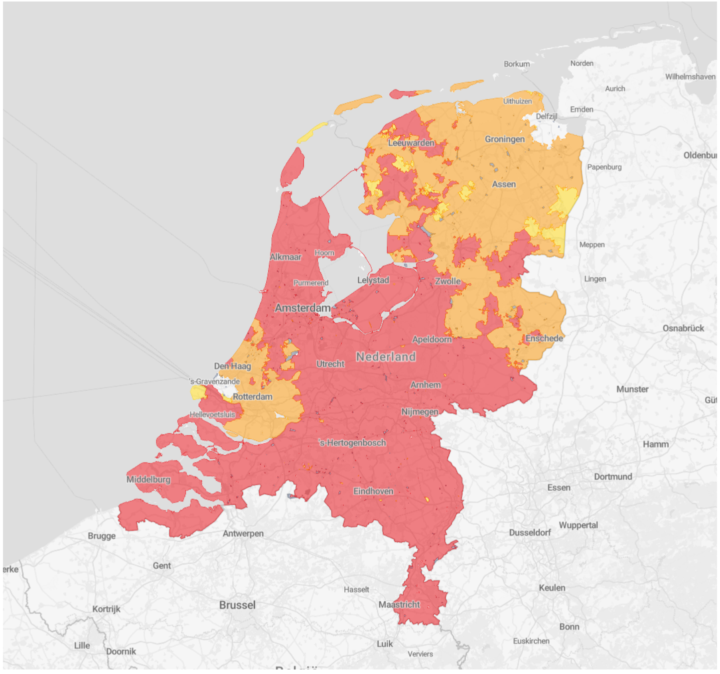

Figure 3.1: Congestion overview of the Netherlands [2]

3.2. Congestion Management

To mitigate this increasing risk of grid overload, policy makers and grid operators have been developing and implementing methods and strategies which balance electricity supply and demand to maintain operational security. These methods, better known as Congestion Management, are mechanisms that utilize flexible loads to remove grid congestion by limiting or shifting energy consumption away from periods or locations of high stress on the network [30]. Flexible loads refer to electricity consumption that can be adjusted in time or intensity without significantly affecting end-user functionality [31]. By leveraging this flexibility, power transfer capabilities are increased and system reliability is enhanced [32]. Congestion management is increasingly vital due to the growing unpredictability of renewable generation and electrification-driven demand. These developments lead to fluctuating and often unpredictable supply and demand patterns, placing considerable strain on grid stability and capacity [29]. Congestion management methods can broadly be categorized into three main groups: market-based methods, dynamic network tariffs, and direct load control [30]. Each approach has its own set of advantages and limitations, influencing their practical implementation and effectiveness.

3.2.1. Market-Based Methods

Market-based methods rely on local flexibility markets (LFMs), where DSOs or TSOs procure flexible capacity from consumers or aggregators to resolve local congestion. In this framework, Demand Response (DR) plays a key role: participants adjust consumption patterns in response to price signals or contractual incentives, effectively turning flexibility into a tradable service [30, 32]. However, LFMs are susceptible to strategic bidding and potential market manipulation, such as withholding available flexibility to inflate market prices, which can result in inflated costs and market inefficiencies [30, 32]. Moreover, LFMs are complex to manage due to the high granularity required for location and time-specific bids, making them challenging to implement effectively at scale [29].

3.2.2. Dynamic Network Tariffs

Dynamic tariffs adjust network charges based on real-time or anticipated grid conditions. Commonly implemented dynamic tariff mechanisms include Critical Peak Pricing (CPP), Network Coincident Peak Charges (NCPC), and Distribution Locational Marginal Prices (DLMP) [30]. Further elaboration on the structure, implementation and limitations of dynamic tariff mechanisms is provided in Section 3.3.

3.2.3. Direct Load Control

Direct load control allows grid operators to remotely limit or control specific high-power flexible devices, such as EV chargers or heat pumps, during congestion events. DLC is highly reliable and straightforward, offering the grid operator direct management of loads to quickly and effectively resolve congestion issues [30]. However, direct load control can raise concerns about fairness and consumer autonomy, particularly if curtailments are frequent or disproportionately affect certain geographical areas or consumer segments. For example, repeated interventions may disrupt business operations or reduce residential comfort, leading to dissatisfaction and potential resistance from affected users [33].

3.2.4. Demand Response

Demand Response refers to the ability of consumers to adjust their electricity usage in response to economic incentives or grid signals. DR acts as a foundational mechanism across multiple congestion management approaches: it underpins dynamic tariffs by encouraging time-shifting of consumption and supports market-based methods by providing tradable flexibility. Effective DR implementation enhances grid reliability, supports renewable integration, and improves cost efficiency [34, 35].

However, widespread adoption of DR faces several barriers. These include implementation complexity, uncertainty in consumer participation, upfront investment costs, and issues of fairness and data privacy. These challenges can disproportionately affect users with limited flexibility capital, defined as the technical, organizational, and behavioral ability to adjust electricity usage in response to external signals, including users such as low-income households or small businesses [31, 36]. Overcoming these challenges requires smart meters, automated control systems, and a supportive regulatory framework [33].

3.2.5. Congestion Management in the Netherlands

The strategy for congestion management in the Netherlands is currently twofold. On one hand, local flexibility markets are coordinated through GOPACS (Grid Operators Platform for Congestion Solutions), a collaborative initiative by Dutch DSOs and the national TSO TenneT. GOPACS enables flexibility providers to submit location-specific bids to relieve grid congestion, thereby addressing local constraints rather than relying on system-wide price signals [37, 38]. This targeted approach ensures that flexibility is activated only where and when it is most needed, improving grid efficiency while reducing the need for costly redispatch or grid reinforcement measures [30].

On the other hand, congestion management may also involve direct load curtailment agreements with large industrial consumers. While these interventions are rarely activated, they remain an essential component of the regulatory toolkit, particularly in cases where market-based flexibility is insufficient or unavailable [30].

However, as these conventional strategies alone have proven insufficient, Dutch grid operators are exploring innovative solutions like alternative transport rights, discussed in subsequent chapter.

3.3. Network Tariffs and Grid Flexibility

Effective congestion management increasingly depends on tariff structures that reflect real-time grid conditions and incentivize flexible electricity use. This section outlines how traditional tariffs function, why they fall short in today's grid context, and what innovations, such as dynamic and non-firm tariffs, are being introduced to improve congestion mitigation.

3.3.1. Limitations of Traditional Tariffs

Network tariffs are charges that electricity users pay for accessing and using the electrical grid. In most European countries, including the Netherlands, these tariffs are defined by the national regulatory agency, in this case, the ACM, in consultation with grid operators and other stakeholders. This includes utilities, consumer groups, and advocates for smart charging, battery storage, and solar energy technologies [39]. The regulator aims to create a tariff structure that fairly recovers network costs while remaining acceptable to the public and market participants [39].

Traditional network tariffs were primarily designed to ensure cost recovery for grid operators, reflecting long-term infrastructure investments. Typically structured as static charges, such as fixed capacity fees or simple volumetric rates, these tariffs offer little incentive for consumers to adjust electricity usage in response to real-time grid conditions [40]. This static design presents several limitations in today's increasingly dynamic energy landscape.

First, static tariffs fail to encourage DR. Consumers face neither adequate financial rewards for shifting consumption to off-peak times nor penalties for contributing to peak demand. As a result, there is little motivation to engage in grid-friendly behavior, exacerbating congestion and driving up infrastructure costs to maintain overcapacity [41, 33, 30, 40].

Second, these tariffs are poorly aligned with the fluctuating nature of renewable energy sources (RES). As intermittent generation from solar and wind increases, so does the need for real-time flexibility. Yet traditional tariffs remain unresponsive to local or temporal variations in supply and demand, which raises operational and balancing costs [30].

Finally, the lack of responsive pricing signals can enable strategic behavior. Inflexible tariff schemes and ill-designed market mechanisms allow grid users to exploit system vulnerabilities, such as by overbooking capacity or shifting loads to inappropriate times, undermining overall efficiency, fairness, and grid stability [40, 41].

To address these challenges, a transition toward more dynamic and cost-reflective tariff structures is needed. These tariffs must incentivize flexible consumption while being supported by advanced metering infrastructure (AMI) and automation technologies that enable real-time pricing, monitoring, and control [36, 40, 33].

3.3.2. Smart Tariffs and Alternative Transport Rights

Smart network tariffs are an emerging concept at the intersection of traditional network tariff design and congestion management mechanisms. They aim to incentivize grid-friendly behavior by incorporating grid conditions into the tariff structure. Examples of smart tariffs include dynamic time-based pricing (e.g. ToU or CPP), capacity subscriptions, critical peak charges, and non-firm or alternative transport rights. These tariffs can adjust to grid conditions, incorporating varying pricing signals that reflect grid congestion, renewable energy availability, and peak demand scenarios. Such tariffs incentivize consumers to shift electricity usage to times when the grid is less congested and renewable energy generation is abundant, optimizing both grid efficiency and sustainability [30, 33]. The relationship between congestion management and these tariff types is illustrated in Figure 3.2.

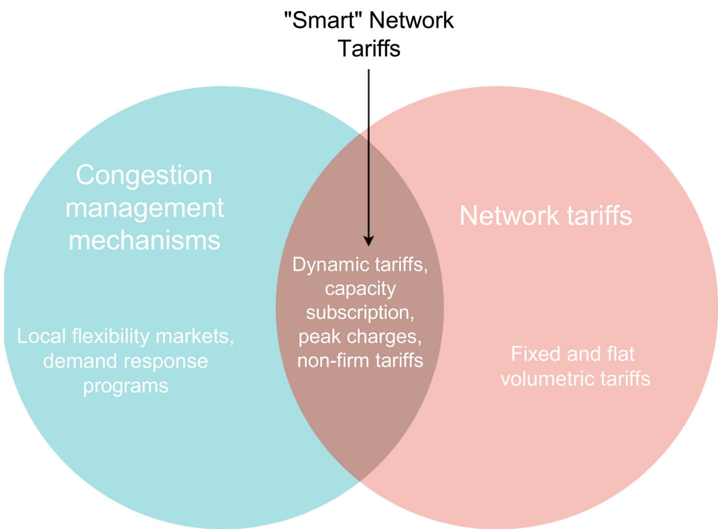

Figure 3.2: Relation of congestion management and network tariffs [30]

3.3.3. Capacity Subscription

Capacity subscription is a smart network tariff model where consumers select a fixed capacity level that defines their maximum contracted grid usage, with favorable rates applied as long as consumption remains within this threshold. If users exceed their subscribed capacity, they face significantly higher volumetric charges, encouraging behavioral adjustments and demand flattening [42].

3.3.4. Dynamic Tariffs

Dynamic tariffs adjust electricity prices based on time-of-use or anticipated grid conditions, encouraging consumers to shift demand away from peak periods or congested locations.

One common form is Time-of-Use (ToU) pricing, which assigns different rates to predefined time blocks, typically distinguishing between peak and off-peak hours. This structure incentivizes consumers to shift flexible loads to off-peak periods, helping flatten demand peaks and reduce grid stress [33, 30].

Critical Peak Pricing (CPP) builds on this by significantly increasing prices during a limited number of pre-announced critical peak events each year. These events are selected based on anticipated grid stress and typically occur a few times annually, providing strong but infrequent incentives to reduce demand [33].

In contrast, Capacity Peak Pricing (CPC) applies higher charges based on actual usage during the highest annual system peak hours, rather than predefined events. This approach encourages consumers to consistently monitor and manage demand throughout the year, as they are penalized based on real grid conditions rather than scheduled notifications [30].

While dynamic tariffs offer strong price signals and can defer costly grid reinforcements, they also introduce price uncertainty for consumers. This variability can disproportionately affect users with limited flexibility capital. As a result, dynamic tariffs may raise concerns regarding fairness and equity in energy access [33].

3.3.5. Non-firm tariffs

Non-firm tariffs are electricity access agreements in which users pay reduced rates in exchange for limited reliability or service priority. Under such arrangements, TSOs or DSOs may curtail access during periods of congestion, maintenance, or grid stress. These mechanisms provide cost-reflective pricing signals and are increasingly used to improve congestion management and capacity allocation in constrained networks [33, 30].

A notable recent development in this area is the introduction of alternative transport rights in the Netherlands. ATR represent a new category of non-firm tariff that differs from conventional approaches in important ways. While traditional non-firm or dynamic tariffs rely on real-time pricing or discretionary operator decisions, ATR are based on predefined contractual conditions. Users accept reduced tariffs in return for fixed limitations on the timing or capacity of grid access [9]. This structure embeds flexibility obligations into the contractual agreement itself, offering higher predictability for consumers and improved enforceability for operators. Unlike more reactive mechanisms, ATR enable targeted, cost-reflective demand response without requiring continuous market participation. This hybrid model combines the stability of firm contracts with the system benefits of flexible consumption.

Although a comprehensive discussion of ATR design and regulatory implementation follows in the next chapter, it is worth briefly highlighting their functional role in congestion mitigation. ATR incentivize large energy consumers to adopt demand response strategies, particularly peak clipping and load shifting, which reduce pressure on the grid during high-stress periods. These strategies are illustrated in Figure 3.3, which shows how demand can either be clipped during peak hours or shifted to off-peak periods.

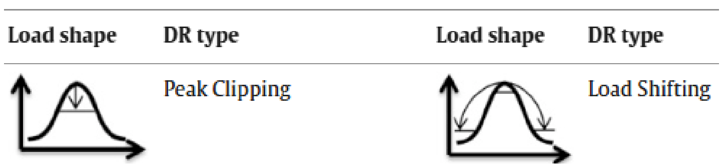

Figure 3.3: Demand Response types as associated with TDTR and TBTR [33]

Through these mechanisms, ATR support more efficient use of existing infrastructure and reduce the need for costly grid expansions, while rewarding operational flexibility in a structured and transparent way [30, 41].

Table 3.1: Overview of Network Tariff Types and Their Mechanisms

Tariff Type	Mechanism	Target Behavior	Pros	Cons
Capacity Subscription	Consumers contract a fixed capacity limit. Favorable rates apply if they stay within this limit; steep charges apply if exceeded.	Encourages flattening of peak loads and predictability in usage.	Simple to implement; provides upfront cost certainty.	Penalizes small overruns harshly; may incentivize over-subscription.
Time-of-Use (ToU) Tariffs	Prices vary depending on predefined time blocks (e.g., day/night or peak/off-peak hours).	Shifts flexible demand to off-peak periods.	Intuitive and predictable for consumers.	Fixed blocks may not align with real-time congestion; limited responsiveness to local grid conditions.
Critical Peak Pricing (CPP)	Significantly higher prices during a few pre-announced critical peak periods per year.	Reduces demand during peak grid stress events.	Strong signal; high reduction impact in few hours.	Requires advance warning and smart metering; unpredictability may affect consumer acceptance.
Capacity Peak Pricing (CPC)	Consumers are charged based on usage during the few highest system peak hours of the year.	Encourages year-round peak awareness and consumption shifting.	Targets true peak hours; high cost-reflectiveness.	Requires smart metering and forecasting; consumers may not know peak hours in real time.
Non-Firm Tariffs (e.g., ATR)	Discounted transport rights in exchange for reduced priority or curtailment. Includes TDTR and TBTR.	Encourages demand reduction during constrained times or locations.	Cost-effective congestion relief without infrastructure expansion.	May create uncertainty (especially for TDTR); depends on operational flexibility and planning systems.

3.4. Conclusion

The Dutch electricity grid is under increasing structural pressure due to the growth of decentralized renewable generation and widespread electrification. Traditional models of network access and tariff design are no longer sufficient to ensure efficient and reliable grid usage. In response, grid operators and policymakers have introduced a range of congestion management strategies, such as market-based methods, dynamic network tariffs, and direct load control, each offering distinct advantages and challenges. Among the most promising developments are emerging mechanisms like smart tariffs and non-firm access agreements, of which an overview can be found in Table 3.1. In particular, the recently introduced ATR provide new opportunities for incentivizing flexible grid usage among large energy consumers. These mechanisms aim to better align user behavior with grid capacity, offering potential relief from congestion without the immediate need for infrastructure expansion.

The next chapter explores the regulatory foundation and design of ATR in more detail, outlining their structure, conditions, and implications for system efficiency and consumer participation.

4

Regulatory Background

This chapter examines the design and implementation of Alternative Transport Rights. It addresses the first sub-question of this thesis:

What are the regulatory requirements of Alternative Transport Rights, and how do they impact the economic costs and benefits for large energy consumers?

Section 4.1 outlines the structure and purpose of ATR, including the two variants: Time-Duration-Based (TDTR) and Time-Block-Based (TBTR). Section 4.2 explains how these mechanisms affect tariff structures and cost outcomes. Finally, Section 4.3 explores adoption challenges from both regulatory and operational perspectives, drawing on literature and stakeholder interviews. Together, these elements provide the regulatory foundation for the operational strategies discussed in the next chapter.

4.1. Alternative Transport Rights

In July 2024, the Dutch authority of consumer and market introduced alternative transport rights as a regulatory intervention. This intervention aims to optimize grid usage and alleviate congestion without requiring immediate large-scale infrastructure expansion. ATR represent a shift from the traditional model of unrestricted transport rights to a more flexible, demand-responsive system. Instead of guaranteeing continuous grid access, ATR defines conditions under which users can adjust their energy consumption or production patterns to support grid stability. A request for ATR can be made for energy consumption, energy supply, or both. This regulatory shift encourages large energy consumers to optimize their electricity use, making better use of available capacity while maintaining fairness and efficiency in the energy market. ATR introduces flexibility in two dimensions: temporally, by requiring users to adapt their electricity usage to specific time windows, and spatially, by targeting areas where grid congestion limits capacity availability. To operationalize this flexibility, the ACM introduced a framework for allocating residual grid capacity to users with adjustable demand profiles [9].

This available residual capacity is indicated in Figure 4.1 as the green area labeled "A". ATR can exclusively utilize this residual capacity in both congested and non-congested areas. In non-congested areas, additional unused capacity exists, represented by the blue area labeled "B" in Figure 4.1. However, this capacity is not available for ATR, as its use would effectively increase peak time transport demand, contradicting the purpose of ATR to reduce rather than increase peak congestion [9]. A combination of conventional transport rights and ATR on the same grid connection is possible, allowing users to balance fixed capacity needs with flexible energy consumption strategies. ATR are implemented in two distinct forms, each with its own operational logic and applicability, which will be examined in the following sections.

4.1.1. Time-Duration-Based Transport Rights

TDTR were introduced on the national high-voltage grid as of April 2025. With TDTR, a connected party has the right to the connected transport capacity for at least 85% of the hours per year, making it suitable for users who can accommodate occasional flexibility in their electricity demand. For the

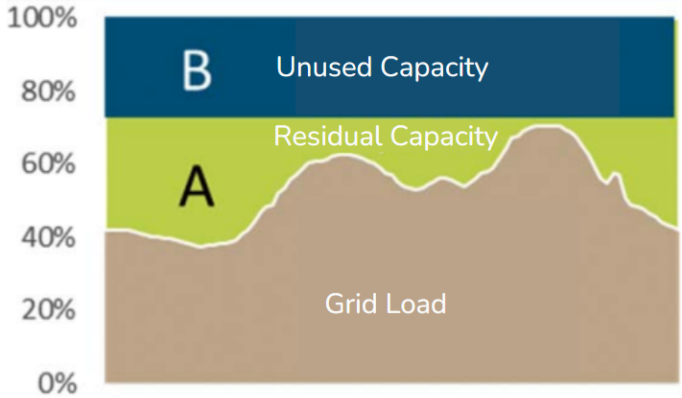

Figure 4.1: Grid Capacity [9]

remainder of the year, the connected party has no certainty about the availability of the contracted transport capacity. To compensate this, the network tariff will be reduced. The connected LEC does not know exactly at what times of the year the transport capacity will be limited. If the situation on the grid requires a limitation of transport capacity, the grid operator informs the connected party the day before. Depending on the available residual capacity, the actual limitation can also in practice be less than 15% per year, but never more. The grid operator (TenneT) will only disconnect the TDTR connected party if, based on daily forecasts, it expects that no residual capacity will be available for the next day [9].

Currently, one party has already entered into a TDTR contract with TenneT. This contract was signed by a large-scale battery storage company, categorized as a large energy consumer, which is well-positioned to offer additional grid flexibility and stability. The contract is scheduled to take effect in October 2025 [43]. According to TenneT's most recent analysis, the nationwide implementation of TDTR contracts could unlock up to 9 gigawatts of additional transmission capacity on the high-voltage grid, equivalent to approximately 40% of the current Dutch peak electricity demand [44].

4.1.2. Time-Block-Based Transport Rights

TBTR were initially scheduled to become available in April 2025; however, this timeline has been postponed due to implementation delays by DSOs, who were unable to operationalize these alternative transport rights within the intended time frame [45]. Initially, TBTR will be introduced exclusively on regional electricity grids and will grant users access to the grid during predefined time blocks. Outside of these contracted periods, the connected party holds no transport rights. Similar to TDTR, TBTR is based on residual grid capacity, meaning that the available time blocks are scheduled outside of typical system peak hours. The definition of peak moments and the extent of available residual capacity vary by location and depend on local grid conditions. As a result, TBTR allows for tailored contracting of time blocks that align with the operational needs of large energy consumers and the capacity limits of the local grid. This mechanism incentivizes electricity consumption during off-peak periods.

The structure of TBTR time blocks can vary, ranging from fixed nightly hours to more flexible weekly or monthly schedules. However, in the current roll out, DSOs have limited TBTR offerings to a nighttime time block, between 00:00 and 06:00 [46, 47, 48].

Together, TDTR and TBTR offer flexible access to grid capacity in exchange for a reduced level of certainty. To reflect this reduced guarantee of service, both mechanisms are accompanied by a revised tariff structure designed to incentivize participation while maintaining cost reflectiveness. The following section outlines how these financial compensations are structured and compares them to traditional access arrangements.

4.2. Financial Compensation

The Dutch network tariff structure for both regional and national grids consists of three components [40]:

- **Fixed Component**: An annual fee charged to recover fixed infrastructure and administrative costs.
- **kW Contracted**: A fee based on the maximum transport capacity that a large energy consumer expects to require at any point during the year. This capacity must be pre-contracted, and the consumer is not permitted to exceed this limit during normal operation [49, 50].
- **kW Max**: A variable monthly fee determined by the actual peak electricity consumption recorded within each calendar month [49, 50].

To incentivize flexible electricity usage, the network tariffs associated with alternative transport rights are deliberately set lower than those of conventional transport rights. As stated in the ACM decision [9], the discount structure is based on the following principles:

Time-Duration-Based Transport Rights

Consumers temporarily forego access to their contracted capacity for up to 15% of the year. To compensate for this limitation, grid operators provide a discount on the consumption-dependent transport tariff. This discount effectively reduces the *kW Contracted* tariff component to zero, as TDTR users are not considered in long-term grid capacity planning. According to grid operators, current insights suggest that a consumer whose transport capacity is limited by a maximum of 15% is unlikely to cause a higher peak in the total load of the national high-voltage grid [9]. Consequently, TDTR consumers do not contribute to expansion investments necessary to guarantee unrestricted access, as fixed transport rights users do. Instead, TDTR consumers only pay based on their actual peak consumption, represented by the *kW Max* tariff, which remains identical to that of users with a fixed transport right.

Time-Block-Based Transport Rights

Consumers have access to the grid only during predefined time blocks. In exchange, they receive a discount on the *kW contracted* tariff, paying only for the hours they have contracted. In the future, if time blocks vary throughout the week or month, a monthly average is applied to determine the tariff. The discount is calculated using the formula:

$$kW contracted, timeblockbased = t/24 * kW contracted, fixed \tag{4.1}$$

where **t** represents the (average) number of contracted hours per day. However, the *kW max* tariff remains unchanged, as it reflects actual grid usage. Within their contracted time blocks, TBTR consumers have the same rights as those with fixed transport rights.

4.2.1. Example TDTR

To illustrate the economic benefits of ATR, the case of the first TDTR contract is reviewed. The adopting party, a large-scale battery storage company, has a peak demand of 300 MW. The 2025 transport tariffs, established by the ACM, are shown in Figure 4.2. This company is connected to the high-voltage grid, which means the relevant tariff components are €73.46 per kW per year for *kW Contracted* and €8.50 per kW per month for *kW Max*.

Assuming the company utilizes its full contracted capacity of 300 MW each month, the total variable annual cost of conventional transport rights is calculated as follows:

$$kW Contracted = €73{,}46 * 300.000 kW = €22.038.000 \tag{4.2}$$

$$kW Max = €8{,}50 * 300.000 kW * 12 months = €30.600.000 \tag{4.3}$$

Under a TDTR contract, the *kW Contracted component* is waived, resulting in an immediate annual cost reduction of €22.04 million. The remaining charge is based solely on the *kW Max* component, totaling €30.6 million. This equates to a variable cost reduction of approximately 41.8% compared to a conventional contract. In reality, most companies do not operate at full peak load throughout the year, which would lead to an even higher discount. According to TenneT, TDTR can reduce transport costs by up to 65% in practice compared to conventional transport rights [43].

	Vastrecht	kW gecontracteerd per jaar	kW max gewogen per maand	kW gecontracteerd per jaar (max 600 uur)	kW max gewogen per week (max 600 uur)
EHS tarieven 2025	12.478,96	54,99	7,14	27,50	2,47
EHS rekenvolumina 2025	22,00	1.391.069	10.929.710	137.224	901.112
HS tarieven 2025	2.760,00	73,46	8,50	36,73	2,94
HS rekenvolumina 2025	97,50	16.178.146	140.103.153	210.992	1.706.069

Figure 4.2: Established rates and calculation volumes 2025 Dutch High-Voltage grid [39]

4.3. Adoption Risks and Challenges for Large Energy Consumers

While alternative transport rights offer the potential to reduce cost and increase grid efficiency, their adoption presents several technical, economic and behavioral challenges. Drawing on stakeholder interviews and academic literature, this section identifies and elaborates on six core categories of barriers.

4.3.1. Uncertainty About Capacity Availability

A key concern for potential ATR users is the uncertainty surrounding grid capacity availability. Under TDTR, users receive only a one-day advance notice when curtailment of their contracted capacity is required. This short notice significantly hampers forward operational planning, particularly in sectors with tightly scheduled processes. As the energy manager of a large flower auctioning hub (I2) noted: “We simply don’t have the systems in place to change our load with 24-hour notice. It affects cooling cycles, lighting, everything.”

In contrast, TBTR provides access during pre-defined time blocks, offering greater predictability. Yet in practice, these time windows may not align with users’ operational demands or production peaks. As explained by the energy management product manager (I3): “The blocks offered don’t match when they really need electricity,” highlighting a mismatch between contractual design and real-world consumption patterns.

4.3.2. High Upfront Investments in Metering and Control Infrastructure

Not all LECs have the infrastructure required to participate in ATR contracts effectively. Smart meters, sub-metering at process level, and control systems such as Energy Management Systems (EMS) are prerequisites. This need is echoed in multiple interviews: *“You can’t control what you can’t measure. Our first advice is always: invest in good metering.” (I3)* This aligns with the broader academic consensus that initial technology investments hinder demand response uptake [33]. Moreover, network tariffs that are fixed on a peak-demand basis can make the business case for these investments less attractive, especially if flexibility increases peak usage temporarily [41].

4.3.3. Organizational and Behavioral Adaptation

Adopting ATR requires not only technical adjustments but also behavioral and organizational changes. Employees need to be trained and educated to operate under flexible power availability, which is a challenge. The flower auction company energy manager (I2) stated: *“It’s difficult to ensure that the entire organization understands why we have to do the things we need to do.”* In addition, changing deeply ingrained production routines, for example, dimming lighting or rescheduling refrigeration, can face internal resistance, particularly when it potentially impacts product quality or employee convenience.

4.3.4. Operational Risk and Compliance Burden

For large energy consumers, the adoption of ATR brings with it a new set of operational responsibilities and risks. Under both TDTR and TBTR arrangements, consumers must strictly comply with the time windows or curtailment instructions communicated by the grid operator. Deviations, referred to as overruns, can pose a threat to grid stability and are met with escalating enforcement measures. After multiple violations, the grid operator may suspend access under the ATR agreement, with reinstatement only possible after corrective steps, such as the installation of automated load control systems. Persistent non-compliance may lead to permanent contract termination [9]. While these safeguards are necessary to maintain grid reliability, they also raise the perceived risk of participation. Several interviewees noted that unforeseen scheduling conflicts, forecasting inaccuracies, or delays in internal communication could lead to unintentional breaches. For organizations lacking real-time monitoring or advanced energy management systems, this introduces considerable uncertainty and administrative strain, especially when adapting to short-notice curtailments under TDTR.

In addition to compliance risk, companies face operational challenges in estimating how much of their demand can be made reliably flexible. If flexibility is overestimated and contracted capacity is scaled back too far, the risk of peak-time overruns increases. This may result in steep penalties or force firms to repurchase capacity at a premium. As one interviewee (I3) remarked: *"You don't want to cut your contracted volume too much and then find yourself paying huge penalties during a peak."*

Together, these issues contribute to a cautious approach among large energy users. Without the right forecasting tools, automation, and internal processes, the perceived risks of non-compliance may outweigh the financial incentives of ATR participation.

4.3.5. Tariff Design and Misaligned Incentives

Even when technical and organizational readiness is in place, the structure of existing network tariffs can undermine the intended flexibility incentives of ATR. A central issue is the *kW Max* component, a monthly peak demand charge based on the single highest hourly consumption within each calendar month. As highlighted by Richstein and Hosseinioun (2020) [41], this pricing model fails to account for short-term flexibility actions that benefit the grid, yet may inadvertently trigger higher costs for users.

Consider a TDTR user who receives a one-day curtailment notice. To preemptively shift demand, the user advances flexible operations such as battery charging or production cycles to earlier hours. Although this action helps avoid congestion during peak hours, it may result in a sharp spike in electricity usage that defines the month's peak and therefore increases the *kW Max* charge. In this way, a behavior that supports grid stability paradoxically reduces the financial benefit of participating in ATR, weakening the incentive for flexible consumption.

Uncertainty about such outcomes also drives conservative contracting strategies. Under TDTR, companies may over-contract capacity to hedge against unplanned disconnections. Under TBTR, they may secure excess capacity to avoid exceeding limits during narrow access windows. While these practices reduce perceived risk, they also contribute to inefficient grid usage and underutilized capacity, undermining the very congestion relief ATR aims to achieve. These issues underscore a fundamental design misalignment: when cost signals do not accurately reflect system benefits, rational users may adopt behaviors counterproductive to grid efficiency. Addressing this requires thoughtful tariff reform.

4.3.6. Limited Awareness and Regulatory Complexity

ATR is still a relatively new mechanism and lacks broad market familiarity. Many businesses remain unclear about its operational requirements, eligibility conditions, and potential benefits. As the greenhouse energy director (I1) noted: *"I haven't seen any company in our sector sign one of these ATR contracts yet. There's too little guidance."* This highlights a wider issue of informational and institutional barriers. Eid et al. (2016) [33] similarly point to regulatory fragmentation and the absence of standardized practices as major obstacles to the broader adoption of demand-side flexibility initiatives.

In summary, while ATR offer considerable potential for improving grid efficiency and reducing energy costs, their adoption is constrained by a range of operational, technical, economic, and institutional barriers. These include short-notice curtailments, high upfront investments in monitoring and control infrastructure, organizational inertia, compliance risks, and tariff structures that may inadvertently discourage flexible behavior. Additionally, limited awareness and regulatory complexity further hinder large-scale implementation.

The subsequent chapter builds upon this regulatory foundation by examining how large energy consumers can operationalize ATR compliance. It explores the role of data-driven energy monitoring, digital control systems, and organizational adaptation in enabling effective and scalable adoption of ATR mechanisms.

5

Operational Adaptation and Scenario Development for ATR Compliance

This chapter explores how large energy consumers can adapt their operational and data-driven practices to meet the requirements of ATR, drawing on qualitative insights from stakeholder interviews. It addresses the second sub-question of this thesis:

How can large energy consumers leverage data and technology to optimize their operational processes to achieve compliance with Alternative Transport Rights?

Section 5.1 highlights the importance of high-resolution monitoring and data visibility. Section 5.2 discusses the role of energy management systems, automation, and enterprise data governance. Section 5.3 identifies sector-specific flexibility strategies and their alignment with ATR requirements. Section 5.4 evaluates the potential and limitations of battery storage. Section 5.5 examines organizational routines and behavioral adaptations that support flexible energy use. Finally, Section 5.6 synthesizes these insights into sectoral flexibility assumptions that serve as model input for the agent-based simulations presented in the following chapters.

5.1. Leveraging Data for Operational Optimization

A central theme emerging from all conducted interviews was the foundational importance of detailed energy data visibility for ATR compliance. The product manager (I3) emphasized the necessity of high-resolution sub-metering, recommending measurement intervals as granular as 30 seconds. He stated explicitly: *”Start by measuring. Know where your energy is going, and when. Only then can you start looking for solutions”* (I3). Such detailed monitoring is crucial for accurately identifying peak demands and determining load-shifting potentials in compliance with both Time-Duration-Based and Time-Block-Based ATR.

Similarly, the energy manager of a greenhouse company (I1) leverages centralized application programming interface (API) driven systems and Power BI analytics to visualize daily consumption data. This enables proactive adjustment of operations, such as modifying heating and lighting schedules in response to predicted energy costs and market signals. The energy manager at a flower auction facility reinforced this point, stressing the importance of high-resolution insights into energy consumption to identify and target peak consumption periods effectively (I2).

5.2. Digital Infrastructure and Automation

Effective ATR implementation relies heavily on advanced digital infrastructures capable of real-time energy management and automated control. The product manager (I3) highlighted the availability of compact, low-cost current measurement sensors, termed ”sugar cube” sensors, which can quickly provide real-time data at the individual group level. He explained how such sensors feed into energy management systems, enabling automated load management: *”Using simple logic, you can, for exam-*

ple, control based on time (think of time-bound contracts) or based on power levels" (I3). Moreover, multiple interviewees emphasized that achieving high-resolution energy visibility is not only a technical challenge but also an organizational one. Effective energy data utilization requires robust Enterprise Data Management (EDM) systems that ensure the consistent collection, integration, governance, and accessibility of energy-related data across business units. Without structured EDM, sub-metering efforts risk producing siloed or fragmented insights, limiting their strategic value for ATR optimization.

In practice, the greenhouse company already employs automated climate computers integrated into an EMS, actively managing power consumption in response to energy prices and peak constraints. According to their deputy energy director (I1), *"There are continuous measurements running, integrated with the climate control system we use. The software ensures we don't exceed the peak; as soon as it detects that the limit is being approached or exceeded, it immediately shuts things down, for example, the LED lights are turned off instantly"*. However, despite substantial automation, some manual oversight remains necessary, particularly to align energy management decisions with crop production cycles controlled separately. These systems are most effective when embedded within a broader EDM framework that standardizes data flows between operational technologies (OT) and corporate information systems (IT). For example, ensuring that climate automation data flows consistently into centralized dashboards and historical analytics systems requires robust data warehousing, quality assurance processes, and metadata management, core elements of effective EDM.

Additionally, advanced automation examples were provided by the product manager (I3), illustrating their manufacturing facility where fully automated production lines and self-driving forklifts strategically operate overnight. He noted: *"Machines run during nighttime not to produce continuously, but to smooth peak energy consumption during daytime operations."* Their automation platform further supports robust load management by executing predefined load-shifting rules independent of external cloud connections.

In contrast, the flower auction currently lacks real-time monitoring but has implemented integrated building management systems capable of dynamically controlling heating, ventilation, air conditioning (HVAC) and lighting loads. Their Energy Manager (I2) believes such systems will be vital for future compliance with ATR scenarios by automatically responding to grid signals, thus effectively managing peak demand conditions.

5.3. Identifying and Utilizing Flexible Loads

Effectively adapting to ATR conditions requires a systematic classification of electricity loads into critical and flexible categories (I3). Flexible loads can then be strategically shifted in time, intensity, or location in response to electricity price signals or ATR-related capacity constraints. Figure 5.1 conceptually illustrates load flexibility. The horizontal axis indicates time or space, and the vertical axis shows electricity intensity. The solid rectangle represents the original, fixed load. The dashed area illustrates how this load could be shifted in timing, duration, or intensity to better align with available grid capacity.

Common examples of flexible loads are HVAC systems, as well as electric vehicle charging infrastructure, which can typically be rescheduled without disrupting core operations. The product manager (I3) emphasized that identifying and managing non-essential loads, such as pre-heating or pre-cooling buildings during off-peak hours, is a key strategy for optimizing energy use and ensuring ATR compliance.

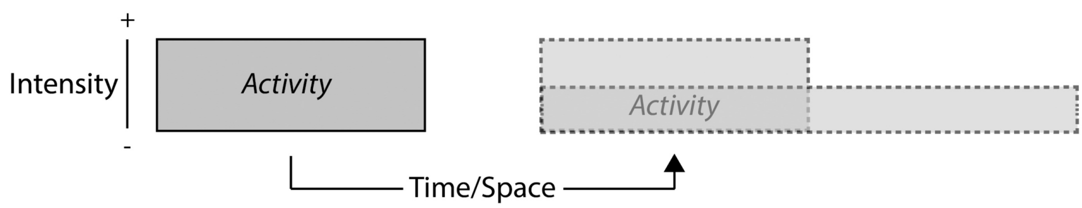

Figure 5.1: Simplistic representation of flexible energy use in time, space or intensity [31]

Importantly, the degree of flexibility differs substantially across sectors due to variations in operational processes, infrastructure maturity, and energy management capabilities (I3). The remainder of this section summarizes the sector-specific insights shared by interviewees.

Agriculture (I1): Greenhouse operations demonstrate high inherent flexibility. Lighting and heating loads can be dynamically scheduled based on grid constraints, and thermal buffering is already widely employed. The Deputy Energy Director noted that CO_2 dosing can also be staggered to smooth demand. Their systems already react to real-time electricity prices, making the sector well-positioned for ATR compliance.

Buildings (I2): At the flower auction facility, HVAC is the primary source of flexibility. The facility has begun investing in refrigeration overcapacity to create thermal buffers that enable nighttime load shifting. However, flexibility remains limited due to aging infrastructure and the absence of real-time monitoring. As the Energy Manager explained: *"I have three major electricity consumers in our company, which spans two million square meters. The first is lighting, but I can't do much with that, since the lights need to be on during auction operations. The second is heating, and the third is cooling. Heating will likely become the largest source of flexibility once we've fully electrified."* These remarks suggest that substantial latent flexibility could be unlocked through electrification and digital upgrades, especially in thermal systems.

Industry (I3): In industrial settings, flexibility is generally constrained by the need for continuous production processes. However, the product manager (I3) emphasized that auxiliary loads, such as electric vehicle charging stations and facility lighting, can be scheduled without affecting core operations. He characterized these non-critical loads as "low-hanging fruit" for achieving ATR compliance with minimal disruption (I3), particularly when automated via EMS platforms.

Transport: Flexibility in the transport sector primarily stems from the timing of EV charging. Commercial fleet operators, particularly those with predictable usage patterns and overnight parking availability, are well-positioned to shift charging activities outside of constrained periods. Given the alignment between TBTR time blocks and vehicle idle hours, this sector holds significant potential for low-cost flexibility through smart charging infrastructure and basic scheduling algorithms, as corroborated by existing literature on transport electrification and demand response [31].

In addition to leveraging sector-specific flexibility through scheduling and automation, many organizations are also exploring technological solutions that can further decouple electricity consumption from grid availability. Among these, battery storage is often highlighted as a key enabler of operational flexibility under ATR constraints. The following section critically examines the role of battery systems in supporting ATR compliance across different sectors.

5.4. The Role of Battery Storage in ATR Compliance

Battery storage systems are frequently cited in both academic and industry literature as promising tools for enabling demand flexibility under constrained grid conditions [13, 11, 51, 52]. In principle, batteries could allow large energy consumers to temporally decouple electricity procurement from consumption, storing energy during periods of low demand or low prices and discharging during times of congestion or limited grid access. This aligns well with the requirements of ATR, which restrict grid access during specific hours or time blocks.

Despite widespread recognition in literature of the flexibility potential of batteries, all three interviewees emphasized that while technically attractive, battery storage is currently too expensive to serve as a viable standalone solution for ATR compliance. The Energy Manager at the flower auction facility (I2) remarked: *"Even if ATR contracts were available, our energy consumption profiles are not yet flexible enough, and the investment in batteries would be too large to be justified."* Instead, the organization prioritizes thermal buffering strategies in its refrigeration systems to achieve flexibility at lower cost.

The product manager for energy management systems (I3) echoed this sentiment, warning that many companies incorrectly oversize battery systems due to poor data resolution: *"A lot of times you see companies calculate their battery needs based on rough assumptions, just adding 10% for degradation and calling it a day. But the real load profile, the true simultaneity of peak demands, is rarely that simple."* He advocated for detailed sub-metering and high-resolution monitoring as a prerequisite for any meaningful battery sizing or return-on-investment analysis.

Similarly, the greenhouse company (I1) viewed batteries as unnecessary in the short term due to its extensive operational flexibility. As the deputy energy director explained: *"Why spend millions on a battery when I can just schedule my lighting and heating differently? The grid pays me to be flexible, not to store."* Their strategy prioritizes control automation and smart scheduling over energy storage infrastructure.

While battery prices may decline in the coming years and their role in system-level flexibility may grow, current consensus among the interviewed experts is that most large consumers can achieve more cost-effective ATR compliance through digital infrastructure upgrades and process flexibility, with battery storage serving only as a potential long-term complement. However, the practical effectiveness of any flexibility strategy ultimately depends on how well it is embedded in organizational routines and decision-making structures. The next section therefore turns to the organizational and behavioral dimensions of ATR compliance, focusing on how companies foster internal alignment, staff awareness, and operational responsiveness to grid constraints.

5.5. Organizational Integration and Behavioral Strategies

Effective operational optimization extends beyond technical capabilities to organizational practices. Centralized energy management teams, as observed in the agriculture sector, facilitate rapid decision-making informed by real-time data and direct communication with operational staff. These capabilities are significantly enhanced by robust enterprise data management systems.

One example of how EDM enables actionable behavior change is the use of visual alerting systems, such as "stoplight systems," which enhance situational awareness on the work floor without requiring full automation (I3). According to the product manager, such a system was implemented at one of their clients using color-coded visual signals connected to the facility's EMS. Wall-mounted displays or LED indicators in production areas change color based on real-time electricity consumption relative to predefined thresholds. Green indicates acceptable usage, orange signals that consumption is nearing the peak threshold, and red alerts staff that the threshold has been exceeded, prompting immediate curtailment actions. As the interviewee stated: *"That is how you can use visual signals to influence behavior and tackle a congestion problem, without automation."*

This form of direct visual feedback fosters shared responsibility across operational levels. It helps bridge the gap between centralized energy management goals and day-to-day production behavior, especially in facilities that may not yet support full automation. As the Energy Manager of the flower auction facility (I2) observed: *"I notice it's difficult to make the entire organization understand why we need to do the things we do."* By making invisible energy flows visibly actionable, these systems serve as a low-cost but effective tool for promoting ATR-compliant behavior in real time. Importantly, the accuracy and reliability of these systems depend on EDM processes that standardize how data is collected, interpreted, and displayed across departments. Without such structure, sub-metered insights risk becoming fragmented or misaligned with operational decision-making.

The flower auction facility also reported success with organizational measures, including regular energy awareness training sessions for operational staff and clear communication of energy management goals. These behavioral interventions complemented technical solutions and EDM-enabled insights, ensuring broader staff engagement and consistent adherence to energy reduction strategies. As the Energy Manager explained: *"No one wastes energy for fun. If you just show how much is being used and where the opportunities lie, that awareness will come naturally."*

5.6. Scenario Justification and Development

Building on the qualitative insights developed in the preceding sections, this part of the chapter translates interview-based findings into quantified, sector-specific flexibility assumptions that serve as input for the agent-based modeling of ATR scenarios. Since ATR are designed exclusively for large energy consumers, the model focuses solely on this group. Households and small to medium-sized enterprises (SMEs) are excluded from the flexibility modeling. Household electricity demand is held constant across all scenarios, while SMEs are not modeled explicitly. This decision stems from two factors: (1) the absence of detailed, disaggregated consumption data for SMEs, and (2) the fact that SMEs are not eligible for ATR contracts in the current regulatory framework. Instead, the sectoral demand profiles in the model are assumed to represent only the LEC portion of electricity consumption within each sector.

This assumption is supported by national statistics: LECs account for at least two-thirds of total electricity consumption in the Netherlands [53, 54], and since households comprise approximately 21% of demand, LECs are estimated to cover at least 85% of non-household electricity use. By excluding SMEs, the model simplifies the demand-side representation while still capturing the majority of flexible consumption relevant for ATR policy analysis. As such, the flexibility assumptions presented below reflect only the realistically adjustable share of demand attributed to LECs.

As highlighted throughout the chapter, flexibility potential also varies significantly between sectors due to differences in technological infrastructure, operational processes, and organizational capabilities. Capturing these sector-specific nuances enables the use of flexibility percentages that reflect not only feasible load adjustments but also the proportion of demand eligible for ATR. Since ATR can be combined with or (partially) substitute conventional transport rights, these percentages effectively represent the maximum shiftable share of demand per sector under different adoption scenarios.

For both TDTR and TBTR, two levels of adoption were modeled: a Full Adoption scenario and a Hybrid Adoption scenario. The Full scenario assumes that all technically feasible flexibility identified in each sector is fully activated in response to ATR requirements. This represents a theoretical upper bound in which energy consumers are fully equipped, both technologically and organizationally, to shift or curtail demand in alignment with contractual constraints.

In contrast, the Hybrid scenario reflects a more transitional and realistic near-term outlook, where only a subset of consumers has implemented the necessary systems, automation, or behavioral routines to respond effectively to ATR conditions. To operationalize this intermediate stage, the flexibility potential for each sector was conservatively set at 50% of the full values. This approach accounts for both technological readiness and varying levels of participation across the consumer base. Modeling both adoption levels enables a comparative assessment of best-case flexibility outcomes versus more realistic near-term responses, supporting robust policy and investment recommendations.

Table 5.1 summarizes the share of each sector's demand that is assumed to be shiftable under the four ATR scenarios. For each scenario, TDTR Full, TDTR Hybrid, TBTR Full, and TBTR Hybrid, the table lists the percentage of flexible load that is assumed as model input. For instance, in the TDTR Full case, 70% of agricultural demand is assumed to be shiftable, whereas under TBTR Hybrid only 25% is assumed. These values reflect stakeholder interview insights and the operational constraints presented earlier.

Table 5.1: Sectoral Flexibility Assumptions per Scenario

Sector	TDTR Full	TDTR Hybrid	TBTR Full	TBTR Hybrid
Agriculture	70%	35%	50%	25%
Buildings	50%	25%	25%	12.5%
Transport	30%	15%	50%	25%
Industry	20%	10%	15%	7.5%

While these percentages are grounded in qualitative insights from expert interviews and supported by sector-specific operational characteristics, they should be interpreted as informed estimates rather than precise measurements. This approximation is appropriate given the scope of this thesis, which does not aim to determine the exact share of flexible electricity demand in each sector. Instead, the primary objective is to evaluate how different levels of ATR adoption, under plausible flexibility conditions, affect electricity system dynamics, particularly in terms of grid loading, demand shifts, and congestion management outcomes. The following sections detail the rationale and derivation of these sector-specific flexibility assumptions.

5.6.1. Time-Duration-Based Transport Rights

Time-Duration-Based Transport Rights involve dynamic grid access constraints imposed by the grid operator during anticipated peak-demand periods. Such constraints are communicated 24 hours in advance. As indicated by all interviewees, accurate demand forecasting, detailed load monitoring, and responsive automated systems are essential for leveraging flexibility within this scenario.

Based on expert assessments from the conducted interviews, the following sectoral flexibility percentages were established for the TDTR Full Adoption scenario:

- **Agriculture Sector (70% flexibility):** Greenhouse operations already exhibit substantial flexibility through thermal buffering and adaptive lighting control. As described by the Deputy Energy Director of the greenhouse company (I1), *"We actively manage energy use in response to real-time price signals and constraints"*. He emphasized that their company could immediately comply with TDTR without major infrastructural changes. However, he also acknowledged that their company is more advanced than others in the sector.
- **Buildings Sector (50% flexibility):** The building sector, represented by the flower auction facility (I2), manages its energy use primarily through HVAC and refrigeration systems. Given their significant energy usage and ability to pre-cool or buffer cooling demand when communicated 24 hours in advance, a realistic flexibility of 50% is assumed.
- **Transport Sector (30% flexibility):** Although electric vehicle fleet charging schedules can be adapted, the share of load from this sector remains moderate. key limiting factor in the transport sector is the uncertainty surrounding the timing of disconnections, which reduces the practical applicability of flexibility (I3). Therefore, 30% flexibility is adopted.
- **Industry Sector (20% flexibility):** Continuous processes dominate industrial operations, with limited capacity for short-notice adjustment. However, the product manager (I3) indicated that auxiliary activities such as lighting and internal logistics can provide limited flexibility. A 20% maximum is deemed realistic.

5.6.2. Time-Block-Based Transport Rights

Time-Block-Based Transport Rights restrict grid access to predefined time blocks. As Dutch DSOs currently only offer TBTR contracts in nighttime blocks (00:00–06:00) [48, 47], this time frame will also be adopted in these scenarios. This scenario leverages predictable, recurring windows of lower grid utilization. While sectors can plan around fixed TBTR blocks more easily than TDTR, the short six-hour window inherently limits the volume of shiftable demand. This shorter window reduces the usable load-shifting potential in sectors with daytime-centric operations or limited night-shift infrastructure.

The following assumptions were made for the TBTR Full Adoption scenario:

- **Agriculture Sector (50% flexibility):** As in the TDTR case, the sector's ability to buffer heating and lighting makes it well-suited to shift load into the night, especially during summer, as there is enough light during the day (I1). However, nighttime-only limits reduce total flexibility compared to TDTR.
- **Buildings Sector (25% flexibility):** The same HVAC and refrigeration flexibility applies, though limited operating hours and occupancy reduce shift potential to 25%, especially as the buildings sector is most active during the day.
- **Transport Sector (50% flexibility):** The fixed nighttime window aligns well with the idle time of electric fleets. This enables a high share of charging to be scheduled during TBTR blocks.
- **Industry Sector (15% flexibility):** Even with the ability to prepare in advance, the share of non-critical processes that can operate solely between 00:00 and 06:00 remains limited and slightly lower than in the TDTR scenario, reflecting the fact that most industrial flexibility is tied to processes that operate outside of the fixed nighttime TBTR window.

These sector-specific flexibility assumptions were operationalized by modifying hourly demand profiles within the simulation environment. A detailed description of how these scenarios were technically implemented in the agent-based model is provided in Section 6.8. The following chapter introduces the modeling framework, data sources, and simulation structure used to assess the system-level impact of ATR adoption under these scenarios.

6 Modeling Approach

This chapter describes the development and structure of the agent-based model used to simulate the impact of ATR on the Dutch electricity grid. Based on the assumptions from the previous chapter, the model captures how large energy consumers adapt their electricity use under TDTR and TBTR scenarios, and how these adaptations affect grid congestion and market dynamics.

The chapter introduces the modeling framework (Section 6.1), outlines data sources and integration steps (Section 6.2), explains how the grid, generation, and demand are represented spatially (Sections 6.3–6.4), and details agent behavior and market interaction (Section 6.6). It concludes with model verification (Section 6.7) and a description of how the ATR scenarios were implemented (Section 6.8).

6.1. Framework Overview

The agent-based model developed in this study is built on the ASSUME framework [25], a modular simulation architecture designed for analyzing electricity markets and grid interactions.

As visualized in Figure 6.1, the framework consists of a set of interacting classes and components that together structure the behavior of the simulation environment. These interacting units (agents) collectively produce emergent system behavior, a hallmark of agent-based modeling approaches [26].

At the core of the framework lies the World class, which manages the overall simulation context, including registered market configurations (Market Config) and actors (UnitsOperator). Each UnitsOperator contains one or more units, either generation or demand resources, characterized by techno-economic attributes and operational behavior. These units adopt specific BiddingStrategy objects that determine how and when they participate in the market, generating Order objects that are submitted to the MarketRole for processing.

The MarketRole handles the orchestration of market activities: collecting orders, clearing the market, and generating dispatch outcomes. It interacts with the market-clearing mechanisms, which defines the approach to demand handling, pricing, and power flow resolution.

The model distinguishes between two core agent types:

- **Generation Agents**, which represent power producers submitting bids to the electricity market.
- **Demand Agents**, which represent consumers with sector-specific load profiles and flexibility characteristics.

These agents interact through market-clearing processes and physical grid constraints, making the framework well-suited for studying the effects of regulatory interventions such as ATR. To represent the Dutch electricity system with sufficient realism, a structured modeling approach was adopted, combining geospatial, economic, and technical datasets to calibrate agent behavior and grid dynamics.

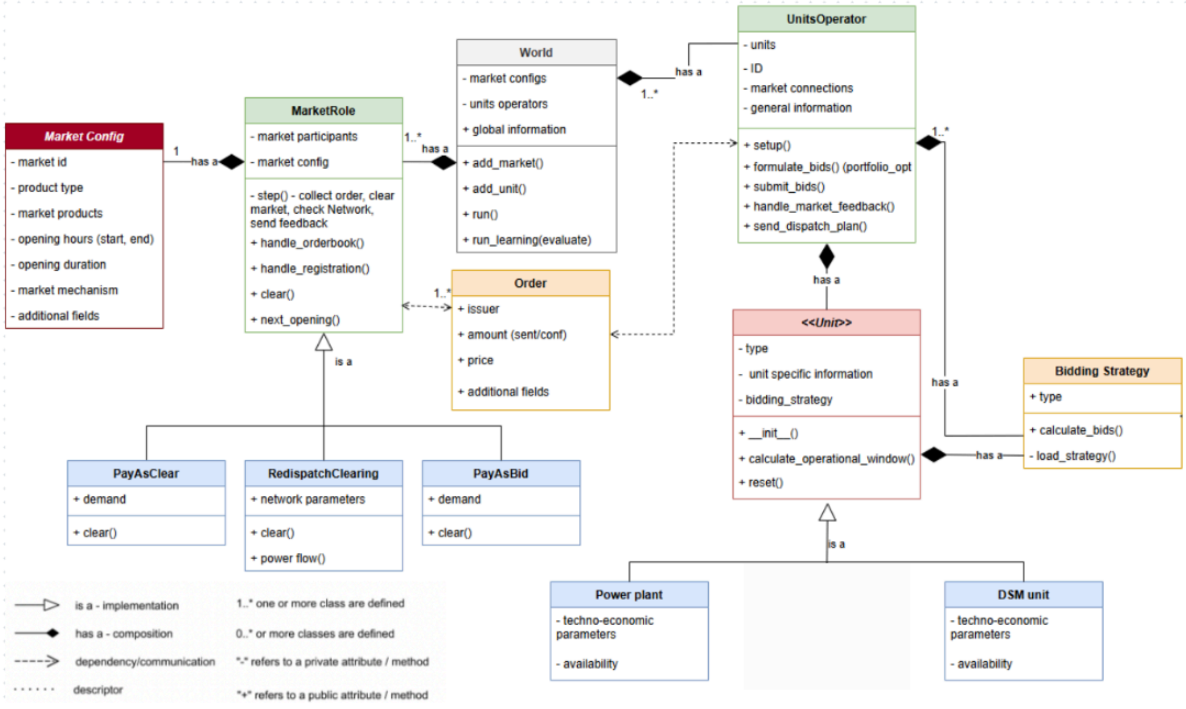

Figure 6.1: Architecture of used part of ASSUME Framework [25]

6.2. Data Sources and Integration

To operationalize the ASSUME framework and enable realistic agent interactions, the model requires detailed input data. These data sources define the physical grid, characterize generation and demand behavior, and inform market and policy conditions. Table 6.1 provides an overview of the key datasets used to initialize and calibrate the model, categorized by their relevance to infrastructure, consumption, production, and pricing dynamics.

After compiling these datasets, several preprocessing steps were required to align them with the structural and temporal needs of the simulation environment. These steps included unit conversion, spatial mapping, and temporal alignment. For example, quarter-hour load data from DSO Liander was aggregated to hourly values, and fuel prices were converted from USD to EUR using the average 2022 exchange rate. These steps ensured alignment with the hourly resolution and geospatial structure required by the ASSUME simulation framework.

The following sections explain how this collected data was implemented within the simulation framework, starting with the modeling of the Dutch electricity grid.

6.3. Grid Representation

To effectively incorporate the spatial and technical components of the Dutch electricity grid, the PYPSA (Python for Power System Analysis) package was integrated into the agent-based model. PYPSA utilizes two primary components for grid modeling: buses and lines.

Buses

Buses represent network nodes or substations within the electricity grid, acting as points where power is injected or extracted. These buses can be either AC (Alternating Current) or DC (Direct Current), reflecting the type of electrical current used for transmission at that node.

AC buses form the majority of the modeled network and represent the standard infrastructure for most of the Dutch high-voltage transmission system. These are used to model typical inter-regional power flows across 220 kV and 380 kV lines, and they are connected via *Line* components that define AC transmission lines, characterized by resistance, reactance, and thermal limits.

Table 6.1: Data and Sources

Subject	Data Object	Data Type	Data Source
Grid infrastructure	• Transmission line capacity, resistance, location • Nominal voltages • Locations of Buses	CSV and numerical parameters	TenneT [55], Liander [56], PDOK [57]
Generation	• Power plant or generator characteristics (Fuel type, max power, efficiency, etc.) • Time series and Generation profiles	CSV	ENTSOE [58], Klimaatmonitor [59], OPSD [60]
Electricity Demand	• Load profiles of residential areas • Load profiles of LEC • Demand unit details (location, max demand)	CSV and numerical parameters	CBS [61], TNO[62], Liander [56]
Market and Forecast data	• Fuel prices • Weather data	CSV	ACM [9], ENTSOE [58], OPSD [60], Epexspot [63], Investing.com [64], Energy Transition Model [65]

DC buses by contrast, are used to model nodes associated with High Voltage Direct Current (HVDC) systems. These are typically found in two main cases:

- Offshore substations, such as converter platforms for offshore wind farms (e.g., Hollandse Kust), where power generated at sea is transmitted to shore via HVDC cables.
- Cross-border inter-connectors, such as connections to the UK, Germany, or Belgium, which often use HVDC technology to facilitate controlled long-distance electricity exchange between countries.

In the model developed for this study, AC buses were used for all inland grid nodes and substations connected by conventional AC lines, which dominate the Dutch onshore transmission system. DC buses were specifically assigned to offshore locations or international border points, where they act as endpoints of HVDC links.

Additionally, each bus is georeferenced using x and y coordinates obtained from TenneT's high-voltage grid dataset [66]. This geographic information enables accurate spatial mapping and supports detailed analysis of the grid's structural topology.

Lines

Lines serve as transmission connections linking pairs of buses and are crucial for modeling electricity flow between different grid points. Each line in PYPSA is characterized by specific technical parameters:

- Reactance (X): Represents the opposition to the change in electric current, significantly influencing power flow patterns.
- Resistance (R): Indicates the opposition to the direct flow of current, contributing to energy losses within the grid.
- Nominal Capacity (S_nom): Specifies the maximum power transmission capability of a line, critical for assessing potential congestion and ensuring system reliability.

These parameters enable the model to calculate line loadings, identify potential bottlenecks, and determine congestion levels accurately.

The power flow through these lines is modeled through a DC power flow approximation, implemented via PyPSA's *lpf()* function. This method assumes fixed voltage magnitudes and small angle differences between buses, allowing for a linearization of the full AC power flow equations. As a result, only active power flows are modeled, while reactive power and voltage magnitude variations are excluded. Despite these simplifications, DC power flow is widely accepted in strategic transmission modeling and congestion studies due to its computational efficiency and sufficient accuracy for high-voltage grid analysis [67, 68, 69]. It is particularly suited for agent-based modeling where iterative market dispatch and power flow calculations must be executed thousands of times. Therefore, the DC approximation enables tractable and reliable congestion evaluation under varying ATR scenarios without compromising on interpretability or scalability.

With the technical modeling structure established, the following subsections describe how it was applied to represent the Dutch electricity system. The first focus is on the national high-voltage transmission grid, which is especially relevant for simulating Time-Duration-Based Transport Rights.

6.3.1. National Grid

The Dutch high-voltage grid consists of lines with voltage levels of 110, 150, 220, and 380 kV. The spatial allocation of these lines and their voltage levels can be seen in Figure 6.2.

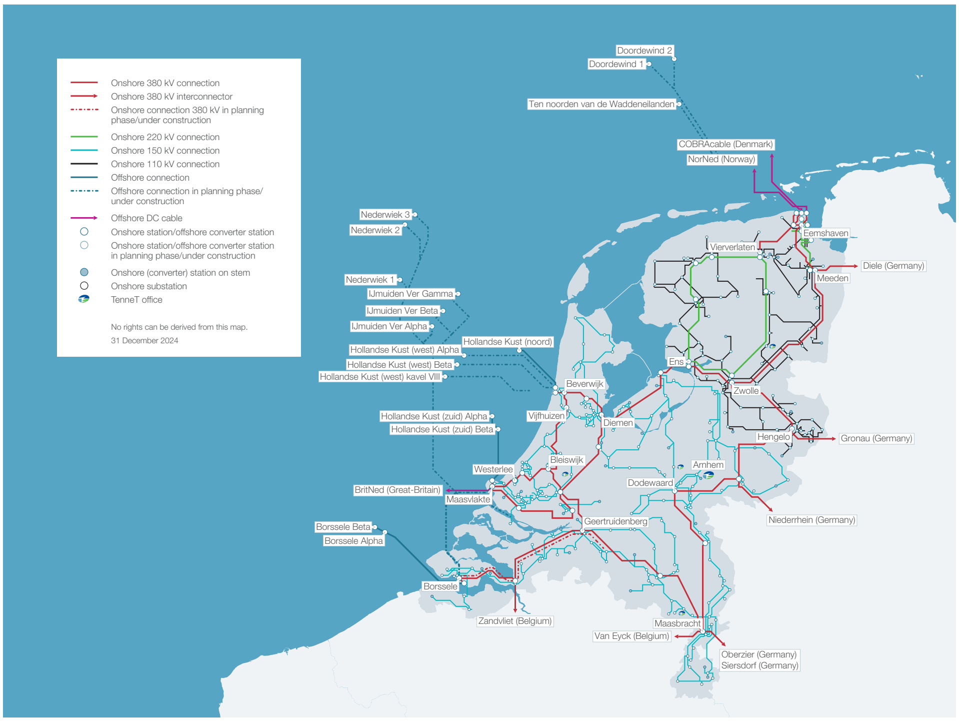

Figure 6.2: On-shore high-voltage electricity grid in the Netherlands [66]

In line with Step 2 of van Dam et al.'s modeling methodology, system identification and decomposition, this study limits its scope to Dutch high-voltage transmission lines operating at 220 kV and 380 kV, as illustrated by the red and green lines in Figure 6.2. These voltage levels constitute the backbone of the national electricity system, enabling long-distance power transport and inter-regional balancing [70]. Concentrating on this segment allows the model to capture the main transmission corridors and congestion hotspots, which are critical for assessing system-wide dynamics. By abstracting from the lower-voltage distribution networks, which are typically omitted in strategic analyses due to their localized effects, the model avoids unnecessary computational complexity while retaining relevance for national congestion studies. Large-scale power plants and aggregated demand from major industrial consumers are therefore mapped directly onto this high-voltage grid. This approach aligns with standard practice in power system modeling and mirrors how grid congestion is typically analyzed by system operators [70, 71, 72]. A visual representation of the modeled grid is shown in Figure 6.3.

Figure 6.3: Visualization of modeled Dutch National HV Grid

6.3.2. Regional Grid

To complement the national-level analysis and enable simulation of Time-Block-Based Transport Rights, the province of Noord-Holland was selected as a regional case study. This region was chosen primarily because of the availability of open geospatial substation data from the Distribution System Operator Liander [56], which provides a solid foundation for spatially explicit modeling. However, while the list of substations was complete, the associated 50–100kV feeder data was fragmented, consisting of, disconnected cable segments lacking circuit identifiers and capacity ratings. As a result, the dataset was unsuitable for direct use in power-flow simulations and required a simplified representation of the regional grid.

To address this data gap, the *equivalent feeder method* was applied. This is an abstraction technique commonly used when detailed distribution network topology is unavailable. In this method, each regional substation is connected to its nearest transmission-level bus via a single synthetic line, known as an equivalent feeder. This creates a simplified radial (star-shaped) network that mirrors the structure of typical DSO–TSO interconnections. While it omits internal feeder topology, it retains the key electrical and spatial relationships necessary for analyzing grid flows and congestion.

This approach was well suited for the case of Noord-Holland. Although the detailed cable infrastructure was not usable, the available substation data enabled construction of a synthetic regional grid. Each equivalent feeder was defined by:

- a length equal to the Euclidean distance to the nearest 220/380 kV transmission-level bus,
- a standard voltage level of 110 kV, reflecting common regional infrastructure [66],
- and a nominal line capacity of 100 MVA, consistent with DSO planning norms.

The method ensures that spatial demand distribution and transmission interface constraints are maintained, critical for congestion analysis. Comparable methods have been employed in previous modeling studies that lacked access to detailed feeder data, such as [73] and [74].

Figure 6.4 shows the regional high-voltage network of Noord-Holland as modeled using the equivalent feeder method. In this abstraction, the synthetic connections between regional substations (from Liander data) and the nearest national transmission substations (from TenneT) are visualized, forming a star-like topology. This spatial layout captures the interface between DSO and TSO infrastructure and illustrates how regional demand centers are linked to the transmission grid. The geographic spread of nodes reflects the actual locations of substations, enabling a geographically informed simulation of congestion dynamics. By simplifying the feeder structure while preserving spatial relationships, the model supports a realistic yet computationally efficient simulation of Time-Block-Based Transport Rights.

Figure 6.4: Visualization of modeled Regional HV Grid with equivalent feeder method

With the regional grid structure established, the next step is to spatially distribute generation and demand across this infrastructure.

6.4. Spatial Mapping of Generation and Demand

This section describes how electricity generation and demand agents are geographically and technically mapped onto the modeled grid, forming the operational basis for system behavior under both baseline and ATR scenarios.

6.4.1. Generation Agents

Electricity generation within the Netherlands comprises both centralized and distributed resources, including natural gas, hard coal, biomass, waste-to-energy, solar photovoltaic (PV), and wind power facilities. In this modeling approach, centralized power plants with capacities exceeding 50 MW, including significant fossil-fuel-based plants and large onshore and offshore wind farms, are represented individually as discrete Generation Agents. Each Generation Agent is assigned to the closest geographically proximate node. Locations for these power plants were sourced from datasets provided by ENTSO-E (the European Network of Transmission System Operators for Electricity) [75] or derived directly from publicly available information on power plant operator websites.

Conversely, generation technologies like solar PV and biomass exhibit more distributed characteristics and are therefore aggregated at a provincial level. Solar generation data were acquired from CBS StatLine [61], and biomass generation was treated similarly. Each provincial aggregate was represented by a singular Generation Agent, subsequently linked to the node with the highest connectivity within that province. This strategy ensures that the distributed nature of these technologies is adequately represented without unnecessary complexity, following the example of [70].

6.4.2. Availability and Technical Characteristics

Power plants inherently possess specific technical characteristics that significantly influence their operational performance and economic competitiveness. Relevant characteristics, such as maximum generation capacity, efficiency, ramp rates, and minimum operational levels, were primarily sourced from the databases provided by ENTSO-E [75] and FLEXNET [76], or directly gathered from the official web pages of the power plants.

Emission factors for conventional power plants were derived from the International Energy Agency (IEA) [77], ensuring consistency with recognized international standards. For renewable energy sources such as solar and wind power, operational availability profiles were based on actual 2022 weather data forecasts provided by ENTSO-E [75]. Given their renewable nature, the emission factors for solar, wind, and biomass were set to zero, reflecting their minimal environmental impact relative to fossil fuel sources. A comprehensive overview of all Generation Agents, detailing their technical characteristics, operational constraints, and geographic node assignments, is provided in Appendix E.

6.4.3. Demand Agents

For modeling clarity and to manage complexity effectively, the total electricity demand in the Netherlands was classified into five distinct sectors, following the categorization proposed by Zomerdijk et al. [70]:

- Households (A)
- Buildings Sector (B)
- Transport Sector (C)
- Agriculture Sector (D)
- Industry Sector (E)

Households Demand

The total Dutch electricity demand data used in this model was sourced from CBS [61]. The reference year chosen for this analysis is 2022, as it represents the latest year with fully available data from CBS. Initially, household electricity demand was collected specifically for the four largest Dutch cities: Amsterdam, Rotterdam, The Hague, and Utrecht. Each sector within these cities was assigned a dedicated demand agent at the respective nodes. In cases where cities contain multiple nodes, the electricity demand was proportionally distributed across these nodes, creating one demand agent per node. Subsequently, provincial household electricity demand was gathered, and the demand attributed to the large cities was subtracted from their corresponding provincial totals. The remaining provincial demand was then distributed across all nodes within each province based on weighted averages, with a demand agent assigned to each node.

Non-residential Demand

The CBS categorizes non-residential electricity demand according to standard business categories (SBI). Table 6.2 provides the mapping of these SBI categories to the five demand sectors introduced earlier.

Demand allocation methods varied by sector, reflecting differences in spatial distribution and operational characteristics. For the buildings sector, demand was processed similarly to household electricity consumption. Provincial consumption figures were distributed across all nodes within each province, assigning one demand agent per node. The transport and agriculture sectors, typically associated with more spatially dispersed infrastructure, followed a comparable method: their provincial electricity demand was evenly allocated across all nodes in the province, again resulting in one agent per node per sector. In contrast, the industry sector, known for its high energy intensity and spatial concentration in large industrial clusters, required a more targeted approach. For each province, the most prominent industrial site was identified (see Table 6.3), and the entire provincial industrial demand was assigned to the node(s) geographically closest to that location. This ensured realistic modeling of localized grid load and reflected the dominant role of large-scale industrial facilities in electricity consumption.

Table 6.2: Allocation of Standard Business Categories to main modeling categories

Code	Sector description	Main category
A	Landbouw, bosbouw en visserij	Agriculture Sector
B	Delfstofwinning	Industry Sector
C	Industrie	Industry Sector
D	Energievoorziening	Industry Sector
E	Waterbedrijven en afvalbeheer	Industry Sector
F	Bouwnijverheid	Industry Sector
G	Handel	Buildings Sector
H	Vervoer en opslag	Transport Sector
I	Horeca	Buildings Sector
J	Informatie en communicatie	Buildings Sector
K	Financiële dienstverlening	Buildings Sector
L	Verhuur en handel van onroerend goed	Buildings Sector
M	Specialistische zakelijke diensten	Buildings Sector
N	Verhuur en overige zakelijke diensten	Buildings Sector
O	Openbaar bestuur en overheidsdiensten	Buildings Sector
P	Onderwijs	Buildings Sector
Q	Gezondheids- en welzijnszorg	Buildings Sector
R	Cultuur, sport en recreatie	Buildings Sector
S	Overige dienstverlening	Buildings Sector
U	Extraterritoriale organisaties	Buildings Sector

Table 6.3: The largest industrial sites per Dutch province

Province	Largest industrial site
Groningen	Delfzijl & Eemshaven [78]
Friesland	De Zwette [79]
Drenthe	Bargermeer [80]
Overijssel	Marslanden-Zuid [81]
Gelderland	Bijsterhuizen [82]
Utrecht	Lage Weide [83]
Noord-Holland	Westpoort Port [84]
Zuid-Holland	Port of Rotterdam [85]
Zeeland	Vlissingen-Oost [86]
Noord-Brabant	Port of Moerdijk [87]
Limburg	Chemelot [88]
Flevoland	Flevokust Port [89]

6.4.4. Load Profiles of Demand Agents

To accurately capture variations in electricity demand over time, realistic load profiles are essential. These load profiles illustrate electricity consumption patterns throughout a given timeframe. In this model, K&O profiles provided by Liander [56], a prominent Dutch DSO, were utilized. The significance of this choice lies in the fact that Liander itself employs these profiles for internal network modeling, thereby enhancing the realism and reliability of this approach. Although the primary dataset for this model is based on 2022 demand data from CBS, the K&O profiles from Liander were sourced from 2023, which is the first year they were publicly available, making them the only available option for load shape modeling.

The K&O profiles represent aggregated annual demand curves specific to broad business categories. These profiles indicate relative consumption patterns, assigning a normalized value to each quarter-hour segment throughout the year. Each relative value denotes the consumption level as a fraction of a company's peak quarterly-hour electricity usage. Every profile reaches a maximum normalized value of 1, signifying the quarter-hour interval during which peak consumption occurs.

To adapt these profiles for the model, quarter-hourly data were aggregated into hourly intervals, after which the data underwent renormalization as described below:

Given that only total annual energy consumption per sector is known E_{annual}, first, the raw hourly shape values h_i were converted into weights w_i that sum to one over the full year:

$$w_i = \frac{h_i}{\sum_{j=1}^{8760} h_j}, \qquad \sum_{i=1}^{8760} w_i = 1. \tag{6.1}$$

These weights w_i represent the fraction of the year's energy allocated to hour i. The hourly energy consumption E_i (in MWh) is then obtained by

$$E_i = w_i \, E_{\text{annual}}, \tag{6.2}$$

ensuring that the sum of hourly consumption values aligns exactly with the known annual total:

$$\sum_{i=1}^{8760} E_i = E_{\text{annual}}. \tag{6.3}$$

The household demand load profile was constructed using a typical residential consumption pattern, generated using [90]. Household demand load profiles are characterized by peak energy use during morning hours and notably higher demand between 17:00 and 19:00 [91].

Regional Demand Allocation

The distinction between the national and regional grid configurations in the model lies in the treatment of buses and lines within the province of Noord-Holland. Since the regional grid is embedded within the national grid, the underlying network structure remains consistent; however, the spatial allocation of demand is adjusted to ensure that regional loads flow through the modeled equivalent feeders. Specifically, demand originally assigned to national high-voltage buses within Noord-Holland is set to zero. Instead, electricity demand in this region is redistributed across regional grid buses using the spatial allocation procedures detailed earlier in this chapter. This adjustment enables a more granular simulation of localized congestion dynamics while preserving the integrity of the overall system topology.

With the spatial and sectoral mapping of generation and demand agents complete, the next step involves calibrating their economic behavior. This requires accurate parameterization of input costs, particularly for fuels and emissions, which directly influence market bids and dispatch decisions in the simulation.

6.5. Fuel and Emission parameters

Fuel data prices were received from sources as: investing.com [64] and Epexspot [63]. Marginal costs of the nuclear plant were retrieved from the Energy Transition Model [65].

To parameterize fuel and emission costs in the model, historical price data for natural gas, coal, uranium, and CO_2 emission allowances were collected from publicly available and reputable sources. Natural gas prices were obtained from the Title Transfer Facility (TTF), the leading European gas trading hub, using daily futures price data for 2022 from Investing.com [64]. Coal price data for 2022 were sourced from Ycharts [92] and Investing.com, based on Newcastle coal futures, which serve as a benchmark for European and Asian markets.

Uranium prices were based on the 2022 average spot price as reported by the Federal Reserve Economic Data (FRED) [93] and converted accordingly. For CO_2 prices, daily historical EU ETS allowance prices (EUAs) were retrieved from Investing.com, capturing the significant price volatility during 2022. Where applicable, average prices were used to ensure temporal consistency with the model's annual time resolution, and all monetary values were converted to euros using the annual average exchange rate.

These fuel and emission cost parameters form the economic foundation for agent decision-making in the model. In particular, they shape the market bids submitted by Generation Agents and influence the broader price formation dynamics. The following section describes how agents use this information to interact within the simulated electricity market, and how their behavior, both fixed and scenario-driven, can shape emergent system outcomes under ATR.

6.6. Agent Behavior and Market Interaction

The ASSUME framework enables a detailed and realistic simulation of how agents interact within electricity markets and physical grid systems. These agents operate under evolving economic incentives and technical constraints, especially in light of regulatory interventions like Alternative Transport Rights. ABM is particularly suited to study such decentralized, socio-technical systems, as it captures how individual behavioral adaptations accumulate into emergent system-level outcomes. In this model, agents interact through iterative, market-based mechanisms that simulate the operational and economic dynamics of real-world electricity systems. Each simulation time step of one hour follows a sequence in which agents submit market bids, the market is cleared, and grid flows are updated accordingly. This tightly coupled simulation loop integrates economic decision-making with physical system constraints, allowing grid congestion and market prices to emerge from localized, time-dependent choices. As Deadman [94] notes, "ABM is a bottom-up approach; rather than explicitly defining overall behavior, system-level behaviors emerge from the actions and interactions of individual agents." This feature makes ABM particularly effective for evaluating how policies like ATR reshape bidding behavior, load shifting, and long-term system performance in a grid increasingly characterized by distributed energy resources [95].

6.6.1. Generation Agents and Merit Order Dispatch

Generation Agents in this model represent power producers that submit generation capacity offers into the electricity market. These agents follow a *naive economic order-of-merit* (*naive eom*) strategy, whereby each agent bids its marginal cost of production. These marginal costs are derived from input parameters such as fuel prices, plant efficiency, and CO_2 emission costs.

The submitted bids are sorted into a merit order, with generation units dispatched in ascending order of marginal cost. Renewable sources, such as wind and solar, are prioritized due to their near-zero marginal costs, followed by fossil-fuel-based generators such as gas and coal plants. The marginal cost of the last generator needed to meet demand in a given hour determines the market-clearing electricity price for that hour. This dispatch mechanism is illustrated in Figure 6.5, which provides a visual representation of how generation units are selected based on their relative marginal costs.

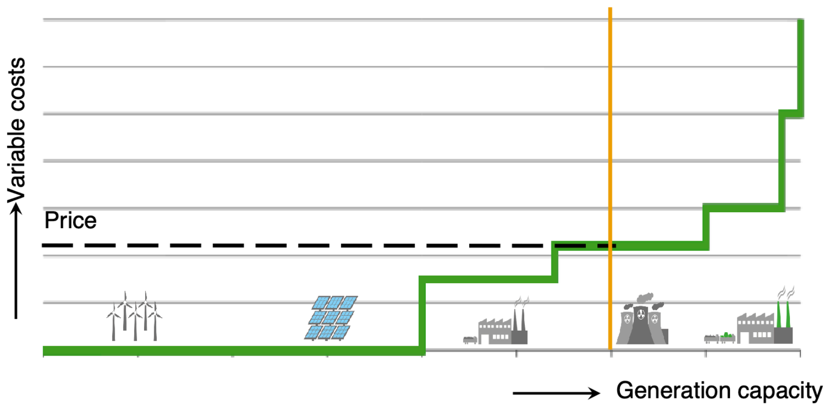

Figure 6.5: Merit-order dispatch visualization, as by [96]

This merit-order dispatch approach ensures electricity is produced at the lowest possible system-wide cost and mirrors the price formation mechanisms used in European day-ahead electricity markets [97]. Moreover, it enables the simulation to capture the effects of external factors, such as fluctuations in fuel prices or CO_2 allowance costs, on generator competitiveness, dispatch frequency, and hourly electricity prices.

6.6.2. Demand Agents and Scenario-Driven Behavior

Unlike Generation Agents, Demand Agents in this study do not submit price-elastic bids. Instead, their consumption behavior is defined through input data derived from the `demand_df` dataset, which aggregates sectoral demand profiles and assigns them to geographic nodes across the modeled grid, as described in the earlier sections of this chapter. These demand values are treated as fixed hourly quantities during each simulation run. However, these demand levels vary across different simulation scenarios, which have been determined in Chapter 5. These scenario-based modifications introduce system-wide effects by altering the load duration curve and triggering different congestion patterns and grid flows.

6.6.3. Simulation Loop and Agent Interplay

At each simulation time step, the following sequence occurs within the agent-based model:

1. **Input Initialization:** Hour-specific demand and generation availability (e.g., RES profiles) are loaded from the input datasets.
2. **Bidding:** Generation Agents submit marginal-cost-based bids. Demand Agents provide fixed demand values based on their scenario based demand input.
3. **Market Clearing:** A central market-clearing algorithm matches supply and demand, setting a market price (uniform pricing) and dispatching generators in merit order.
4. **Grid Dispatch:** Using the PyPSA power flow engine, the electricity is dispatched through the modeled power lines.
5. **Data Logging:** Results on generator dispatch, line loadings, grid flows and market prices are stored.

This integrated simulation structure enables the model to reflect not only economic interactions between agents but also their physical consequences on the electricity grid. As parameters such as demand, availability, or fuel prices change, so does the interplay between agents, altering merit order outcomes, triggering different congestion patterns, and ultimately affecting the system-wide operational efficiency and cost.

6.6.4. Software Implementation

In line with Step 5 of van Dam et al.'s modeling methodology [27], the conceptual model was translated into a working simulation using Python. The software implementation integrates the ASSUME agent-based modeling framework with the PyPSA power system analysis library, enabling dynamic interaction between economic behavior and physical grid constraints.

The model was implemented as a modular Python codebase consisting of the following components:

- **Data preprocessing scripts**, responsible for cleaning, transforming, and aligning input datasets, such as generation profiles, demand patterns, grid topology, and fuel prices, into model-ready formats.
- **Scenario input folders**, containing structured input files for each scenario, including demand and generation agents, load profiles, renewable availability (wind and solar), fuel prices, and grid topology (buses and lines).
- **Market dispatch modules**, implementing the bidding behavior of Generation Agents based on marginal cost and executing the merit-order dispatch logic, in line with the ASSUME framework.
- **Grid simulation loop**, which integrates PyPSA's linear power flow function (`lpf()`) to compute hourly line flows, grid utilization, and potential congestion.
- **Main simulation script**, which initializes all agents, loads scenario parameters, and executes the full hourly simulation loop across the modeled year.
- **Logging and output utilities**, which record key simulation results, such as prices, dispatch levels, and line flows, and export them for post-processing and visualization.

The model architecture is designed for flexibility, allowing rapid scenario testing while maintaining computational efficiency. Version control (Git) was used to track all development steps, ensuring reproducibility. The full project repository can be found on: https://github.com/jardzwaan/Thesis.git.

This implementation forms the technical backbone for all scenario experiments, integrating agent behavior with grid dynamics in a transparent and reproducible way. The following section details how the model was systematically verified to ensure that the code faithfully reflects the intended conceptual design.

6.7. Model Verification

Model verification, corresponding to Step 6 of van Dam et al.'s ABM development process [27], was undertaken to ensure that the implemented agent-based model faithfully reproduces the conceptual framework described in Step 3. Unlike model validation, which evaluates alignment with empirical reality (see Section 7.1), verification focuses on the correctness of the internal logic, computational implementation, and technical consistency of the model.

To verify the model's structure and behavior, the following strategies were employed:

- **Code Review and Debugging:** The entire Python codebase was systematically inspected through iterative manual reviews and debugging sessions. Special attention was paid to the instantiation of agents, the configuration of network topologies, and the logic governing the hourly simulation loop.
- **Unit and Integration Testing:** Isolated functions, such as those for demand allocation, agent dispatch, and power flow computation, were tested with controlled inputs to confirm expected outputs. These unit tests were complemented by integration tests across multiple simulation steps to ensure proper interaction between model components.
- **Agent Behavior Monitoring:** Key output variables, including generation bids, nodal demand levels, and transmission line flows, were monitored during runtime. Logs and intermediate output files were analyzed to confirm consistency with theoretical expectations, such as merit-order behavior and spatial demand distributions.
- **Extreme Scenario Testing:** The model was subjected to small-scale simulations under artificial boundary conditions, e.g. extremely high generation capacity or peak demand levels. These stress tests were used to verify that agents respond appropriately under edge conditions, and that the system remains stable and physically interpretable.
- **Sanity Checks with Reduced Input Sets:** Simplified simulations with a limited number of agents and nodes were conducted to trace model logic step by step. These controlled experiments allowed direct comparison between expected and actual model behavior, improving traceability and debugging efficiency.

Together, these verification procedures provided confidence that the agent-based model accurately implements the intended conceptual design. No inconsistencies, programming errors, or illogical behaviors were detected. With the technical integrity of the model established, the next step is to operationalize the research scenarios. The following section details how the TDTR and TBTR were implemented to simulate their effects on the systems behavior.

6.8. Scenario Implementation

6.8.1. Implementation of TDTR Scenarios

To model the Time-Duration based Transport Rights scenarios, identified in Chapter 5. The following steps were taken:

1. Baseline Simulation The baseline scenario uses the unaltered demand profile $D_{\text{orig}}(t, s)$, where t indexes hourly time steps and s denotes sector–province combinations (e.g., buildings in Zuid-Holland). This baseline serves as a reference scenario to assess market outcomes prior to the application of any TDTR measures.

2. Identification of Peak Hours National The 15% busiest hours were identified based on total national demand:

$$D_{\text{total}}(t) = \sum_{s} D_{\text{orig}}(t, s) \tag{6.4}$$

The set of peak hours $\mathcal{T}_{\text{high}}$ was determined by selecting the top 15% of hours with the highest $D_{\text{total}}(t)$:

$$|\mathcal{T}_{\text{high}}| = \lfloor 0.15 \times 8760 \rfloor = 1314 \tag{6.5}$$

3. Sector-Specific Flexibility Constraints Each sector s was assigned a flexibility coefficient $\alpha_s \in [0, 1]$, representing the proportion of demand that can be shifted away from peak hours. For example:

$$\alpha_{\text{industry}} = 0.15 \tag{6.6}$$

4. Load Reduction During Peak Hours For each s and $t \in \mathcal{T}_{\text{high}}$, the demand reduction is given by:

$$\Delta D(t, s) = \alpha_s \cdot D_{\text{orig}}(t, s) \tag{6.7}$$

The interim adjusted demand becomes:

$$D_{\text{interim}}(t, s) = D_{\text{orig}}(t, s) - \Delta D(t, s) \tag{6.8}$$

5. Load Redistribution to Off-Peak Hours The total removed demand per sector is:

$$M_s = \sum_{t \in \mathcal{T}_{\text{high}}} \Delta D(t, s) \tag{6.9}$$

This amount is redistributed uniformly over the remaining $R = 7446$ off-peak hours:

$$\delta D(t, s) = \frac{M_s}{R}, \quad \forall t \notin \mathcal{T}_{\text{high}} \tag{6.10}$$

The final adjusted demand profile is:

$$D_{\text{TDTR}}(t, s) = \begin{cases} D_{\text{orig}}(t, s) - \Delta D(t, s), & \text{if } t \in \mathcal{T}_{\text{high}} \\ D_{\text{orig}}(t, s) + \delta D(t, s), & \text{if } t \notin \mathcal{T}_{\text{high}} \end{cases} \tag{6.11}$$

6. Python Implementation This transformation was implemented in Python using Pandas:

- The original demand data was loaded into a DataFrame.
- National total demand was computed to identify $\mathcal{T}_{\text{high}}$.
- For each sector–province column, demand in peak hours was reduced by α_s, and the removed energy was redistributed uniformly to the off-peak hours.
- The adjusted demand profiles were exported as new CSV files for integration into the ASSUME simulation.

7. Validation

(a) **Energy Conservation:** Total annual demand per column is preserved.

(b) **Controlled Intervention:** Peak-hour demand never falls below $(1 - \alpha_s) \cdot D_{\text{orig}}(t, s)$.

(c) **Temporal Smoothing:** Redistribution avoids creation of new artificial peaks.

(d) **Heterogeneity:** Sector-specific flexibility values allow realistic behavioral modeling.

6.8.2. Implementation of TBTR Scenarios

The Time-Block-Based Transport Rights scenario imposes fixed grid access constraints during predefined nighttime hours (00:00–06:00). To simulate this in the model, a fixed portion of sector-specific demand is shifted into these TBTR block hours, while maintaining the original annual energy consumption for each sector–province pair.

1. Definition of TBTR Block The TBTR block consists of a six-hour interval from midnight to 06:00:

$$\mathcal{T}_{\text{TBTR}} = \{t \in [1, 8760] \mid t \bmod 24 \in [0, 1, 2, 3, 4, 5]\} \tag{6.12}$$

2. Sectoral Flexibility Inputs Two scenario configurations were modeled:

- **Full Adoption:** Buildings (25%), Transport (50%), Agriculture (50%), Industry (15%)
- **Hybrid Adoption:** Buildings (12.5%), Transport (25%), Agriculture (25%), Industry (7.5%)

3. Load Reduction Outside TBTR Hours For each demand column:

$$D_{\text{adj}}(t, s) = \begin{cases} D_{\text{orig}}(t, s), & \text{if } t \in \mathcal{T}_{\text{TBTR}} \\ (1 - \alpha_s) \cdot D_{\text{orig}}(t, s), & \text{if } t \notin \mathcal{T}_{\text{TBTR}} \end{cases} \tag{6.13}$$

4. Redistribution Into TBTR Block Hours Total removed demand:

$$M_s = \sum_{t \notin \mathcal{T}_{\text{TBTR}}} [\alpha_s \cdot D_{\text{orig}}(t, s)] \tag{6.14}$$

Redistributed evenly over all TBTR block hours:

$$\delta D(t, s) = \frac{M_s}{|\mathcal{T}_{\text{TBTR}}|}, \quad \forall t \in \mathcal{T}_{\text{TBTR}} \tag{6.15}$$

Final TBTR-adjusted demand profile:

$$D_{\text{TBTR}}(t, s) = \begin{cases} D_{\text{adj}}(t, s) + \delta D(t, s), & \text{if } t \in \mathcal{T}_{\text{TBTR}} \\ D_{\text{adj}}(t, s), & \text{otherwise} \end{cases} \tag{6.16}$$

5. Python Implementation The implementation was done using a Python function `apply_tbtr_shift()`:

- Accepts a Pandas DataFrame with sector–province demand profiles.
- Reduces a fixed percentage of each column's demand outside TBTR hours.
- Evenly redistributes the removed load across all TBTR block hours.
- Returns a new demand DataFrame with TBTR adjustments.

6. Validation

(a) **Energy Conservation:** Total annual demand per column is preserved.
(b) **Temporal Integrity:** Shifted load is confined strictly to 00:00–06:00 hours.
(c) **Controlled Implementation:** Redistribution matches sectoral flexibility assumptions.
(d) **No Overcompensation:** TBTR block hours receive only the shifted load, avoiding unrealistic peaks.

7

Results

This chapter presents the outcomes of the agent-based modeling simulations and answers the third and fourth sub-questions of this research:

What are the expected effects of Time-Duration-Based Transport Rights on electricity demand profiles, grid congestion, and electricity prices?

What are the expected effects of Time-Block-Based Transport Rights on electricity demand profiles, grid congestion, and electricity prices?

Section 7.1 outlines the validation of the agent-based model, followed by a comprehensive analysis of the TDTR (Section 7.2) and TBTR scenarios (Section 7.3). Finally, Section 7.4 investigates the underlying drivers of electricity price increases observed in both scenarios.

7.1. Model Validation

To ensure the robustness, credibility, and applicability of the developed agent-based model, a structured validation procedure was conducted, adhering to Step 9 of the methodology described by van Dam et al. [27], and following established validation principles from Sargent [98] and Zomerdijk et al. [70].

7.1.1. Conceptual Validation

Conceptual validation verified the correctness and suitability of the underlying assumptions and theoretical framework representing the Dutch electricity system. Specifically, this included confirming the accuracy of hourly demand and generation distributions, spatial allocations of generation and demand entities, and linear network flow approximations. These elements were cross-referenced with publicly available methods and reports from TenneT [71, 76], ensuring the conceptual integrity of the model.

7.1.2. Computerized Model Verification

Computerized model verification involved systematic debugging and consistency checks across core computational processes. As previously described in Section 6.7, this included verifying the correct spatial mapping of demand agents, the accurate instantiation of generation agents, and the enforcement of operational constraints such as load balance, capacity limits, and dispatch logic. These procedures were carried out through controlled test runs, diagnostic logging, and cross-validation of simulation outputs. No computational discrepancies were identified, confirming the model's technical accuracy and internal consistency.

7.1.3. Operational Validation

Operational validation was conducted using the Baseline simulation for the representative scenario year (2022). Key performance metrics, including load profiles, electricity prices, and generation by technology type, were compared against historical data sourced from the ENTSO-E Transparency Platform [75] and the database of the International Energy Agency [99].

Load Profile Validation

Figure 7.1 presents a comparison between the model-generated hourly electricity load and the historical ENTSO-E data for the Netherlands in 2022. The top panel shows the modeled electricity demand, while the bottom panel displays the historical reference data. Both plots reflect the hourly system-wide load in gigawatts (GW) over the full calendar year.

The simulated total annual electricity consumption amounts to 91.4 TWh, whereas the historical value is 100.4 TWh. The primary reason for this discrepancy lies in inherent model simplifications. Specifically, sectoral and provincial electricity use were derived from CBS end-use data (see Section 6.4), which accurately reflects the distribution of electricity consumption across sectors and regions. However, this dataset does not account for transmission and distribution losses (approximately 4.9 TWh) [99], nor for net import and export balances (approximately 4.3 TWh) [99]. Collectively, these factors account for the observed variance.

Minor deviations in the hourly load curve are largely explained by the use of aggregated demand profiles as input data. Despite these simplifications, the temporal pattern of the modeled demand corresponds with historical data, confirming the model's suitability for scenario analyses.

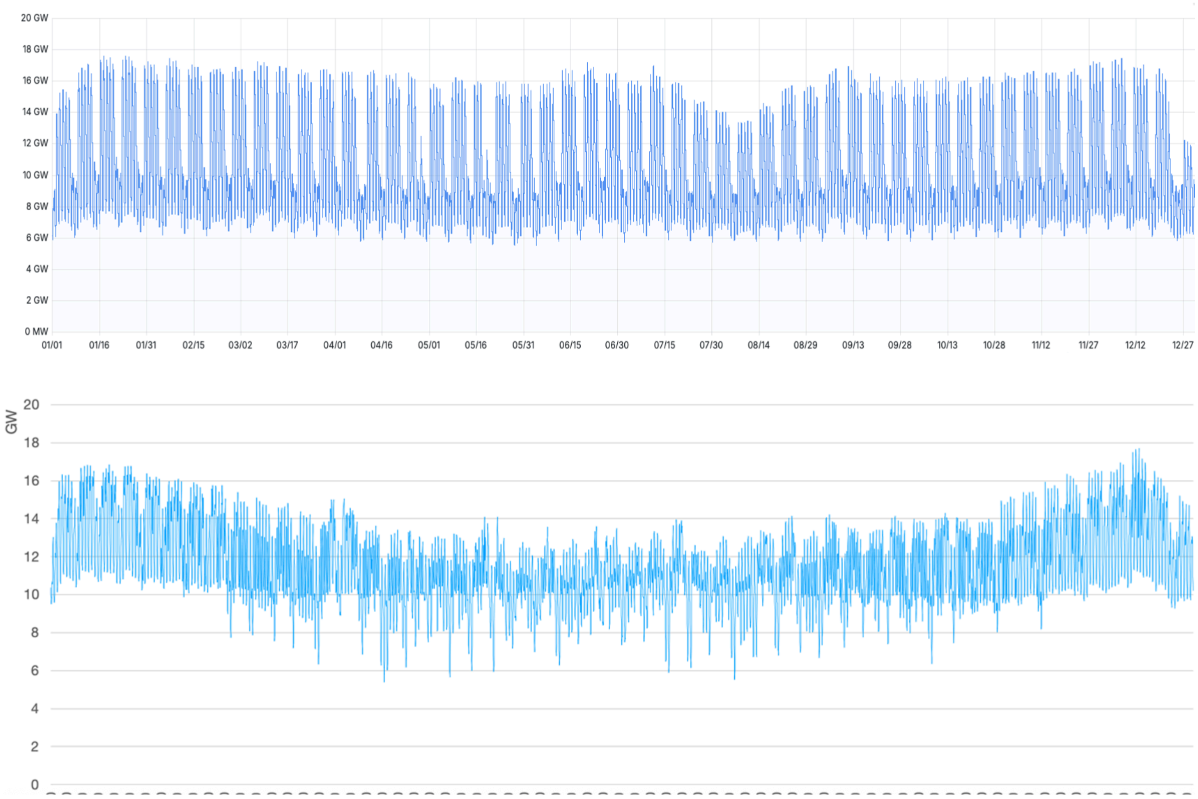

Figure 7.1: Hourly total Dutch electricity demand (Load in GW) in model output (above) and ENTSO-E Data [75] (below)

Price Validation

Figure 7.2 provides further operational validation by comparing simulated electricity prices to historical ENTSO-E day-ahead market data for 2022. The simulated average electricity price (€221/MWh) is slightly lower than the historical average (€241/MWh). This difference is primarily due to the slightly reduced overall demand modeled. Nonetheless, the model successfully captures key price volatility episodes, such as significant price spikes in February/March and August/September. These episodes are traceable to geopolitical events, specifically the invasion of Ukraine and the sabotage of the Nord Stream pipelines [100].

The strong alignment between simulated and historical price trajectories proves the model's capability to replicate realistic market dynamics and price fluctuations, thereby validating its applicability for assessing the effectiveness of ATR contracts in managing grid congestion.

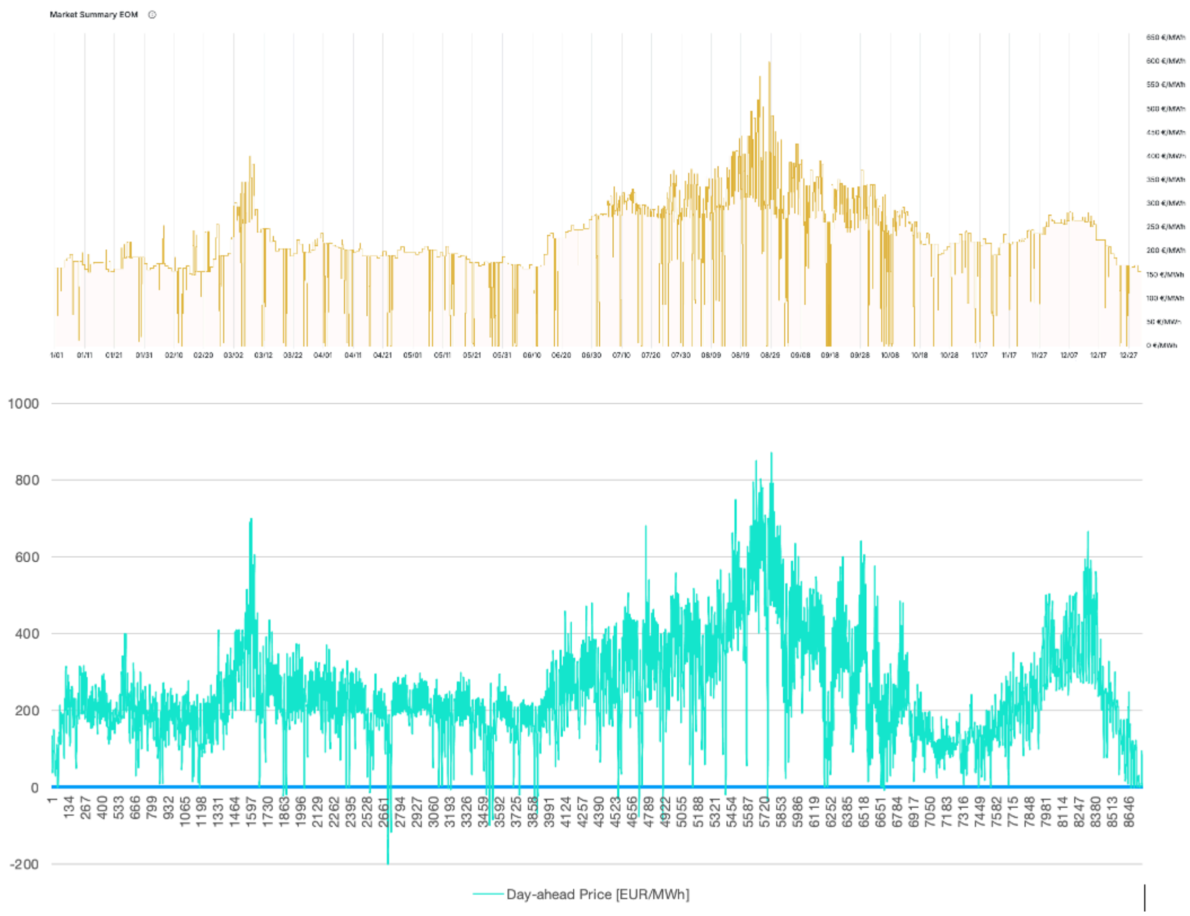

Figure 7.2: Hourly electricity price (€/MWh) in model output (above) and ENTSO-E historical data Day-Ahead prices [75] (below)

Generation Mix Validation

The final metric for operational validation is the breakdown of electricity generation by technology type, as depicted in Figure 7.3. The figure shows, for each month in 2022, two stacked bars: the left column represents the simulated generation mix, and the right column shows the corresponding historical data from IEA statistics [99]. Each bar is segmented by generation technology, with consistent coloring across months to aid comparison.

While the model slightly underestimates total monthly generation volumes, consistent with earlier discussed simplifications, the relative shares of generation technologies are largely preserved. For instance, the dominance of fossil gas and wind in the Dutch energy mix is clearly reflected, as is the seasonal increase in solar output during summer months.

This visual comparison confirms that, despite simplifications in plant-level dispatch and fuel pricing, the model accurately captures the technology composition and seasonal variation of the Dutch power system. This supports its validity for scenario analysis focused on system-level behavior and generation trends.

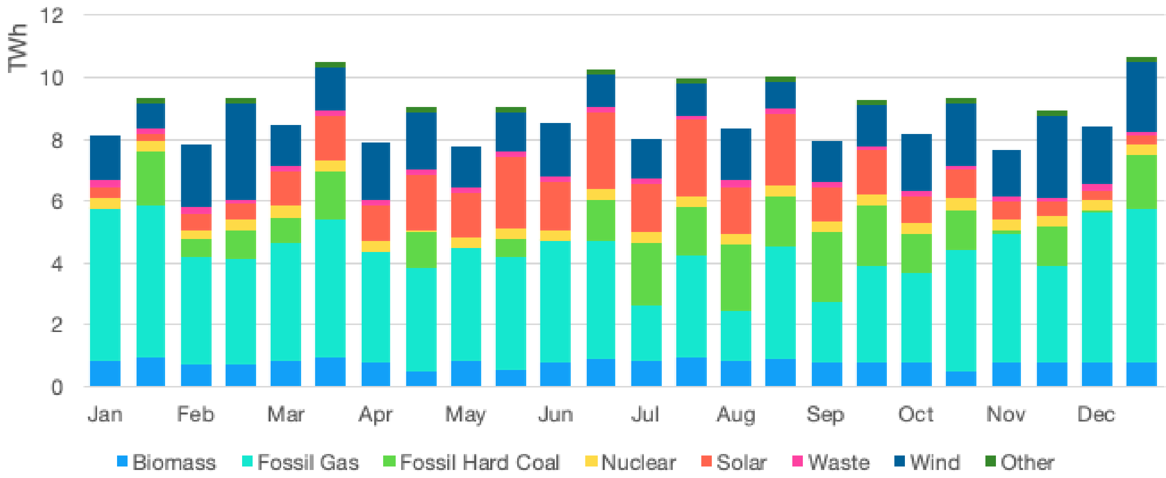

Figure 7.3: Simulated (left column) and historical [99] (right column) monthly generation stacks for 2022.

Regional Grid Validation

Since the regional model retains the same generation agents, merit-order dispatch mechanism, and fuel price assumptions as the validated national model, the generation component requires no additional validation. Only the spatial allocation of demand and the grid topology differ through the inclusion of regional substations and equivalent feeder lines. Therefore, the generation dispatch logic and market dynamics can be considered validated by the operational validation results presented in Section 7.1.

7.1.4. Summary of Validation Results

Synthesizing the findings from load profile, electricity price, and generation technology validations, the model demonstrates sufficient accuracy and reliability for its intended purpose. The close alignment between simulated outcomes and historical benchmarks establishes confidence in the model's predictive capability, supporting its use for evaluating the ATR scenarios outlined in Chapter 5. The subsequent sections present the outcomes of these scenario analyses.

7.2. TDTR Scenarios

This section presents the simulation results for Time-Duration-Based Transport Rights , evaluating their impact on electricity demand profiles, market prices, and grid congestion. The analysis compares three adoption scenarios: baseline (no TDTR), hybrid (partial adoption), and full implementation, to assess how TDTR contracts influence load volatility, generation dispatch, and transmission system performance.

7.2.1. Load Curve and Demand Volatility

The impact of Time-Duration-Based Transport Rights on electricity demand patterns becomes evident by comparing yearly system load curves across baseline, hybrid, and full scenarios, as shown in Figure 7.4. This figure displays the hourly demand throughout the year for each scenario, where the baseline (blue line) shows significantly sharper peaks and deeper valleys compared to the flatter load profiles of the hybrid (green) and full TDTR (yellow) simulations. These visual differences illustrate TDTR's role in smoothing electricity demand by encouraging load shifting away from peak periods and toward off-peak hours.

Table 7.1 summarizes the numerical differences in system behavior across these scenarios. In the baseline case, the maximum system load reaches 17.6 GW and the minimum load drops to 5.5 GW, indicating substantial daily and seasonal volatility. With partial TDTR adoption (hybrid), the maximum load is reduced to 15.2 GW and the minimum load rises to 5.9 GW. Under full TDTR implementation, the maximum and minimum loads are 15.6 GW and 6.3 GW, respectively. The average system load remains stable across all scenarios at 10.5 GW, which confirms that total electricity use is conserved.

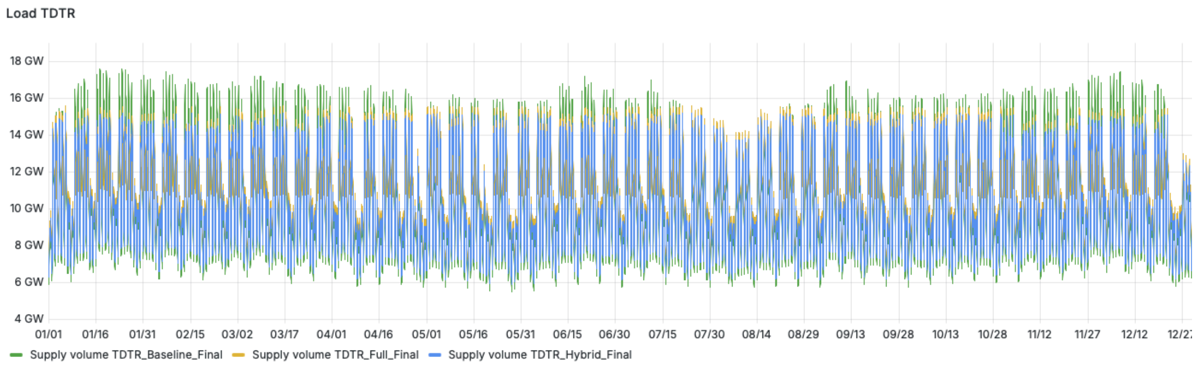

Figure 7.4: Load Curve (Year) for three TDTR simulations

Table 7.1: Comparison of TDTR Simulation Metrics

Simulation	Average price	Total cost	Max Load	Min Load	Mean Load	Total volume
TDTR_Baseline	219 €/MWh	€20 551 397 956	17.6 GW	5.5 GW	10.5 GW	91.4 TWh
TDTR_Hybrid	225 €/MWh	€20 915 985 693	15.2 GW	5.9 GW	10.5 GW	91.4 TWh
TDTR_Full	229 €/MWh	€21 141 066 431	15.6 GW	6.3 GW	10.5 GW	91.4 TWh

Interestingly, peak loads under full TDTR (15.6 GW) slightly exceed those in the hybrid scenario (15.2 GW). This indicates nuanced interactions between extensive load shifting and network operations, suggesting that higher TDTR adoption levels may redistribute demand in ways occasionally elevating certain peaks compared to intermediate adoption.

When focusing on a shorter time interval, such as the month of June (Figure 7.5), it is clearly illustrated that TDTR is effective in clipping peak demands, redistributing load into traditionally lower-demand intervals. This pattern confirms the intended function of TDTR in improving load management and efficiency.

7.2.2. Electricity Prices

The simulation results reveal a modest yet consistent increase in average electricity prices across the TDTR scenarios, as reported in Table 7.1. The baseline scenario yields an average price of €219/MWh, which rises to €225/MWh under the hybrid TDTR scenario and further to €229/MWh in the full adoption case.

This upward price trend is not extensively discussed in the reviewed academic or policy literature, requiring a deeper investigation into its underlying causes. While TDTR contracts are primarily designed to reduce system stress and enhance grid reliability by shifting demand away from peak periods, the simulations indicate that this load redistribution can introduce unintended price effects. Specifically, the

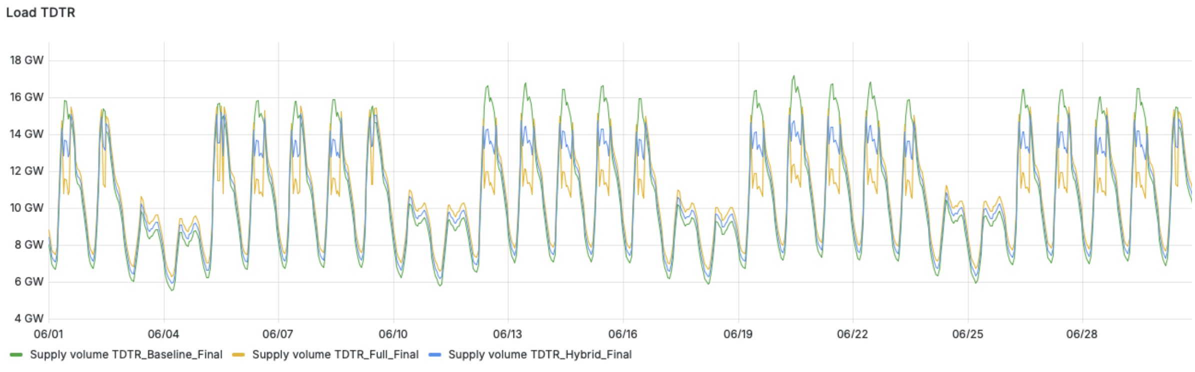

Figure 7.5: Load Curve (June) for three TDTR simulations

changes in temporal demand profiles influence which generators are dispatched in each hour, thereby affecting market-clearing prices through the merit-order mechanism.

A detailed explanation of this dynamic, including how off-peak fossil generation and marginal pricing behavior drive these increases, is provided in Section 7.4.

7.2.3. Grid Congestion and Transmission Utilization

Grid flow metrics are shown in Tables 7.2 and 7.3. Table 7.2 summarizes the main grid-level flow indicators, including total absolute flow, peak hourly flow, and the exact timestamp of peak transmission. These results corroborate TDTR's benefits, showing that peak hourly flows are significantly reduced from 62.2 GW in the baseline scenario to 59.1 GW (hybrid) and 59.6 GW (full). Notably, total absolute flows slightly increase, from 252 TWh (baseline) to 253 TWh under both TDTR scenarios. This marginal rise is attributable to altered generation dispatch patterns and slightly longer transmission paths required by centralized plants compensating for local generation curtailed during shifted peak hours. These values suggest that TDTR reshapes the temporal and spatial distribution of electricity flows, relieving peak stress on the grid without reducing overall utilization.

Table 7.2: Grid Flow Metrics TDTR Simulations

Simulation	Sum Absolute flow	Peak Hourly Flow	Peak Load Time
TDTR_Baseline	252 TW	62.2 GW	2022-03-06 09:00:00
TDTR_Hybrid	253 TW	59.1 GW	2022-10-10 10:00:00
TDTR_Full	253 TW	59.6 GW	2022-10-06 09:00:00

Detailed analysis of individual line loadings, fully documented in Appendix D.2, reveals only one line exceeding capacity under baseline conditions: line 46, which reaches a peak loading of 101%. This line is a 220 kV transmission link between the provinces of Groningen and Drenthe, an area identified by TenneT as structurally congested in both its 2022 operational reports and subsequent 2024 research [101]. Under the hybrid and full TDTR scenarios, peak loading on this critical line decreased to 95.8% and 95.7%, respectively.

Table 7.3 complements the system-level metrics by showing the average and peak loading levels across all transmission lines. Average line loading remains virtually unchanged across scenarios, staying close to 17.4%, which confirms that the network is broadly utilized in a similar way regardless of TDTR implementation. In contrast, mean peak loading, which reflects the maximum utilization of the most stressed lines, declines from 53.67% in the baseline to approximately 52.1% under both TDTR scenarios. While modest in absolute terms, this reduction indicates that TDTR effectively relieves congestion pressure on critical bottlenecks in the grid during high-demand periods, without significantly altering the overall usage of transmission infrastructure.

Table 7.2 shows that the timing of peak system load differs across the baseline, hybrid, and full TDTR scenarios. However, spatial analysis of grid flows during these respective peak hours reveals that the same critical transmission lines consistently experience high loading, indicating persistent bottlenecks

Table 7.3: Average & Peak line loading power lines per TDTR Scenario

Simulation	Mean Average Loading	Mean Peak Loading
TDTR_Baseline	17.37 %	53.67 %
TDTR_Hybrid	17.41 %	52.14 %
TDTR_Full	17.41 %	52.10 %

regardless of the TDTR adoption level. This is visualized in Figure 7.6, which presents congestion maps for each scenario at their respective peak moments. In these maps, green lines represent line loading below 50%, orange lines indicate loading between 50% and 80%, and red lines show heavily loaded lines exceeding 80%. Notably, a recurring cluster of red and orange lines appears in the northern and northeastern part of the country across all three scenarios, confirming that certain transmission corridors remain structurally congested despite temporal demand reshaping through TDTR.

(a) TDTR Baseline Simulation (b) TDTR Hybrid Simulation (c) TDTR Full Simulation

Figure 7.6: Congestion map most congested hour per simulation

7.2.4. Summary of TDTR Scenario Impacts

The TDTR simulations demonstrate that Time-Duration-Based Transport Rights can meaningfully improve grid performance by smoothing electricity demand and reducing system-level peaks. Both hybrid and full adoption scenarios show reductions in maximum load compared to the baseline, while minimum load levels increase, resulting in a flatter load curve. These shifts confirm TDTR's intended role in promoting demand-side flexibility and mitigating load volatility, without altering overall electricity consumption.

Electricity prices show a moderate but consistent increase across adoption levels, rising from €219/MWh in the baseline to €229/MWh under full implementation. This suggests that while TDTR improves physical system performance, the resulting demand redistribution affects the merit-order dispatch.

From a grid congestion perspective, TDTR proves effective in reducing peak hourly flows and slightly alleviating stress on critical transmission lines. Total transmission volumes remain stable, while peak flows decline by up to 3.1 GW. Congestion maps and line-level metrics indicate a modest reduction in peak loading on structurally congested lines, although persistent bottlenecks, especially in the north and northeast, remain visible across all scenarios. These results highlight the structural nature of certain grid constraints, which TDTR alone cannot resolve. A consolidated overview of the TDTR scenario outcomes, highlighting the advantages and disadvantages, is provided in Table 7.4.

7.3. TBTR Scenarios

Having evaluated the impact of TDTR on the national high-voltage grid, this section analyzes the effects of Time-Block-Based Transport Rights on the regional grid. Evaluating electricity demand patterns, load volatility, and grid use based on the three simulated scenarios: baseline, hybrid, and full implementa-

Table 7.4: Summary of TDTR Scenario Outcomes

Scenario	Advantages	Disadvantages
TDTR Hybrid	• Peak load reduced: 17.6 → 15.2 GW • Load volatility lowered • Peak grid flow decreased • Critical line loading improved	• Average price increases: €219 → €225/MWh • Slight increase in total grid flow (252 → 253 TWh)
TDTR Full	• Peak load reduced: 17.6 → 15.6 GW • Grid stress reduced during peak hours • Further critical line relief	• Average price increases: €219 → €229/MWh • Secondary peak emerges due to demand rebound • Local congestion patterns may shift

tion.

7.3.1. Load Curve and Demand Volatility

TBTR contracts incentivize electricity consumers to shift flexible demand into a designated off-peak time window, specifically from 00:00 to 06:00. This structured temporal incentive alters regional demand patterns and affects system-wide load volatility.

A full-year comparison of system load curves under the baseline, hybrid, and full TBTR scenarios is provided in Appendix D.1, which illustrates the broader temporal effects of TBTR across the year. To improve readability, Figure 7.7 focuses on the month of June, offering a clearer view of daily load shifts induced by TBTR adoption.

Figure 7.7: Load Curve (June) for three TBTR simulations

In the hybrid scenario (blue line), TBTR leads to moderate reductions in peak demand compared to the baseline (green line). The maximum load decreases from 3.36 GW to 3.07 GW, reflecting a successful redistribution of demand into underutilized nighttime hours. Similarly, the minimum load rises from 1.08 GW to 1.12 GW, demonstrating that TBTR, like TDTR, effectively reduces load curve volatility by clipping peaks and filling valleys.

However, the full TBTR scenario (yellow line) reveals a counter-intuitive outcome: the system peak actually increases to 3.55 GW. As shown in D.2, this excess peak emerges between mid-March and mid-October, following the spring clock change. By shifting all flexible demand into the fixed block 00:00 -06:00, a slight increase in the load of each sector at 05:00 (the last hour of the block) becomes amplified. While each sector individually contributes only a modest increase, the cumulative effect is a sharp increase in total system load.

This effect is further illustrated in Figure 7.8, which shows a seasonal increase in peak electricity demand under the full TBTR scenario following the spring clock change in March. Figure 7.9 breaks down this pattern by sector, revealing how synchronized ramping of flexible loads across different sectors amplifies the morning peak. Rather than resolving the issue of peak demand, this shift effectively relocates the problem to a new time interval. While the early-night hours are better utilized, the fixed nature of the TBTR time block introduces a secondary peak shortly after 05:00, reducing the overall effectiveness of load shifting. This highlights a key insight: in the absence of demand staggering or intelligent control mechanisms, rigid block-based flexibility schemes may alleviate traditional peaks but simultaneously create new temporal bottlenecks, undermining system-wide efficiency gains.

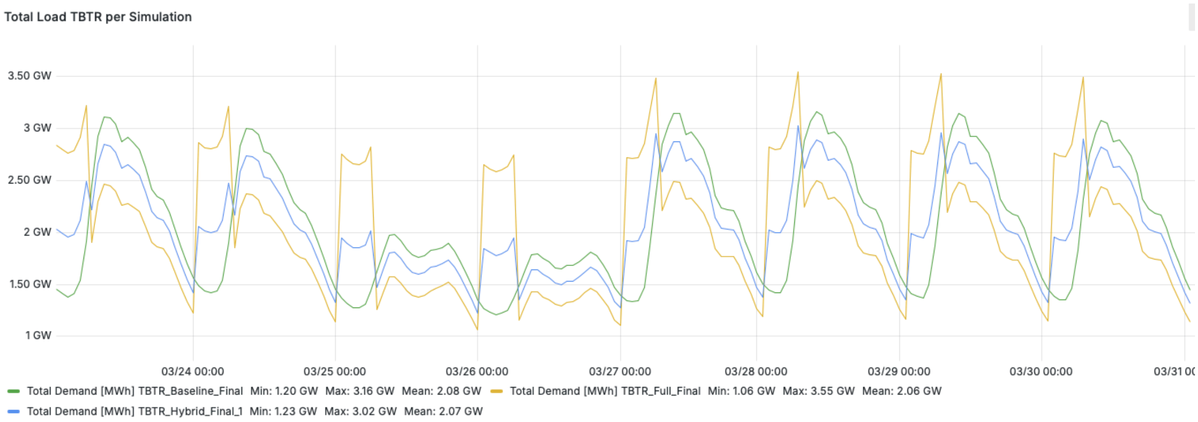

Figure 7.8: TBTR Simulations Load during clock change (March 27th)

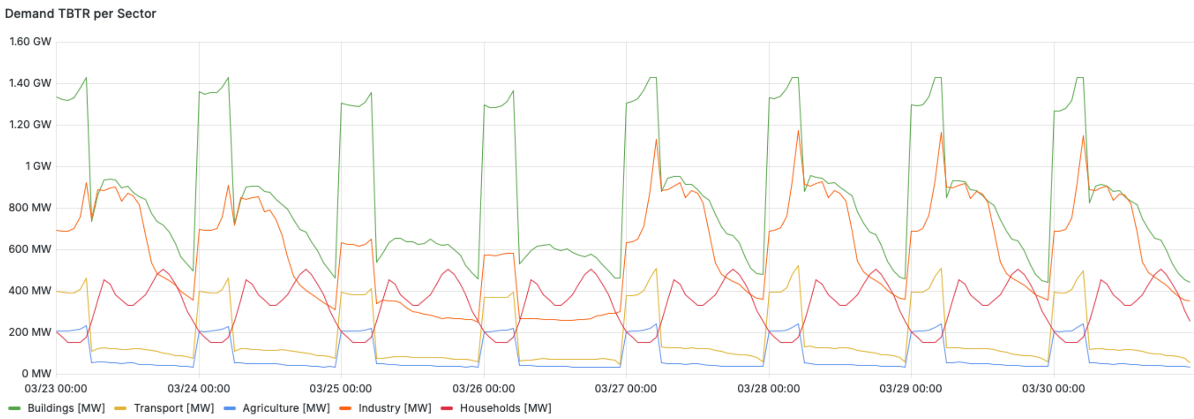

Figure 7.9: TBTR Sectoral Load during clock change (March 27th)

7.3.2. System Load Metrics and Electricity Prices

Table 7.5 presents a comparative overview of key performance metrics for the three TBTR simulation scenarios, including average electricity price, total system cost, and minimum, maximum, and mean system load. These metrics provide insight into how TBTR affects overall demand profiles and financial outcomes at the system level.

Despite the rise in peak load in the full scenario, the mean load remains constant across all simulations at 2.01 GW, showing that overall energy consumption is preserved and the increase in peak is purely a temporal shift. On the pricing side, the average electricity price remains stable at €221/MWh in both hybrid and full scenarios, compared to €219/MWh in the baseline. Similarly, total system costs remain within a narrow range, despite minor shifts in dispatch and load concentration. These minimal price differences reflect the fact that TBTR adjustments are applied only to the regional grid, while financial values in the model are determined at national level. The small increase in price compared to the baseline scenario suggest that the financial impact of TBTR follows the same logic as that of TDTR, which will be further analyzed in Section 7.4.

Table 7.5: Comparison of TBTR Simulation Metrics
*Please note that the financial values are set at national-level, while TBTR is only implemented on the regional grid

Simulation	Average price*	Total cost*	Max Load	Min Load	Mean Load
TBTR_Baseline	219 €/MWh	€20 547 770 666	3.36 GW	1.08 GW	2.01 GW
TBTR_Hybrid	221 €/MWh	€20 639 348 251	3.07 GW	1.12 GW	2.01 GW
TBTR_Full	221 €/MWh	€20 613 863 865	3.55 GW	0.97 GW	2.01 GW

7.3.3. Grid Flow Metrics and Line Loading Impacts

While the previous subsection assessed how TBTR reshapes temporal demand patterns and system-wide load dynamics, this section explores the corresponding impacts on spatial grid flows and transmission line loading. After all, changes in when electricity is consumed also affect where and how it moves across the network.

As established in the previous subsections, full TBTR implementation introduces a pronounced secondary peak around 05:00 due to synchronized demand rebound at the end of the time block. Table 7.6 supports this observation, presenting key system-wide metrics, which compare total flow volumes, peak hourly flows, and the temporal occurrence of those peaks. The hybrid scenario demonstrates reduced peak flows and load volatility, while the full scenario exhibits a temporal shift in congestion, peaking at 05:00 rather than the typical morning period.

Table 7.6: Grid Flow Metrics TBTR Simulations

Simulation	Sum Absolute Flow	Peak Hourly Flow	Peak Load Time
TBTR_Baseline	17.5 TW	3.4 GW	2022-01-17 08:00:00
TBTR_Hybrid	17.5 TW	3.0 GW	2022-01-17 08:00:00
TBTR_Full	17.0 TW	3.2 GW	2022-04-04 05:00:00

To complement the system-level results, Table 7.7 reports line-level congestion indicators. It summarizes peak loadings across all transmission lines per scenario, including the highest observed value (*Max Peak Line Loading*) and the average across all lines (*Mean Peak Line Loading*). In the hybrid scenario, the maximum peak loading drops from 199.0 MW to 180.2 MW, confirming that partial TBTR adoption alleviates pressure on the most heavily used lines. The mean also decreases to 112.3 MW. However, in the full TBTR case, the *Max Peak Line Loading* increases to 209.1 MW, and the *Mean Peak Line Loading* rises to 131.4 MW. This confirms that excessive uniform load-shifting leads to new localized bottlenecks, particularly near the tail end of the block period. Full line loading results for TBTR simulations can be found in the Appendix D.3.

Table 7.7: Summary of Line Loading Metrics Across TBTR Scenarios

Metric	TBTR Baseline	TBTR Hybrid	TBTR Full
Max Peak Line Loading [MW]	199.0	180.2	209.1
Min Peak Line Loading [MW]	107.7	98.1	100.1
Mean Peak Line Loading [MW]	124.7	112.3	131.4

These findings highlight the delicate balance required when implementing fixed time-block mechanisms such as TBTR. While hybrid adoption yields measurable grid benefits, full-scale application without granular demand controls risks generating unintended congestion peaks, both temporally and spatially.

7.3.4. Summary of TBTR Scenario Impacts

The TBTR simulations reveal that while Time-Block-Based Transport Rights can effectively redistribute flexible demand to off-peak hours, their rigid temporal structure introduces important trade-offs. In the hybrid scenario, TBTR successfully reduces peak demand and raises minimum load, confirming its role in mitigating load volatility. However, the full TBTR implementation produces a system-wide morning peak due to synchronized demand recovery at the end of the block, which offsets some of the intended congestion relief benefits.

Grid metrics confirm that overall electricity consumption and transmission volumes remain stable, indicating that TBTR primarily affects when electricity is consumed rather than how much. Peak hourly flows and critical line loading are modestly reduced, though some bottlenecks persist due to structural grid constraints. Financial outcomes remain largely unaffected at the national level, with electricity prices and total system costs showing minimal variation across scenarios.

These results underline a key insight: the effectiveness of TBTR is highly sensitive to adoption levels and temporal design. Without demand staggering or smarter control mechanisms, rigid block-based flexibility schemes risk creating new temporal bottlenecks, even as they relieve traditional ones. To consolidate these findings, Table 7.8 summarizes the main outcomes of the TBTR scenarios, indicating their advantages and disadvantages.

Table 7.8 provides an overview of the TBTR scenario outcomes.

Table 7.8: Summary of TBTR Scenario Outcomes

Scenario	Advantages	Disadvantages
TBTR Hybrid	• Peak load reduced: 3.36 → 3.07 GW • Load volatility lowered (Min Load: 1.08 → 1.12 GW) • Peak grid flow decreased: 3.4 → 3.0 GW • Line loading reduced (Max: 199.0 → 180.2 MW)	• Average price increase: €219 → €221/MWh • Effects localized to regional grid only
TBTR Full	• Load smoothing during early night hours • Effective redistribution of demand into off-peak	• System peak increased: 3.36 → 3.55 GW • New congestion peak at 05:00 due to demand bunching • Line loading worsened (Max: 199.0 → 209.1 MW)

7.4. Electricity Price Increase Analysis

The electricity price increases identified in the simulation results for both the TDTR and TBTR scenarios can be explained by examining shifts in generation dispatch dynamics under the merit-order principle. Given that electricity prices are determined at the national level, the TDTR scenarios, which encompass broader system-level adjustments, will be the primary focus for this analysis.

Under the merit-order principle (as described previously in Section 6.6.1), electricity generation units are dispatched sequentially based on ascending marginal costs. Renewable energy sources, such as wind and solar, are prioritized due to their near-zero marginal costs, followed by progressively costlier fossil-based generation units, typically coal and natural gas plants. With the implementation of TDTR, a substantial proportion of electricity demand is shifted from peak to off-peak periods, significantly altering the temporal distribution of generation dispatch.

Although shifting demand away from peak hours reduces the use of the highest-cost peak-time generators, it simultaneously introduces new demand peaks during traditionally lower-demand periods, especially during nighttime when solar generation is unavailable. As a result, this shifted load increasingly relies on fossil-fuel-based generation units situated further down the merit order, notably natural gas plants, thereby shifting the price-setting mechanism toward more expensive sources.

Importantly, the upward pressure on prices is not confined solely to off-peak hours. The adjusted demand profile also raises consumption levels during hours that previously were largely met by low-cost renewable or baseload generation in the baseline scenario. These slight increments in demand can push total system load marginally above thresholds where additional fossil-fueled generation units must be dispatched, even in periods of moderate overall consumption. Given the exceptionally high fossil fuel prices in 2022, largely resulting from geopolitical disruptions caused by the war in Ukraine and associated energy supply challenges [102, 103], these incremental shifts in generation dispatch result in disproportionately large increases in electricity prices.

Thus, the combination of increased fossil-fuel-based dispatch during both traditionally off-peak and moderately loaded hours contributes to more frequent and higher price-setting by expensive generation units. This mechanism clearly explains the observed elevation in average electricity prices across the TDTR scenarios. Figure 7.10 illustrates this phenomenon: the hybrid (blue) and full (yellow) TDTR scenarios exhibit consistently elevated prices relative to the baseline (green), remaining at higher price levels for extended periods or experiencing fewer low-price intervals.

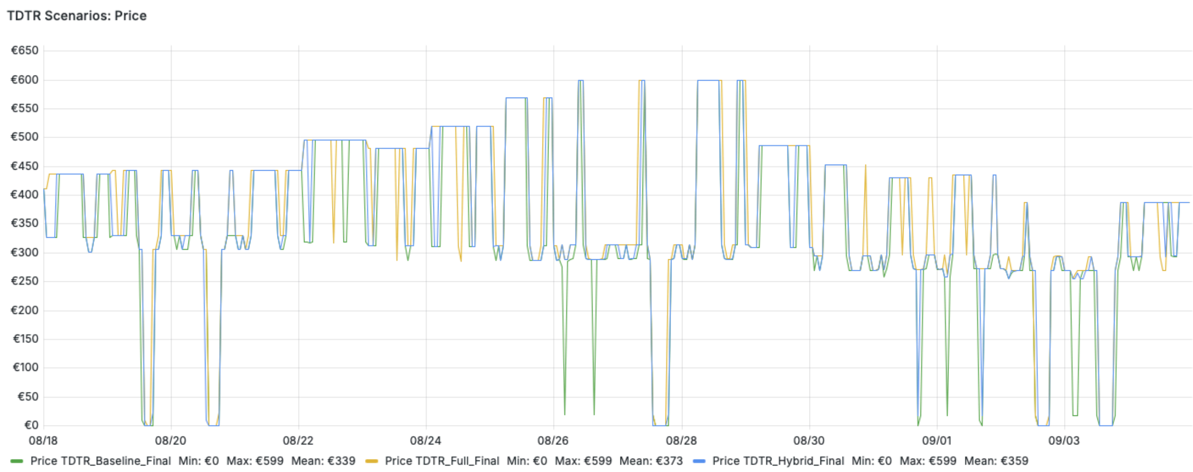

Figure 7.10: Electricity prices under TDTR scenarios during the period of exceptionally high fuel prices (August/September 2022)

7.4.1. Fuel Price Sensitivity Analysis

To further assess whether the electricity price increases observed in the 2022 simulations were driven primarily by ATR-induced demand shifts or by the exceptionally volatile fossil fuel prices of that year, the TDTR scenarios were re-simulated using coal and natural gas prices from 2023, a period marked by significantly lower and more stable fuel markets [104]. The results, presented in Table 7.9, show a substantial drop in absolute electricity prices across all scenarios, with the baseline falling to €142/MWh and the full TDTR scenario to €145/MWh.

Despite the lower overall price level, the same upward trend persists: average prices increase incrementally with greater TDTR adoption. This confirms that the observed price elevation is not solely an artifact of 2022's fuel market volatility, but is partially endogenous to the temporal load shifting introduced by TDTR. Shifting demand to previously off-peak hours structurally alters the dispatch profile in a way that increases reliance on more expensive marginal units, even under calmer market conditions.

This finding reinforces the conclusion that while TDTR improves system flexibility and grid performance, it may introduce systematic upward pressure on prices, especially in contexts with limited low-cost off-peak generation.

Table 7.9: Electricity Prices in TDTR Scenarios Using 2023 Coal and Gas Prices

Metric	TDTR Baseline	TDTR Hybrid	TDTR Full
Electricity price [€/MWh]	142	144	145

8
Discussion

This chapter critically reflects on the research outcomes by connecting insights from stakeholder interviews with results from the agent-based simulations. Section 8.1 summarizes the main findings, while Section 8.2 interprets their broader implications for policy, regulation, and system-level behavior. Section 8.3 discusses the academic contribution and methodology, followed by Section 8.4, which outlines key limitations. Section 8.5 presents targeted recommendations for stakeholders, and Section 8.6 identifies directions for future research.

8.1. Summary of Results

The qualitative research highlighted critical factors influencing the adoption and effective implementation of alternative transport rights among large energy consumers. Stakeholder interviews underscored the foundational importance of accurately identifying and leveraging operational flexibility. Effective ATR compliance requires detailed, high-resolution sub-metering to accurately pinpoint flexible loads and real-time control capabilities through advanced digital infrastructures and enterprise data management. Additionally, it became evident that successful adoption hinges on significant organizational and behavioral adjustments, including fostering staff awareness and embedding energy flexibility strategies within operational routines. While battery storage was frequently discussed, interviewees emphasized that digital infrastructure upgrades and process flexibility are currently more cost-effective for achieving ATR compliance.

The qualitative insights informed the quantitative scenario modeling, wherein different sector-specific flexibility potentials were translated into agent-based model parameters. In analyzing the TDTR scenarios, the simulations demonstrated clear effectiveness in reducing peak electricity demand, with maximum system loads decreasing notably from 17.6 GW in the baseline scenario to approximately 15.2 GW and 15.6 GW in the hybrid and full adoption scenarios, respectively. TDTR scenarios consistently demonstrated their intended functionality in smoothing electricity demand curves and reducing peak congestion on the grid. Nevertheless, these positive impacts were accompanied by moderate increases in average electricity prices, rising from €219/MWh in the baseline scenario to €225/MWh (hybrid) and €229/MWh (full). This unexpected effect is attributed to the redistribution of demand into off-peak periods characterized by lower renewable generation, consequently triggering dispatch of costlier fossil-based generation plants. Notably, re-simulations conducted with 2023 fossil-fuel prices confirmed that these price increases persisted irrespective of fuel price volatility, highlighting a structural and significant insight.

The evaluation of TBTR, implemented at the regional level, yielded nuanced outcomes. Partial (hybrid) adoption effectively reduced peak demand from 3.36 GW to 3.07 GW, improving grid utilization and mitigating congestion in line with policy intentions. However, the full-scale TBTR scenario generated an unexpected secondary peak demand of 3.55 GW around 05:00, primarily due to synchronized demand increase within the fixed off-peak time block.

Additionally, the simulations provided detailed insights into the spatial impacts on grid congestion and line loading, confirming reductions in critical line loadings under hybrid adoption scenarios. However, they also indicated persistent congestion points, suggesting that ATR alone might not fully resolve structural grid bottlenecks without coordinated investments in infrastructure or supplementary flexibility measures.

8.2. Interpretation of Results

The simulation results and stakeholder interviews underline that while technical potential for demand-side flexibility exists across multiple sectors, it remains largely underutilized. Many large energy consumers have yet to develop the internal capacity or awareness needed to actively engage with regulatory tools such as ATR. Interviewees noted that their organizations often lack clear internal ownership of grid-related adaptation, and in some cases, awareness of new transport rights was still limited. This lack of preparedness undermines the effectiveness of well-intentioned regulatory mechanisms and represents a missed opportunity to reduce congestion in a cost-effective and equitable manner.

From an organizational perspective, this points to a need for increased capacity building, not only in terms of technological capabilities, but also in governance, communication, and data management. Organizations must be empowered to identify their own flexibility potential, and equipped with the tools, data, and regulatory clarity to act on it. Enhanced transparency and knowledge sharing, whether through grid operators, regulatory bodies, or sectoral associations, could help bridge this gap between potential and practice.

Moreover, the research illustrates how regulatory interventions can have broad ripple effects on societal actors beyond their direct economic incentives. For instance, even when ATR contracts offer cost savings, their adoption may be hindered by operational uncertainty, unclear responsibilities, or mismatched planning cycles between businesses and regulatory frameworks. These barriers highlight that societal readiness is not just about technical feasibility, but also about institutional alignment and behavioral change.

When integrated into a wider systems perspective, the findings of this research offer significant practical insights into how regulatory mechanisms like TDTR and TBTR can be leveraged to manage energy demand and enhance grid stability. These insights are particularly relevant in light of the fundamental transition in the electricity system from stable, fossil-based generation to a more variable and weather-dependent renewable supply. Historically, electricity systems have favored rigid consumption patterns that align with the constant output of fossil fuel power plants. In contrast, the rapid growth of renewable energy sources introduces substantial volatility and uncertainty into electricity supply. Ideally, flexible demand and energy storage solutions would immediately respond to periods of abundant renewable generation, optimizing efficiency and reducing costs. However, the existing electricity infrastructure and regulatory framework, initially designed for stable, predictable consumption, often cannot accommodate such dynamic shifts.

This transition creates a central paradox: while renewable generation requires flexibility, the existing system incentivizes rigidity. Two insights from this thesis illustrate this paradox.

First, there is an inconsistency in flexibility incentives embedded in current tariff structures. ATR are explicitly designed to encourage flexible energy use, yet mechanisms like the capacity-based charge ("kW max") penalize consumers for short-term peak demand. This can disproportionately affect flexible users, whose attempts to shift or consolidate their load may unintentionally lead to higher peak charges, discouraging the very behavior ATR aims to promote.

Second, simulation results reveal that shifting demand to off-peak hours can paradoxically result in higher electricity prices. Off-peak periods often coincide with low renewable output, requiring the dispatch of costlier fossil-fuel plants. Thus, while congestion may be alleviated, the economic benefits of flexibility are not always realized.

These findings highlight a core tension in the energy transition: the structural misalignment between the technical needs of a renewable-based system and the economic signals provided by existing infrastructure and regulation. Addressing this contradiction is essential for designing effective policies and market mechanisms that genuinely support a sustainable and flexible electricity system.

In the context of the Netherlands, where grid congestion has become a critical bottleneck for decarbonization and electrification goals, this research reinforces the view that demand-side interventions such as ATR can play an important, yet partial, role. While ATR offer a promising regulatory mechanism to stimulate more conscious and flexible electricity use, they cannot resolve structural grid limitations in isolation. Physical constraints on the grid, especially in regions facing persistent transport capacity shortages, require complementary solutions to improve alignment of demand with renewable supply.

Nonetheless, ATR can be viewed as a step in the right direction. Beyond their immediate functional value, they represent a shift in regulatory thinking: from unconditional access and static pricing toward conditional, dynamic, and time-sensitive frameworks that better reflect the operational realities of a renewables-based power system. Fully embracing this transition will require more than isolated instruments. A broader re-evaluation of electricity pricing mechanisms, tariff structures, and market incentives is essential. Aligning these structural elements with the flexibility needs of a decarbonized system is a prerequisite for addressing congestion challenges, ensuring system reliability, and unlocking the full potential of clean energy technologies.

8.3. Reflection

8.3.1. Academic Contribution

This thesis contributes to three interrelated academic fields: regulatory economics in liberalized electricity markets, agent-based modeling for congestion management, and organizational behavior in energy system transitions. As ATR are a recent development, this study fills a notable gap in academic literature by examining their design, implementation, and systemic effects through both qualitative and quantitative methods.

A key academic contribution of this thesis lies in highlighting a structural misalignment between the operational needs of renewable-dominated electricity systems and the regulatory incentives currently in place. While the demand for system flexibility is well established in energy transition literature, this study adds empirical and simulated evidence showing that existing tariff structures can inadvertently discourage adaptive behavior. By examining how ATR mechanisms interact with legacy pricing models, the research surfaces underexplored tensions that may limit the real-world impact of flexibility-oriented policies. This insight contributes to a growing body of work that calls for the co-evolution of technical systems and institutional design, and underscores the need for more holistic policy evaluation frameworks that account for behavioral and systemic feedbacks.

Moreover, the agent-based model developed in this research offers a replicable tool for future academic work. Its modular design allows for adjustment and extension of sector-specific flexibility assumptions, supporting studies exploring varying adoption scenarios, dynamic behavioral responses, or spatially explicit grid constraints. The findings regarding unintended consequences of both TDTR and TBTR adoption highlight the need for regulatory frameworks that are adaptable, context-sensitive, and responsive to feedback from system actors.

The interdisciplinary methodology, integrating stakeholder insights with detailed grid simulations, represents another academic contribution. It provides a more holistic view of congestion management than studies that treat flexibility either as a purely technical optimization problem or as a matter of behavioral readiness. This blended approach enables more realistic assessments of policy feasibility and implementation dynamics in complex socio-technical systems.

Finally, while the analysis is situated in the Dutch context, the challenges it surfaces are internationally relevant. The study offers transferable insights for policymakers, researchers, and system operators working in other countries where renewable integration, congestion, and demand-side flexibility are converging issues.

8.3.2. Methodological Reflection

The mixed-methods approach employed in this study effectively combined qualitative insights from expert interviews with quantitative agent-based modeling. This dual approach was essential given the novelty ATR and the limited empirical foundation available in existing literature. By triangulating conceptual understanding, stakeholder perspectives, and simulated system-level outcomes, the study produced a more context-sensitive and comprehensive analysis.

The selection of this approach was driven by the complex socio-technical nature of the research subject. Grid congestion, one of the most pressing challenges in the Dutch energy transition, intersects with regulatory, behavioral, and technical dimensions. Exploring how ATR could alleviate congestion required a framework capable of capturing both system-level consequences and stakeholder behavior. A purely qualitative analysis would have fallen short in evaluating emergent and unintended effects of ATR mechanisms, while a purely quantitative approach would have lacked the necessary insights into organizational attitudes, data readiness, and operational practices of large energy consumers, factors pivotal to regulatory success.

Nevertheless, several methodological challenges arose. The qualitative component was constrained by the recency of ATR as a policy innovation, which meant that little academic or empirical material was available to guide the interview design or thematic analysis. Moreover, collecting stakeholder input proved difficult, as many large energy consumers were unfamiliar with ATR or lacked a clearly designated employee responsible for grid-related decision-making. As a result, identifying appropriate interviewees required extensive outreach, and the comprehensiveness of the insights was often limited by the roles and expertise of respondents.

An added complexity was the translation of qualitative findings into quantitative model parameters. Stakeholder narratives needed to be formalized into assumptions about sector-specific flexibility, which introduced interpretative uncertainty. These transformations, while guided by interview input and academic benchmarks, highlight a general challenge in integrating human-centered insights into formal simulation environments.

The quantitative component, executed through an agent-based modeling framework, offered notable advantages. It enabled detailed simulation of decentralized decision-making processes and allowed for sector-specific flexibility modeling under various ATR regimes. The modular structure of the model is a particular strength, as it facilitates future adjustments and extensions, such as incorporating dynamic behavioral learning or sector-specific adoption patterns. This adaptability positions the model as a valuable tool for future researchers and policymakers seeking to explore how varying levels of demand-side responsiveness influence outcomes like grid congestion and price volatility.

In summary, while the mixed-methods design introduced certain complexities, it proved indispensable in addressing the multidimensional nature of the research question. The methodology enhanced the validity and relevance of the findings, particularly by bridging theoretical modeling with real-world operational considerations. Nonetheless, despite efforts to mitigate methodological and modeling challenges, several limitations remain, both in the construction of the model and in the empirical scope of the study. These are discussed in section 8.4.

8.3.3. Personal Reflection

This section reflects on the personal learning curve I experienced during the course of this thesis, highlighting key developments in my perspective, skills, and methodological approach.

Embarking on this thesis project, I felt enthusiastic and motivated by the relevance and urgency of grid congestion as a critical issue in today's energy landscape. Initially, I was eager to explore this challenge comprehensively, choosing a mixed-method approach to effectively capture both technical details and social dimensions.

In the quantitative component, my original ambition was to construct a highly detailed model of the entire Dutch electricity grid. However, I quickly recognized that fully capturing every aspect of such a complex system was neither practically feasible nor efficient given the timeframe of the project. This realization significantly shaped my research process and taught me valuable lessons in project scoping. I learned to identify and prioritize the most critical elements of the electricity grid for modeling, define clear and realistic assumptions, and substantiate these assumptions rigorously through previous research and stakeholder consultations.

Similar lessons were echoed in the qualitative aspect of my research. Initially, my goal was to conduct extensive interviews, aiming to gather as many insights as possible. However, I encountered challenges due to low awareness and limited availability of experts familiar with ATR. Consequently, I needed to strategically target specific individuals and carefully filter the gathered information to extract the most relevant insights. This experience highlighted a crucial aspect of my learning journey: there will always be more data, more perspectives, and more avenues to explore, but the essence of effective research lies in clearly defining the research scope and efficiently determining the most valuable information within that scope.

Reflecting on my broader perspective regarding grid congestion and the energy transition, I initially viewed these issues primarily as technological and financial challenges. Throughout the research process, my viewpoint evolved substantially. As I engaged more deeply with policy frameworks and the complexities of real-world applications, I came to appreciate the interconnectedness of technological feasibility, regulatory maturity, stakeholder participation, and economic viability. It became clear that these factors must progress in parallel, as delays in any single area can impede overall progress. Consequently, I now perceive the challenge of grid congestion not as an isolated task but as a part of a comprehensive system-wide transformation to a sustainable energy transition that demands synchronized progress across multiple dimensions.

If I were to undertake my thesis again, equipped with the knowledge and experience gained, I would still choose a mixed-method approach, but I would place greater emphasis on qualitative research. Specifically, I would explore more deeply how ATR aligns with broader sustainability and energy transition goals in the Netherlands. I believe this would strengthen the robustness of the modeling outcomes and enhance their practical relevance.

Overall, this thesis experience has significantly enriched my academic and professional development, profoundly influencing my approach to interdisciplinary research and complex system challenges.

8.4. Limitations

While this thesis provides meaningful insights into the design and implications of alternative transport rights, its findings must be interpreted in light of several modeling and methodological limitations. Like all simulation-based research, the results are contingent upon the assumptions, data quality, and scope of the chosen framework.

First, the accuracy and predictive power of the agent-based model depend heavily on the quality and granularity of input data. While significant effort was made to ensure realistic representation, uncertainties and simplifications, such as aggregation of demand data and use of generic flexibility assumptions, inevitably affect the precision of results.

Additionally, the linear power-flow approximation utilized in this model simplifies real-world grid operations by ignoring reactive power and voltage constraints. While widely accepted for strategic congestion studies, this simplification may overlook localized operational constraints, potentially underestimating congestion effects and necessary remedial actions.

Moreover, the scenario-based approach, while beneficial for comparative analysis, assumes static behavioral responses and predefined flexibility levels. In reality, consumer behavior and market responses are dynamic and may evolve unpredictably due to changes in market conditions, technological advancements, or policy interventions. These dynamic factors were not captured fully in the present study.

Furthermore, the model does not include redispatch mechanisms or flexibility markets. As a result, it cannot quantify the potential cost-saving effects of reduced redispatch interventions under ATR adoption. This omission limits the ability to assess the full economic impact of ATR mechanisms, particularly the trade-off between market price increases and reduced system operation costs.

The model also lacks a full sensitivity analysis of key parameters, particularly the sectoral flexibility coefficients. Due to computational constraints, with each simulation taking approximately two hours, it was not feasible to perform a sufficient number of runs to systematically test model robustness. Scenario-based assumptions were instead prioritized, given the exploratory nature of the study. Nonetheless, future work could enhance model rigor by including targeted sensitivity analysis where computational resources allow.

Finally, the reliance on expert interviews introduces potential biases and limitations in generalizability.

While valuable for practical insights, stakeholder responses reflect individual experiences and perspectives, which may not universally represent all LECs.

While the limitations of this study warrant caution in interpreting specific quantitative outcomes, they do not detract from the broader system-level insights gained through the integration of simulation results and stakeholder perspectives. These findings underline the urgency for coordinated action across technical, institutional, and regulatory domains. The next section builds on this by outlining concrete strategies to enhance the implementation of alternative transport rights and better align system operations with stakeholder capabilities.

8.5. Recommendations

This section offers targeted, actionable recommendations for large energy consumers, system operators, and policymakers. Drawing on the system-level insights developed in this study, the goal is to support more effective deployment of alternative transport rights while addressing the persistent structural and operational misalignments that hinder their success.

Large Energy Consumers

LEC play a central role in unlocking demand-side flexibility and stand to benefit from ATR through reduced grid tariffs and enhanced control over their energy costs. However, realizing these benefits requires more than the adoption of new technologies; it calls for strategic foresight, robust data infrastructure, and organizational commitment.

A crucial first step is the identification and operationalization of flexible demand within their processes. To achieve this, LECs should invest in advanced sub-metering and energy monitoring infrastructure. Such systems provide the high-resolution data needed to identify flexible loads, track usage patterns, and respond effectively to ATR signals. Enterprise data management plays a key role here by integrating operational data across systems, ensuring consistency, accessibility, and real-time visibility. This data-driven foundation allows organizations to evaluate flexibility potential, monitor performance, and demonstrate compliance with ATR conditions.

In parallel, integrating digital infrastructure is essential. Advanced energy management systems with automated control capabilities enable real-time responsiveness to external triggers, such as grid constraints or dynamic price signals. These systems must be capable of orchestrating adjustments across diverse operational components, including production equipment, HVAC systems, electric vehicle charging, and greenhouse climate controls, depending on the sector involved.

Yet technical capability alone is insufficient. Flexibility must also be embedded within the organization itself. This means establishing internal governance structures, appointing responsible energy managers, and ensuring that operational protocols incorporate flexibility considerations. Behavioral strategies, such as targeted training, visual alert systems, and performance monitoring, can promote a culture of responsiveness, making flexibility a core operational principle rather than an ad hoc response.

In sum, for LECs to successfully participate in ATR schemes and support broader grid stability, they must align people, processes, and technology around structured data management and operational adaptability.

Grid Operators

Grid operators play a pivotal role in orchestrating ATR mechanisms to ensure they support rather than compromise grid stability. This requires continuous monitoring and iterative refinement of ATR design. As shown by the emergence of secondary peaks in the full TBTR scenario, operators must remain vigilant to unintended system effects. Adjusting the temporal design of ATR, such as revising block definitions, implementing rolling windows, or introducing stochastic flexibility periods, can help prevent concentrated load and distribute demand more evenly across time.

A critical prerequisite for this role is the readiness of data infrastructure, especially at the distribution level. Although TBTR contracts were scheduled to become available to large consumers as of April 1st, 2024, DSOs were unable to operationalize this product on time due to insufficient visibility into local residual capacity. Enabling dynamic, conditional access to the grid requires daily, high-resolution insight into the evolving state of grid capacity. This is not yet fully in place. DSOs must therefore accelerate investments in real-time data collection, monitoring tools, and internal IT systems to support transparent and reliable ATR activation. The delay in implementation has forced grid operators to offer ad hoc solutions to requesting companies, highlighting the urgency of improving the digital infrastructure required to underpin these regulatory instruments.

In parallel, grid operators should enhance their communication and engagement with large energy consumers. Beyond publishing technical documentation, they should proactively provide guidance, dashboards, and accessible support services to clarify the structure of ATR contracts, explain participation procedures, and build trust. More tailored outreach and interactive communication platforms can reduce informational asymmetries and foster broader engagement.

Lastly, operators can support LECs by offering scenario simulation tools and structured feedback. When organizations can assess the potential implications of ATR under different operational strategies, they are more likely to participate effectively. Performance reports, such as congestion impact summaries or compliance evaluations, can create valuable feedback loops, reinforcing adaptive learning and aligning participant behavior with broader system objectives

Policy Makers
This research underscores a core challenge for policymakers in the energy transition: the growing disconnect between the technical needs of a renewables-based electricity system and the economic signals embedded in existing tariff structures. While mechanisms like ATR aim to promote flexible electricity use, they currently coexist with legacy tariffs that can inadvertently penalize the very behavior ATR is intended to encourage. This tension risks undermining policy effectiveness and delaying the adoption of demand-side solutions.

To address this structural misalignment, policymakers are encouraged to critically examine how existing pricing mechanisms and tariff structures can be made more supportive of flexibility. Rather than prescribing a specific solution, this research highlights the importance of investigating how dynamic, time-sensitive, or differentiated tariff models might better reflect the operational realities of a decarbonizing power system. Aligning economic incentives with system needs will be essential for unlocking the full potential of ATR and similar mechanisms.

In parallel, addressing practical barriers to adoption remains vital. Many large energy consumers lack the technological infrastructure or organizational readiness to fully engage with ATR. To support broader participation, policymakers should consider expanding targeted funding schemes that lower the upfront cost of critical enablers, such as sub-metering, automation systems, and local energy storage. These instruments can help accelerate the diffusion of flexibility, enabling technologies, particularly in sectors with high potential to alleviate local congestion.

Finally, building institutional capacity is a precondition for success. Awareness of ATR remains limited, and many organizations require clearer guidance on how to interpret and implement these new contractual options. Coordinated outreach efforts, including sector-specific best, practice platforms, training programs, and accessible implementation toolkits, can play a crucial role in closing this knowledge gap.

Ultimately, ATR should be viewed as part of a broader shift in regulatory thinking, away from static, unconditional access and toward more dynamic, responsive models of grid participation. Realizing this vision will require ongoing policy attention, not just to individual mechanisms, but to the coherence and adaptability of the entire regulatory and economic framework underpinning the sustainable electricity system of the future.

8.6. Further Research

This section outlines several directions for future research that build upon the modular agent-based modeling framework developed and applied in this thesis. This framework offers a flexible and adaptable foundation, well-suited for integrating additional data sources, behavioral components, and evolving system configurations. Its modularity provides a robust platform for extending the current analysis of congestion management strategies ATR.

Building on this foundation, future research could focus on several areas to enhance the accuracy, realism, and policy relevance of the model. To begin with, improving the granularity and quality of input data, such as incorporating high-resolution consumption profiles and detailed local grid topology, would increase model precision and contextual relevance. Furthermore, extending the modeling framework to support full AC power-flow simulations, including reactive power and voltage constraints, would offer deeper insights into voltage stability and allow for more accurate identification of localized grid bottlenecks.

Moreover, there is substantial value in incorporating dynamic representations of consumer behavior and market responses. Future studies could integrate adaptive learning algorithms and agent-based decision-making processes to better reflect how large energy consumers and market participants adjust over time in response to evolving market signals, regulatory changes, and technological innovations. Such additions would improve the model's capacity to reflect real-world dynamics and support more robust policy evaluations.

Furthermore, future research would benefit from explicitly modeling redispatch mechanisms. Although the current study demonstrated the effects of ATR on electricity prices and grid flows, it did not capture redispatch operations, their costs, or spatial constraints. Incorporating features such as security-constrained economic dispatch or nodal pricing could enable a more comprehensive assessment of total system costs and trade-offs between market dynamics and operational interventions.

In addition, integrated assessments of complementary technologies and practices, such as energy storage, electric vehicles and distributed energy resources, would provide a more holistic understanding of system-wide interactions. Evaluating the combined impact of these technologies on grid stability, congestion relief, and market efficiency would enhance the applicability of model outcomes to long-term energy transition strategies.

Further research could also broaden the scope of stakeholder engagement. Expanding the empirical base through larger-scale qualitative interviews or quantitative surveys across various sectors would increase the generalizability and relevance of findings. Engaging a more diverse group of stakeholders, including policymakers, system operators, technology providers, and industry associations, would also help validate assumptions and refine implementation pathways.

Finally, targeted sensitivity analyses and scenario-based explorations should be incorporated to strengthen model robustness. Testing the effects of variations in key parameters, such as sectoral flexibility, ATR design specifications, and technology adoption rates, would allow for a better understanding of model sensitivities and help inform more resilient and adaptive policy strategies.

9 Conclusion

This chapter concludes the thesis by synthesizing the answers to the four sub-questions introduced in Chapter 1, drawing from the findings presented in Chapter 4, Chapter 5, and Chapter 7. Section 9.1 addresses each sub-question in turn, followed by Section 9.2, which formulates an integrated answer to the main research question guiding this study.

9.1. Answering the Sub-Questions

This section answers the sub-questions in the order in which they were introduced.

Sub-Question 1: What are the regulatory requirements of Alternative Transport Rights, and how do they impact the economic costs and benefits for large energy consumers?

Alternative transport rights, introduced by the Dutch Authority for Consumers and Markets in 2024, represent a regulatory shift from guaranteed and unrestricted electricity transport rights to a model based on conditional, flexible access. Designed to address growing grid congestion without necessitating immediate infrastructure expansion, ATR encourage large energy consumers to adapt their electricity use to the temporal and spatial realities of grid availability. By reallocating access based on residual capacity, ATR provide a framework for aligning system efficiency with economic incentives.

ATR are implemented through two distinct contractual forms, each tied to a specific grid level. Time-Duration-Based Transport Rights are currently available only on the national high-voltage grid, operated by TenneT. Under TDTR, consumers are granted access to their contracted transport capacity for at least 85% of the hours per year, with up to 15% potentially curtailed depending on system conditions. Curtailment notifications are issued a day in advance, requiring consumers to respond to short-notice limitations. In contrast, Time-Block-Based Transport Rights are introduced on the regional grids operated by DSOs. TBTR provide access to electricity only during predefined time blocks, currently limited to nighttime hours (00:00–06:00), that fall outside local peak periods. These time blocks are determined based on local congestion patterns and available residual capacity.

In both cases, participation in ATR requires that consumers possess the technical and organizational capacity to adjust their electricity consumption in accordance with these limitations. Moreover, ATR contracts are designed to be compatible with, conventional transport rights; users can combine fixed and flexible rights across different portions of their load but must adhere strictly to the conditions of each.

The financial structure accompanying ATR reflects the reduced certainty of access by offering lower network tariffs. For TDTR users on the national grid, the ”kW Contracted” component of the tariff, normally associated with long-term grid planning and infrastructure recovery, is waived entirely. Users pay only the ”kW Max” charge, which reflects their highest actual monthly usage. This shift can result in substantial cost savings, particularly for consumers with high contracted capacity and predictable usage patterns. For TBTR users on regional grids, the ”kW Contracted” charge is reduced in proportion to the average number of hours per day during which access is granted, while the ”kW Max” charge remains unchanged. These adjusted tariffs are intended to make flexible access financially attractive, especially for consumers capable of rescheduling operations to off-peak periods.

However, the economic benefits of ATR are tempered by several operational, technical, and regulatory barriers. One of the primary challenges is the uncertainty surrounding curtailment under TDTR. The one-day advance notice complicates operational planning, particularly for sectors with tightly scheduled or inflexible production processes. Even TBTR, while more predictable, may offer access windows that are misaligned with real-world energy needs, reducing the practical value of participation.

Participation in ATR also requires significant upfront investments in digital infrastructure. Smart meters, sub-metering at the process level, and automated control systems such as Energy Management Systems are necessary for real-time monitoring and compliance. For many firms, the business case for such investments is not immediately favorable, especially when existing tariff structures impose penalties for peak demand even when overall consumption behavior supports grid stability. The monthly ”kW Max” tariff, for instance, may inadvertently penalize consumers for advancing load in anticipation of curtailments, behavior that technically supports the grid but raises costs due to short-term peaks.

Beyond the technical domain, organizational readiness plays a critical role. ATR participation often requires shifts in internal routines, staff training, and cross-departmental coordination to ensure compliance with flexible access conditions. Non-compliance can trigger enforcement actions, ranging from warnings to suspension or termination of ATR agreements. This regulatory risk adds to the complexity of adoption and discourages participation among risk-averse firms.

Finally, the novelty of ATR and limited market communication have hindered broad uptake. Many LECs are still unfamiliar with the mechanisms and obligations associated with ATR contracts, and sector-specific guidance remains scarce.

In sum, the regulatory requirements of ATR introduce a more dynamic and responsive model of grid access that offers meaningful economic benefits to large energy consumers capable of adjusting their operations. TDTR and TBTR provide targeted mechanisms for high-voltage and regional grids, respectively, each offering tariff reductions in exchange for reduced certainty of access. While the financial incentives are considerable, especially under TDTR, the full realization of ATR’s potential depends on the ability of firms to overcome technical, behavioral, and institutional challenges. Addressing issues such as curtailment uncertainty, misaligned tariff components, and limited awareness will be critical to achieving the intended goals of congestion relief and efficient grid usage.

Sub-Question 2: How can large energy consumers leverage data and technology to optimize their operational processes for Alternative Transport Rights compliance?

LECs can leverage data and technology to optimize their operations for compliance with ATR by embedding high-resolution energy monitoring, digital automation, and structured data governance into their operational and organizational routines. ATR compliance requires aligning electricity consumption with dynamically constrained or predefined grid access windows, either through TDTR, which entail curtailments with limited notice, or TBTR, which offer access during fixed off-peak periods. Meeting these requirements demands an integrated approach that combines granular visibility, flexible infrastructure, and responsive organizational practices.

Central to ATR compliance is the acquisition and real-time processing of detailed energy data. High-frequency sub-metering, at intervals of 30 seconds or less, enables firms to identify peak consumption moments, assess the flexibility of specific loads, and simulate curtailment scenarios. Interviewees consistently stressed that operational optimization begins with measurement: without precise insight into when and where energy is used, no effective flexibility strategy can be deployed. Visualization platforms such as Power BI and centralized API-based dashboards allow energy managers to track load patterns and anticipate price or capacity signals, facilitating proactive adjustments to heating, lighting, and process schedules.

Once energy visibility is established, digital infrastructure, EMS and automation, becomes critical. These systems allow for real-time load control based on predefined rules, such as curtailing non-essential systems when thresholds are approached or activating loads during TBTR access hours. Advanced sensors and control logic can automate such decisions with minimal manual intervention, while ensuring that operational constraints (e.g., crop cycles in agriculture or thermal comfort in buildings) are respected. However, to realize the full potential of such systems, LECs must also invest in Enterprise Data Management capabilities that ensure data integration across business units, maintain quality, and standardize interpretation. Without EDM, automation efforts may remain siloed or misaligned with broader strategic objectives.

Sector-specific applications further illustrate how data and technology enable ATR compliance. In agriculture, greenhouse operators use climate control systems linked to EMS to dynamically manage heating and lighting loads based on grid signals and internal thresholds. In buildings, thermal buffering through overcapacity in refrigeration or HVAC systems allows for nighttime load shifting, especially when combined with electrification strategies. In transport, the timing of electric vehicle charging aligns naturally with TBTR windows, and smart charging algorithms can optimize load without compromising mobility needs. While industrial operations face more rigid process constraints, auxiliary loads like lighting and internal logistics present lower-hanging opportunities for automation and scheduling.

Battery storage is frequently proposed as a technical solution for ATR compliance, offering the theoretical ability to decouple consumption from procurement. However, interviewees agreed that batteries are currently often cost-prohibitive and inefficiently deployed without supporting data infrastructure. Instead, most viewed batteries as a long-term complement rather than a near-term prerequisite, advocating instead for flexible scheduling and process-level automation as more cost-effective pathways.

However, technical systems alone are not sufficient. For ATR participation to be effective and scalable, energy flexibility must be embedded in the organization's governance and operational culture. Appointing responsible energy managers, aligning cross-departmental workflows, and ensuring that flexibility considerations are reflected in operational protocols are essential steps. Behavioral strategies, such as visual alert systems, energy awareness programs, and structured performance monitoring, can reinforce responsiveness and foster a culture of shared responsibility. These organizational enablers ensure that flexibility becomes an integrated operational capability, rather than a reactive or temporary adjustment. While much of this must be driven internally, it is also supported by clear communication from system operators and policymakers, who play a key role in creating the predictable and transparent conditions under which LECs can confidently invest in and implement flexibility strategies.

In sum, LECs can effectively optimize their operations for ATR compliance by deploying granular monitoring tools, automating load control through EMS, and institutionalizing energy management within a robust EDM framework. These technological and organizational adaptations enable firms to shift demand intelligently in line with grid constraints, reduce transport tariffs, and support broader system stability, while minimizing operational disruptions and compliance risks.

Sub-Question 3: What are the impacts of adopting Time-Duration-Based Transport Rights by large energy consumers on congestion management effectiveness and the overall stability of the Dutch national grid?

The adoption of TDTR by large energy consumers LECs has a demonstrably positive impact on congestion management and the operational stability of the Dutch national electricity grid. By incentivizing flexible demand behavior through tariff reductions, TDTR mechanisms enable a redistribution of electricity consumption away from high-stress intervals, thereby supporting grid efficiency without requiring immediate infrastructure expansion.

Simulation results confirm that TDTR adoption reduces load volatility and peak system stress. In both hybrid and full adoption scenarios, maximum hourly electricity demand declines substantially compared to the baseline (from 17.6 GW to 15.2 GW and 15.6 GW, respectively), while minimum demand increases, resulting in a flatter national load curve. These shifts reduce the incidence and severity of network congestion, particularly during traditionally critical hours. Additionally, TDTR leads to a decrease in peak hourly transmission flow by up to 3.1 GW and alleviates loading on structurally congested lines, most notably a key 220 kV line in the Groningen-Drenthe corridor, without altering the total volume of electricity transported. This demonstrates that TDTR improves temporal utilization of the grid and eases pressure on known bottlenecks.

Despite these physical benefits, this thesis identifies nuanced trade-offs. At high adoption levels, synchronized load shifting may inadvertently create new peaks during formerly off-peak hours, occasionally exceeding peak reductions observed under hybrid scenarios. This suggests the potential for rebound effects when flexibility is concentrated without adequate staggering. Moreover, TDTR adoption consistently raises average electricity prices, by approximately €6–10/MWh, due to altered dispatch patterns. Load shifting into off-peak periods increases reliance on fossil-based generation (particularly natural gas) during hours previously dominated by low-cost renewables or baseload plants. While the price increase is modest relative to the system-level flexibility gains, it nonetheless persists even under calmer fuel market conditions, as demonstrated by the 2023 sensitivity analyses. This finding presents a new insight, revealing that TDTR-induced load shifting structurally alters dispatch patterns in ways that introduce a consistent, albeit limited, upward pressure on electricity prices.

Overall, TDTR enhances congestion management effectiveness by lowering peak loads, smoothing demand profiles, and reducing line loading on critical infrastructure. It contributes to greater operational stability of the Dutch high-voltage grid by enabling more responsive and efficient use of residual capacity. However, the magnitude of these benefits depends on adoption levels, demand-side coordination, and the availability of off-peak low-cost generation. To maximize its stabilizing effect, TDTR should be supported by granular control strategies, updated tariff models, and broader system planning that accounts for the dynamic nature of rebound peaks and shifting congestion patterns.

Sub-Question 4: What are the impacts of adopting Time-Block-Based Transport Rights by large energy consumers on congestion management effectiveness and the overall stability of the regional grid?

The adoption of TBTR by large energy consumers introduces both beneficial and adverse effects on congestion management and the overall stability of the Dutch regional grid. TBTR contracts provide access to the grid during predefined off-peak time blocks, currently limited to the 00:00–06:00 window, and aim to redistribute demand away from congested periods. By incentivizing load shifting into these underutilized hours, TBTR offers a non-infrastructural tool for improving temporal load distribution and relieving stress on the distribution network.

Simulation results confirm that hybrid TBTR adoption effectively reduces system peaks, lowers load volatility, and improves grid utilization. Peak demand decreases from 3.36 GW to 3.07 GW, and line loading on the most congested regional links is also alleviated, with maximum peak line loading declining from 199.0 MW to 180.2 MW. These improvements occur without altering the total electricity demand or transmission volumes, confirming that TBTR reshapes the temporal profile of electricity use without increasing system strain.

However, full TBTR adoption introduces new challenges. When all flexible demand is shifted into the same six-hour block, cumulative effects lead to a synchronized peak near the end of the block, particularly around 05:00, resulting in a new system-wide peak of 3.55 GW. This secondary peak emerges due to the rigid structure of TBTR and the lack of load-staggering mechanisms across sectors. As a result, maximum line loading rises above baseline levels, creating localized bottlenecks and undermining some of the intended congestion relief. These findings illustrate a core limitation: while TBTR reduces traditional peaks, it risks creating new temporal concentrations of demand if adopted at scale without sufficient control logic or automation.

Importantly, the average electricity price remains stable across scenarios, increasing only marginally (from €219/MWh to €221/MWh), as TBTR operates on the regional grid and does not significantly affect national merit-order dispatch outcomes. Nonetheless, the financial and operational efficiency of TBTR depends on how well load shifting is coordinated across participating consumers.

In sum, TBTR can enhance regional grid stability and reduce peak congestion when moderately adopted and supported by digital control infrastructure. However, its rigid temporal design poses significant challenges at higher adoption levels, especially in the absence of demand staggering. To safeguard its effectiveness, TBTR implementation must be paired with intelligent automation strategies and potentially more dynamic or rolling block designs that avoid synchronized rebound effects and unintended congestion shifts.

9.2. Answering the Main Research Question

This thesis sought to answer the main research question: *How can large energy consumers in the Dutch electricity market adapt their operational and data-driven practices to effectively utilize new alternative transport rights, and what impact will these adaptations have on grid congestion?*

The findings demonstrate that meaningful adaptation requires a dual transformation, both technical and organizational. Technically, large energy consumers must invest in high-resolution monitoring, automation, and enterprise-wide data integration to synchronize electricity use with the dynamic constraints imposed by ATR. Organizationally, flexibility needs to be embedded in decision-making processes, governance structures, and daily operations. Without this internal alignment, the full benefits of ATR cannot be realized. When adopted in a moderately coordinated manner, ATR can substantially alleviate grid congestion without the need for immediate infrastructure expansion. TDTR reduces national peak loads and relieves stress on critical transmission corridors, while TBTR enhances regional load distribution under hybrid adoption. Crucially, these improvements are achieved without increasing total electricity consumption, reflecting a more efficient temporal use of grid capacity.

Yet, the research also reveals structural misalignments. Existing tariff structures often fail to incentivize flexibility and, in some cases, penalize behavior that supports grid stability. Furthermore, shifting demand into off-peak hours can increase system costs by relying more heavily on fossil-based generation during periods of low renewable output. These effects underscore a disconnect between the technical needs of a renewable-based system and the economic signals shaping consumer behavior. Addressing this requires not only a more intelligent implementation of ATR, but also a fundamental reconsideration of tariff design, electricity pricing, and regulatory coherence. While ATR cannot resolve deep-seated grid constraints on their own, they mark a necessary shift toward more dynamic and responsive models of grid access.

In this light, ATR represent a timely regulatory innovation that reflects the operational realities of a variable, renewables-driven electricity system. But their success depends not just on consumer readiness, but on broader system alignment, across market incentives, institutional frameworks, and grid operator capabilities. Only through such alignment can ATR realize their full potential in mitigating congestion and accelerating the transition toward a flexible, reliable, and sustainable electricity system.

9.3. Use of Artificial Intelligence

During the development of this thesis, artificial intelligence (AI) tools, including language models, were used to support the writing process. These tools assisted in refining the structure, improving clarity and readability, and enhancing formatting and layout consistency. At no point were AI tools used to generate original research content, perform data analysis, or replace critical thinking and domain-specific judgment.

All substantive content, analysis, interpretations, and conclusions presented in this thesis are entirely my own work and responsibility. AI-supported suggestions were reviewed, adapted, and integrated thoughtfully to ensure academic integrity and alignment with the objectives of this research.

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A

Appendix: Literature Review

Table A.1: Initial Literature review: Search terms and results

Search Terms	Hits	Selected
"Grid congestion" AND "contracts"	12	1
"Energy" AND ("Congestion" OR "Grid Congestion") AND "Netherlands"	65	3
("Large-scale energy users" OR "Industrial energy consumers" OR "Energy-intensive users" OR "Industrial energy users") AND "Demand Response"	7	1
"Energy Consumers" AND ("Load control" OR "Demand Shifting" OR "Demand Flexibility")	26	2
"Load control" AND ("demand-side management" OR "demand response strategies") AND "Energy storage"	53	3
"Demand flexibility" s.AND ("renewable integration" OR "energy storage systems")	45	2
"Grid congestion" AND ("energy storage technologies" OR "battery systems")	7	1
"Grid flexibility" AND ("distributed energy resources" OR "renewable integration")	62	1
"Demand-side management" AND ("grid flexibility technologies" OR "energy efficiency") AND "Energy Storage"	31	1

Table A.2: Initial Literature Review: Selected Articles

Authors	Year	Title	Cited by	DOI	Subjects (Keywords)
Hennig, R. J., de Vries, L. J., Tindemans, S. H.	2024	Risk vs. restriction—An investigation of capacity-limitation based congestion management in electric distribution grids	4	`https://doi.org/10.1016/j.enpol.2023.113976`	Congestion management, capacity subscription, flexibility
Roldán-Blay, C., Escrivà-Escrivà, G., Roldán-Porta, C.	2019	Improving the benefits of demand response participation in facilities with distributed energy resources	42	`https://doi.org/10.1016/j.energy.2018.12.102`	Demand response, energy storage, optimal energy management

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Authors	Year	Title	Cited by	DOI	Subjects (Keywords)
Razmara, M., Bharati, G. R., Hanover, D., Shahbakhti, M., Paudyal, S., Robinett, R. D.	2017	Building-to-grid predictive power flow control for demand response and demand flexibility programs	109	`https://doi.org/10.1016/j.apenergy.2017.06.040`	Demand response, predictive control, solar PV
Dong, B., Li, Z., Taha, A., Gatsis, N.	2018	Occupancy-based buildings-to-grid integration framework for smart and connected communities	45	`https://doi.org/10.1016/j.apenergy.2018.03.007`	Smart grid, predictive control, occupancy
Nagy, Z., Henze, G., Dey, S., Arroyo, J., Helsen, L., Zhang, X.	2023	Ten questions concerning reinforcement learning for building energy management	38	`https://doi.org/10.1016/j.buildenv.2023.110435`	Reinforcement learning, energy management
Fleschutz, M., Bohlayer, M., Braun, M., Murphy, M. D.	2023	From prosumer to flexumer: Case study on the value of flexibility in decarbonizing the multi-energy system of a manufacturing company	16	`https://doi.org/10.1016/j.apenergy.2023.121430`	Multi-energy system, decarbonization, flexibility
Immonen, A., Kiljander, J., Aro, M.	2020	Consumer viewpoint on a new kind of energy market	43	`https://doi.org/10.1016/j.epsr.2019.105891`	Energy markets, demand flexibility
Hubert, N. D., Biely, K., Kamp, L. M., de Vries, G.	2024	Do laundry when the sun shines: Factors that promote load-shifting in Dutch households with solar panels	0	`https://doi.org/10.1016/j.erss.2024.103514`	Loadshifting, solar energy, behavior change
Behrangrad, M.	2015	A review of demand side management business models in the electricity market	256	`https://doi.org/10.1016/j.rser.2015.03.033`	Demand side management, smart grid, renewable integration
Zhang, K., Prakash, A., Paul, L., Blum, D., Alstone, P., Brown, R.	2022	Model predictive control for demand flexibility: Real-world operation of a commercial building with photovoltaic and battery systems	56	`https://doi.org/10.1016/j.adapen.2022.100099`	Model predictive control, photovoltaics

Continued on next page...

Authors	Year	Title	Cited by	DOI	Subjects (Keywords)
van der Holst, B., Verhoeven, G., van Schooten, L., Dukovska, I., Nguyen, P., Morren, J.	2025	On synergies between congestion management instruments: The Dutch case-study	0	https://doi.org/10.1016/j.segan.2025.101623	Congestion management, grid tariffs
Zakeri, B., Syri, S.	2015	Electrical energy storage systems: A comparative life cycle cost analysis	1396	https://doi.org/10.1016/j.rser.2014.10.011	Energy storage, comparative analysis
Schulz, J., Rosenberg, F., Scharmer, V. M., Zaeh, M. F.	2020	Characterization of Energy Consumers in Production Systems with Renewable On-Site Power Generation	2	https://doi.org/10.1007/978-3-030-57993-7_3	Energy consumption, micro-grid
Dronne, T., Roques, F., Saguan, M.	2021	Local flexibility markets for distribution network congestion-management in center-western Europe: Which design for which needs?	14	https://doi.org/10.3390/en14144113	Flexibility markets, congestion management
Gholian, A., Mohsenian-Rad, H., Hua, Y.	2016	Optimal industrial load control in Smart Grid	85	https://doi.org/10.1109/TSG.2015.2468577	Industrial load control, smart pricing

B
Interview Questions

A. General Business & Energy Profile (General)

1. In a few sentences, can you describe your company's operations and its energy consumption profile?
2. What are your primary sources of electricity (e.g., grid, on-site generation, renewables)?
3. Do you have a connection to the regional grid or the national grid?
4. How does electricity cost impact your business operations and strategic decision-making?
5. Does your company currently have enough connected capacity, or would an expansion be desirable?
   → *If so, do you experience any problems getting this extra capacity because of grid congestion?*

B. Awareness & Perception of Alternative Transport Rights (SQ1)

6. Are you familiar with the new ATR contracts (Time-Duration-Based and Time-Block-Based Transport Rights)?
7. Have you considered adopting ATR (whichever is relevant based on your grid connection)? If so, what were the deciding factors?
8. What benefits do you see in adopting ATR (e.g., cost savings, grid stability, sustainability goals)?
9. Do you foresee any challenges in adopting these contracts (e.g., operational adjustments, compliance issues)?
10. **[Only for TDTR]** How does uncertainty in grid connection affect your willingness to adopt TDTR?

C. Impact on Energy Management Strategies (SQ2)

11. Do you currently manage electricity demand during peak and off-peak hours? If so, how?
12. What role do energy storage systems (e.g., batteries) or distributed energy resources (DERs) like solar panels or windmills play in your operations?
13. If adopting ATR, which of your processes could realistically be shifted to off-peak hours without affecting core operations?
14. What are the main challenges you foresee in aligning your operational planning with ATR conditions?

D. Enterprise Data Management & Technology (SQ2)

15. What systems or tools does your company currently use to monitor and analyze electricity consumption?
16. How is your electricity consumption data currently used in operational decision-making?
    (E.g., does it inform production scheduling, cost allocation, or real-time system controls?)

17. Who in your organization is responsible for managing and analyzing energy data, and how is this information shared across departments?
18. Would implementing ATR require changes to your current IT infrastructure or energy management systems?
19. What kind of data automation or system integration would help your organization fully leverage ATR?

C

Interview Summaries

C.1. Interview Energy Director Glass House Farming Company

Energy Profile and Infrastructure

Each location typically uses a combined heat and power (CHP) unit (gas turbine), providing electricity, heat, and CO_2 for enhanced plant growth. Lighting is supplied by dimmable LED and SON-T lamps, mainly during winter months. Most sites have direct or ring connections to medium voltage (MS) networks, with some connected to high-voltage (HS) substations.

Thermal buffers are widely used to store surplus heat, enabling temporal decoupling between heat production and demand. Flexibility is embedded through smart switching between internal generation and external grid imports, depending on real-time electricity prices.

Grid Congestion and Expansion Constraints

Some sites, especially in Dinteloord, face network expansion limitations due to congestion. Netbeheerders (DSOs) have paused new capacity approvals, forcing the company to delay further LED lighting installations at some locations.

Awareness and Readiness for Alternative Transport Rights (ATR)

While not initially familiar with the specific ATR terminology, the interviewee recognized that their company already operates in line with the principles of these contracts:

- **Time-Duration-Based Transport Rights (TDTR)**: 85% guaranteed grid access, 24-hour advance notification for curtailment, and reduced transport tariffs.
- **Time-Block-Based Transport Rights (TBTR)**: predefined usage blocks tied to lower network charges.

They expressed strong readiness for such mechanisms due to their existing real-time responsiveness to electricity market prices and their internal systems for import peak control and LED dimming.

Operational Flexibility and Control Systems

The company employs:

- Continuous metering and import limitation enforcement through automated control systems.
- Climate computers and internal software that shut off lighting or scale generation if import thresholds are approached.
- Centralized energy management across all sites, coordinated with the director of cultivation.

Response times range from 10 minutes (CHP) to instantaneous (LED dimming). Quarter-hour granularity is expected to become standard under ATR implementation.

Storage and Renewable Integration

- **Thermal storage** is fully utilized across all sites.
- **Battery storage** is not used due to the high costs and short duration capacity relative to demand (e.g., 8 MW of lighting per site).
- **Solar PV** is not widely adopted due to limited roof space and shading concerns, though it may be used for thermal contributions in the future.
- **Wind** is unfeasible due to permitting barriers and uncertain generation profiles.

Strategic and Sectoral Challenges

The main challenge is sector-wide awareness and adoption. Few companies currently use ATRs, though the interviewee believes that early adopters (like themselves) can trigger broader interest. He noted the importance of industry webinars and the need for clearer communication by sector associations.

Data Use and Automation

Energy operations are highly automated:

- All metering data is centrally collected via APIs and analyzed using Power BI.
- Daily energy costs and profitability are monitored, with automated adjustments to CHP operations and electricity bids.
- The next step is deploying AI-based strategies to optimize intraday trading and forecasting.

Conclusion

This greenhouse operation exemplifies a high level of technical preparedness and operational flexibility, making it well-suited to adopt and benefit from ATRs. The sector's embedded buffering capacity and dynamic energy behavior position it as a valuable contributor to grid balancing, with significant potential for scaling best practices across horticulture and other energy-intensive industries.

C.2. Interview Flower Auctioning Company

Energy Profile and Sources

The energy profile shows pronounced early morning peaks due to auction operations starting around 6:00 a.m., with significantly lower demand during nights and weekends. Primary sources of electricity include:

- Grid connections (networks depending on site),
- Geothermal heat (Trias Naaldwijk project),
- Rooftop solar PV (notably in Eelde and Rijnsburg).

Operational and Strategic Energy Considerations

Historically, electricity costs did not significantly influence strategy, but price volatility has changed this. The company now actively develops an energy strategy focused on:

- Electrification of heating systems (replacing gas-fired boilers),
- Improving energy flexibility,
- Integrating smart energy management systems (EMS).

Challenges Related to Grid Congestion

Grid congestion poses major constraints, especially in Aalsmeer and Rijnsburg, where capacity limits prevent further site expansion. Aalsmeer East is currently being considered for alternative contracts, though flexibility of tenant demand remains a challenge.

View on Alternative Transport Rights (ATR)

The interviewee is aware of both Time-Block-Based (TBTR) and Time-Duration-Based (TDTR) transport rights. However, current flexibility is insufficient to benefit from these mechanisms. Particularly for TDTR, 24-hour notice from TenneT is only useful if adaptive capacity is already integrated. In the long term, the company sees potential to shift heating and cooling loads, especially through thermal buffering.

Flexibility Potential and Technological Outlook

Flexibility could eventually be developed in:

- **Cooling and heating processes**, by oversizing equipment and creating thermal buffers,
- **Energy storage systems**, which are under consideration, especially for winter operation.

Lighting, although a major consumer, offers limited flexibility due to operational constraints. An Energy Management System with technical staff is already in place to optimize and monitor energy use daily.

Organizational and Cultural Barriers

Internal awareness and organizational change are key challenges. Translating high-level energy strategy to operational behavior requires continuous communication and engagement with staff. Practical examples include adjusting cooling temperatures during idle periods or using EMS to monitor deviations and spot opportunities for improvement.

Role of IT and Automation

Future improvements depend on IT systems capable of integrating:

- Contractual capacity constraints,
- Energy prices and weather forecasts,
- Real-time operational and sustainability data.

While many vendors claim to offer such solutions, none fully deliver on the complexity required.

Position on ATRs in Long-Term Strategy

The interviewee sees ATRs as a useful *temporary solution* but warns against treating them as a permanent end-state. In his view, over-reliance on ATRs could constrain economic development. They should instead incentivize smart capacity use while structural grid investments continue.

Conclusion

The interview illustrates the complex interplay between energy strategy, technological potential, operational constraints, and organizational readiness. While ATRs offer a path toward optimized grid use, meaningful adoption depends on enhancing internal flexibility, technological integration, and sector-wide learning.

C.3. Interview Energy Management Company

Industry Challenges

The interviewee highlighted that grid congestion and electrification are growing concerns for industrial consumers. Companies increasingly receive rejection notices from Dutch DSOs (e.g., Liander) for additional capacity. Exceeding contractual demand limits can result in substantial fines, reinforcing the need for better energy management.

Organizational Response

To address these challenges, the company offers flexible energy solutions, particularly through smart monitoring and control technologies. A key insight was the importance of **measuring before acting**. Many firms lack detailed consumption profiles, and implementing time- or load-based contracts without these insights is ineffective. For example, the interviewee's own factory resolved peak-load issues by transitioning to 24/7 production, using automated systems to spread energy usage more evenly.

Experience with Alternative Transport Rights

The interviewee was familiar with Time-Block-Based Transport Rights (TBTR) and emphasized that such mechanisms only deliver value if firms can align their operational patterns with time-dependent constraints. Without granular insight into power usage over time, adopting ATR contracts is risky.

Flexibility and Load Shifting

The company advises clients to distinguish between **preferent** (must-run) and **non-preferent** (flexible) electrical loads. Examples of flexible processes include pre-heating buildings at night, deferring electric vehicle charging, or shifting HVAC usage outside of peak hours. However, process-critical loads like ovens or freezers must remain uninterrupted. Tailored advice is necessary depending on the sector and use case.

Energy Management System (EMS)

The company's *InSite* system is a vendor-agnostic, locally hosted EMS solution. It enables:

- Real-time energy monitoring using simple current sensors.
- Automation based on time schedules, power thresholds, or environmental conditions.
- Load shedding or behavioral nudging through visual cues (e.g., traffic lights) and alarms.

This flexibility enables cost-effective peak shaving without requiring full automation.

Battery Storage Considerations

The interviewee cautioned against relying on batteries as a default solution due to high costs and frequent oversizing. Instead, batteries should be used as a *last resort* or supplementary tool after maximizing flexibility and insight. Sizing should be based on high-resolution usage data rather than estimated peak loads.

Optimal Strategy for ATR Adoption

The ideal setup combines:

- A robust EMS system,
- Granular energy monitoring,
- Behavioral interventions,
- Strategic deployment of battery storage.

The interviewee was skeptical of full-disconnection ATR contracts (TDTR) due to operational risks and uncertainty but viewed TBTR as a more realistic interim solution. He also cited a promising project in Stad aan 't Haringvliet involving an **energy hub** with shared capacity, central EMS, short-term battery storage, and long-term hydrogen storage—a scalable model applicable to industrial parks.

Conclusion

This interview reinforces the importance of data-driven, context-specific energy management strategies. Firms can benefit from ATRs only if they possess detailed insight into their consumption patterns and deploy flexible, automated solutions. One-size-fits-all approaches, such as default battery installations or blind adoption of disconnection contracts, are unlikely to succeed without tailored planning.

D
Appendix: Results Data

D.1. Appendix: Load Curve TBTR Simulations

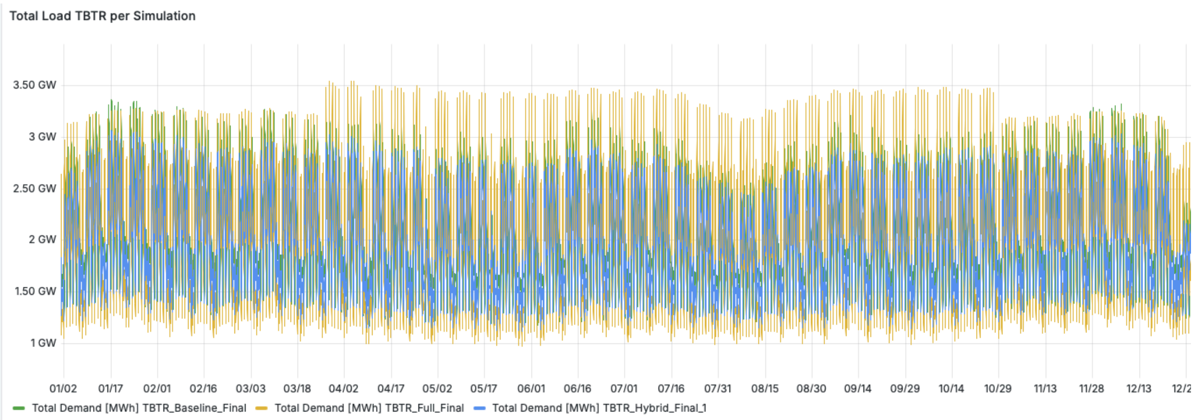

Figure D.1: Load Curve (Year) for three TBTR simulations

D.2. Appendix: Line Loading Results TDTR Simulations

Table D.1: Line Loading Results TDTR Baseline Scenario

line	simulation	avg_loading%	peak_-loading%
line 46	TDTR_Congestion_Baseline_Final	37.80	101.00
line 38	TDTR_Congestion_Baseline_Final	37.70	97.80
line 40	TDTR_Congestion_Baseline_Final	34.50	96.90
line 47	TDTR_Congestion_Baseline_Final	27.30	93.10
line 22	TDTR_Congestion_Baseline_Final	31.30	92.90
line 11	TDTR_Congestion_Baseline_Final	29.00	87.30
line 10	TDTR_Congestion_Baseline_Final	22.90	86.40
line 3	TDTR_Congestion_Baseline_Final	28.00	83.90
line 4	TDTR_Congestion_Baseline_Final	26.60	82.10
line 37	TDTR_Congestion_Baseline_Final	24.30	81.20

Continued on next page

Table D.1 – continued from previous page

line	simulation	avg_loading_-pct	peak_loading_-pct
line 2	TDTR_Congestion_Baseline_Final	21.00	81.10
line 36	TDTR_Congestion_Baseline_Final	29.70	79.50
line 58	TDTR_Congestion_Baseline_Final	27.80	78.10
line 24	TDTR_Congestion_Baseline_Final	25.40	75.00
line 32	TDTR_Congestion_Baseline_Final	22.20	74.80
line 31	TDTR_Congestion_Baseline_Final	22.60	74.80
line 44	TDTR_Congestion_Baseline_Final	34.50	74.20
line 5	TDTR_Congestion_Baseline_Final	32.90	73.40
line 45	TDTR_Congestion_Baseline_Final	19.20	71.30
line 0	TDTR_Congestion_Baseline_Final	19.40	69.80
line 39	TDTR_Congestion_Baseline_Final	26.20	68.10
line 55	TDTR_Congestion_Baseline_Final	12.40	66.90
line 56	TDTR_Congestion_Baseline_Final	22.80	66.40
line 7	TDTR_Congestion_Baseline_Final	27.90	66.40
line 42	TDTR_Congestion_Baseline_Final	23.70	60.30
line 57	TDTR_Congestion_Baseline_Final	18.50	57.60
line 41	TDTR_Congestion_Baseline_Final	23.90	54.50
line 48	TDTR_Congestion_Baseline_Final	14.70	52.90
line 27	TDTR_Congestion_Baseline_Final	19.60	51.10
line 8	TDTR_Congestion_Baseline_Final	17.90	50.90
line 14	TDTR_Congestion_Baseline_Final	19.70	48.70
line 12	TDTR_Congestion_Baseline_Final	15.80	48.50
line 52	TDTR_Congestion_Baseline_Final	11.30	45.10
line 16	TDTR_Congestion_Baseline_Final	9.61	44.50
line 9	TDTR_Congestion_Baseline_Final	11.20	42.60
line 1	TDTR_Congestion_Baseline_Final	9.93	41.90
line 50	TDTR_Congestion_Baseline_Final	15.80	41.30
line 49	TDTR_Congestion_Baseline_Final	8.99	39.40
line 13	TDTR_Congestion_Baseline_Final	14.80	38.70
line 28	TDTR_Congestion_Baseline_Final	7.40	36.50
line 51	TDTR_Congestion_Baseline_Final	9.73	35.90
line 20	TDTR_Congestion_Baseline_Final	7.37	35.90
line 26	TDTR_Congestion_Baseline_Final	15.50	35.70
line 29	TDTR_Congestion_Baseline_Final	8.24	35.20
line 18	TDTR_Congestion_Baseline_Final	9.96	34.90
line 19	TDTR_Congestion_Baseline_Final	9.06	34.00
line 35	TDTR_Congestion_Baseline_Final	8.70	32.60
line 30	TDTR_Congestion_Baseline_Final	7.61	32.00
line 25	TDTR_Congestion_Baseline_Final	14.00	31.10
line 21	TDTR_Congestion_Baseline_Final	7.51	30.60
line 23	TDTR_Congestion_Baseline_Final	6.51	28.20

Continued on next page

Table D.1 – continued from previous page

line	simulation	avg_loading_-pct	peak_loading_-pct
line 15	TDTR_Congestion_Baseline_Final	6.83	27.20
line 34	TDTR_Congestion_Baseline_Final	4.67	25.30
line 53	TDTR_Congestion_Baseline_Final	6.56	24.70
line 54	TDTR_Congestion_Baseline_Final	3.41	19.40
line 33	TDTR_Congestion_Baseline_Final	6.08	14.30
line 43	TDTR_Congestion_Baseline_Final	4.20	6.43
line 17	TDTR_Congestion_Baseline_Final	1.71	4.44
line 6	TDTR_Congestion_Baseline_Final	1.23	1.86

Table D.2: Line Loading Results TDTR Hybrid Scenario

line	simulation	avg_loading_-pct	peak_loading_-pct
line 38	TDTR_Congestion_Hybrid_Final	37.70	97.80
line 46	TDTR_Congestion_Hybrid_Final	37.60	95.80
line 40	TDTR_Congestion_Hybrid_Final	34.40	92.00
line 47	TDTR_Congestion_Hybrid_Final	27.10	90.90
line 22	TDTR_Congestion_Hybrid_Final	31.10	88.30
line 10	TDTR_Congestion_Hybrid_Final	22.70	85.20
line 11	TDTR_Congestion_Hybrid_Final	28.90	81.80
line 3	TDTR_Congestion_Hybrid_Final	27.80	79.80
line 4	TDTR_Congestion_Hybrid_Final	26.40	78.20
line 2	TDTR_Congestion_Hybrid_Final	20.80	77.00
line 37	TDTR_Congestion_Hybrid_Final	24.20	76.20
line 36	TDTR_Congestion_Hybrid_Final	29.70	75.80
line 58	TDTR_Congestion_Hybrid_Final	27.70	75.40
line 44	TDTR_Congestion_Hybrid_Final	34.40	74.40
line 24	TDTR_Congestion_Hybrid_Final	25.20	72.50
line 32	TDTR_Congestion_Hybrid_Final	22.00	71.40
line 31	TDTR_Congestion_Hybrid_Final	22.40	70.90
line 0	TDTR_Congestion_Hybrid_Final	19.20	70.20
line 45	TDTR_Congestion_Hybrid_Final	19.20	69.10
line 39	TDTR_Congestion_Hybrid_Final	26.30	68.10
line 5	TDTR_Congestion_Hybrid_Final	32.70	66.60
line 55	TDTR_Congestion_Hybrid_Final	13.10	63.90
line 56	TDTR_Congestion_Hybrid_Final	22.70	63.10
line 7	TDTR_Congestion_Hybrid_Final	27.80	60.60
line 57	TDTR_Congestion_Hybrid_Final	18.60	57.80
line 42	TDTR_Congestion_Hybrid_Final	23.60	55.50
line 41	TDTR_Congestion_Hybrid_Final	23.90	52.40
line 27	TDTR_Congestion_Hybrid_Final	19.70	51.10

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Table D.2 – continued from previous page

line	simulation	avg_loading%	peak_-loading%
line 8	TDTR_Congestion_Hybrid_Final	17.70	50.90
line 48	TDTR_Congestion_Hybrid_Final	14.60	50.90
line 14	TDTR_Congestion_Hybrid_Final	19.70	47.30
line 16	TDTR_Congestion_Hybrid_Final	10.10	46.00
line 12	TDTR_Congestion_Hybrid_Final	16.00	45.50
line 9	TDTR_Congestion_Hybrid_Final	11.20	43.70
line 50	TDTR_Congestion_Hybrid_Final	15.90	41.30
line 49	TDTR_Congestion_Hybrid_Final	9.56	40.70
line 1	TDTR_Congestion_Hybrid_Final	9.74	39.90
line 52	TDTR_Congestion_Hybrid_Final	11.40	39.00
line 29	TDTR_Congestion_Hybrid_Final	8.51	38.50
line 20	TDTR_Congestion_Hybrid_Final	7.57	37.20
line 26	TDTR_Congestion_Hybrid_Final	15.50	36.40
line 28	TDTR_Congestion_Hybrid_Final	7.36	36.30
line 13	TDTR_Congestion_Hybrid_Final	14.90	36.00
line 51	TDTR_Congestion_Hybrid_Final	10.10	35.90
line 18	TDTR_Congestion_Hybrid_Final	10.20	34.90
line 19	TDTR_Congestion_Hybrid_Final	9.10	34.00
line 30	TDTR_Congestion_Hybrid_Final	7.87	32.80
line 21	TDTR_Congestion_Hybrid_Final	7.81	32.70
line 35	TDTR_Congestion_Hybrid_Final	8.78	31.80
line 23	TDTR_Congestion_Hybrid_Final	6.70	31.60
line 25	TDTR_Congestion_Hybrid_Final	14.00	31.50
line 15	TDTR_Congestion_Hybrid_Final	7.01	28.10
line 53	TDTR_Congestion_Hybrid_Final	6.65	22.90
line 34	TDTR_Congestion_Hybrid_Final	4.85	22.30
line 54	TDTR_Congestion_Hybrid_Final	3.52	20.50
line 33	TDTR_Congestion_Hybrid_Final	6.54	13.30
line 43	TDTR_Congestion_Hybrid_Final	4.20	6.09
line 17	TDTR_Congestion_Hybrid_Final	1.71	4.44
line 6	TDTR_Congestion_Hybrid_Final	1.23	1.78

Table D.3: Line Loading Results TDTR Full Scenario

line	simulation	avg_loading%	peak_-loading%
line 38	TDTR_Congestion_Full_Final	37.80	97.80
line 46	TDTR_Congestion_Full_Final	37.50	95.70
line 40	TDTR_Congestion_Full_Final	34.30	91.60
line 47	TDTR_Congestion_Full_Final	26.90	91.10
line 22	TDTR_Congestion_Full_Final	31.00	87.60

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Table D.3 – continued from previous page

line	simulation	avg_loading_-pct	peak_loading_-pct
line 10	TDTR_Congestion_Full_Final	22.50	84.50
line 11	TDTR_Congestion_Full_Final	28.70	82.50
line 36	TDTR_Congestion_Full_Final	29.60	81.30
line 3	TDTR_Congestion_Full_Final	27.70	77.90
line 37	TDTR_Congestion_Full_Final	24.10	76.30
line 4	TDTR_Congestion_Full_Final	26.30	76.00
line 58	TDTR_Congestion_Full_Final	27.60	75.60
line 44	TDTR_Congestion_Full_Final	34.40	75.50
line 2	TDTR_Congestion_Full_Final	20.80	72.80
line 24	TDTR_Congestion_Full_Final	25.10	72.60
line 0	TDTR_Congestion_Full_Final	19.10	70.30
line 45	TDTR_Congestion_Full_Final	19.20	69.60
line 32	TDTR_Congestion_Full_Final	21.90	69.60
line 31	TDTR_Congestion_Full_Final	22.30	68.60
line 39	TDTR_Congestion_Full_Final	26.30	68.10
line 55	TDTR_Congestion_Full_Final	13.30	65.70
line 5	TDTR_Congestion_Full_Final	32.70	65.40
line 56	TDTR_Congestion_Full_Final	22.60	61.90
line 7	TDTR_Congestion_Full_Final	27.70	59.20
line 57	TDTR_Congestion_Full_Final	18.70	55.60
line 41	TDTR_Congestion_Full_Final	23.90	53.90
line 42	TDTR_Congestion_Full_Final	23.60	53.80
line 8	TDTR_Congestion_Full_Final	17.60	53.50
line 27	TDTR_Congestion_Full_Final	19.70	51.10
line 48	TDTR_Congestion_Full_Final	14.50	50.20
line 14	TDTR_Congestion_Full_Final	19.70	48.90
line 12	TDTR_Congestion_Full_Final	16.00	47.70
line 16	TDTR_Congestion_Full_Final	10.50	47.40
line 9	TDTR_Congestion_Full_Final	11.10	44.30
line 49	TDTR_Congestion_Full_Final	9.84	42.30
line 52	TDTR_Congestion_Full_Final	11.40	42.20
line 50	TDTR_Congestion_Full_Final	16.00	41.30
line 1	TDTR_Congestion_Full_Final	9.70	38.90
line 13	TDTR_Congestion_Full_Final	14.80	38.20
line 20	TDTR_Congestion_Full_Final	7.74	37.80
line 26	TDTR_Congestion_Full_Final	15.50	36.70
line 19	TDTR_Congestion_Full_Final	9.15	36.40
line 51	TDTR_Congestion_Full_Final	10.30	35.90
line 28	TDTR_Congestion_Full_Final	7.42	35.30
line 18	TDTR_Congestion_Full_Final	10.30	33.90
line 30	TDTR_Congestion_Full_Final	7.87	33.30

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Table D.3 – continued from previous page

line	simulation	avg_loading_-pct	peak_loading_-pct
line 29	TDTR_Congestion_Full_Final	8.57	33.20
line 35	TDTR_Congestion_Full_Final	8.81	32.90
line 21	TDTR_Congestion_Full_Final	7.89	32.50
line 25	TDTR_Congestion_Full_Final	14.00	31.50
line 23	TDTR_Congestion_Full_Final	6.74	28.30
line 15	TDTR_Congestion_Full_Final	7.12	27.60
line 53	TDTR_Congestion_Full_Final	6.72	23.80
line 34	TDTR_Congestion_Full_Final	4.97	23.30
line 54	TDTR_Congestion_Full_Final	3.65	19.10
line 33	TDTR_Congestion_Full_Final	6.78	13.60
line 43	TDTR_Congestion_Full_Final	4.20	6.25
line 17	TDTR_Congestion_Full_Final	1.72	4.44
line 6	TDTR_Congestion_Full_Final	1.23	1.82

D.3. Appendix: Line Loading Results TBTR Simulations

Table D.4: Line Loadings TBTR Baseline (MW)

line	simulation	min_loading_MW	avg_loading_MW	peak_loading_MW
line 79	TBTR_Congestion_Baseline_Final	58.7	113.0	199
line 65	TBTR_Congestion_Baseline_Final	58.7	113.0	199
line 83	TBTR_Congestion_Baseline_Final	58.7	113.0	199
line 87	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 62	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 73	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 74	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 76	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 78	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 80	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 81	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 82	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 84	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 85	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 86	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 68	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 69	TBTR_Congestion_Baseline_Final	39.3	72.9	120
line 66	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 67	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 61	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 77	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 70	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 71	TBTR_Congestion_Baseline_Final	35.2	65.0	109

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Table D.4 – continued from previous page

line	simulation	min_loading_MW	avg_loading_MW	peak_loading_MW
line 72	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 63	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 64	TBTR_Congestion_Baseline_Final	35.2	65.0	109
line 75	TBTR_Congestion_Baseline_Final	35.2	65.0	109

Table D.5: Line Loadings TBTR Hybrid (MW)

line	simulation	min_loading_MW	avg_loading_MW	peak_loading_MW
line 79	TBTR_Congestion_Hybrid_Final	58.7	113.0	180.0
line 65	TBTR_Congestion_Hybrid_Final	58.7	113.0	180.0
line 83	TBTR_Congestion_Hybrid_Final	58.7	113.0	180.0
line 87	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 62	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 73	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 74	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 76	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 78	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 80	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 81	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 82	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 84	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 85	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 86	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 68	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 69	TBTR_Congestion_Hybrid_Final	40.7	72.7	108.0
line 66	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 67	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 61	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 77	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 70	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 71	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 72	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 63	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 64	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1
line 75	TBTR_Congestion_Hybrid_Final	35.2	64.8	98.1

Table D.6: Line Loadings TBTR Full (MW)

line	simulation	min_loading_MW	avg_loading_MW	peak_loading_MW
line 79	TBTR_Congestion_Full_Final	52.6	113.0	209
line 65	TBTR_Congestion_Full_Final	52.6	113.0	209
line 83	TBTR_Congestion_Full_Final	52.6	113.0	209

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Table D.6 – continued from previous page

line	simulation	min_loading_MW	avg_loading_MW	peak_loading_MW
line 87	TBTR_Congestion_Full_Final	36.1	72.8	125
line 62	TBTR_Congestion_Full_Final	36.1	72.8	125
line 73	TBTR_Congestion_Full_Final	36.1	72.8	125
line 74	TBTR_Congestion_Full_Final	36.1	72.8	125
line 76	TBTR_Congestion_Full_Final	36.1	72.8	125
line 78	TBTR_Congestion_Full_Final	36.1	72.8	125
line 80	TBTR_Congestion_Full_Final	36.1	72.8	125
line 81	TBTR_Congestion_Full_Final	36.1	72.8	125
line 82	TBTR_Congestion_Full_Final	36.1	72.8	125
line 84	TBTR_Congestion_Full_Final	36.1	72.8	125
line 85	TBTR_Congestion_Full_Final	36.1	72.8	125
line 86	TBTR_Congestion_Full_Final	36.1	72.8	125
line 68	TBTR_Congestion_Full_Final	36.1	72.8	125
line 69	TBTR_Congestion_Full_Final	36.1	72.8	125
line 66	TBTR_Congestion_Full_Final	30.9	64.8	117
line 67	TBTR_Congestion_Full_Final	30.9	64.8	117
line 61	TBTR_Congestion_Full_Final	30.9	64.8	117
line 77	TBTR_Congestion_Full_Final	30.9	64.8	117
line 70	TBTR_Congestion_Full_Final	30.9	64.8	117
line 71	TBTR_Congestion_Full_Final	30.9	64.8	117
line 72	TBTR_Congestion_Full_Final	30.9	64.8	117
line 63	TBTR_Congestion_Full_Final	30.9	64.8	117
line 64	TBTR_Congestion_Full_Final	30.9	64.8	117
line 75	TBTR_Congestion_Full_Final	30.9	64.8	117

E

Example Input Files

This appendix contains examples of the files used as input for the agent-based model. Full input files can be found at: https://github.com/jardzwaan/Thesis.git.

Table E.1: Generator Parameters Used in Simulation (powerplant_units.csv)

Name	Technology	Bidding	Fuel	EF	Max P	Min P	Eff.	Add. Cost	Operator	Node	RU	RD	Hot	Warm	Cold	Min. OT	Min. DT
Eemshaven 1	Hard coal	flexible_eom	Hard coal	0.82	1580	711	0.40	1.30	RWE	NL0 8	474	474	30.4	47.5	69.3	8	4
Hollandse Kust Zuid	Wind offshore	flexible_eom	Renewable	0.00	1420	0	1.00	0.00	renewables_operator	NL0 31	0	0	0	0	0	0	0
Eemshaven 2	Gas	flexible_eom	Natural gas	0.20	1410	141	0.60	3.50	RWE	NL0 8	1269	1269	140	140	140	1	1
Claus	Gas	flexible_eom	Natural gas	0.20	1304	130	0.60	3.50	RWE	NL0 6	1174	1174	140	140	140	1	1
Maasvlakte	Hard coal	flexible_eom	Hard coal	0.82	1070	482	0.40	1.65	Uniper	NL0 15	321	321	30.4	47.5	69.3	8	4
Enecogen	Gas	flexible_eom	Natural gas	0.20	928	93	0.60	3.50	Eneco	NL0 15	835	835	140	140	140	1	1
Velsen	Gas	flexible_eom	Natural gas	0.20	869	87	0.60	3.50	Vattenfall	NL0 27	782	782	140	140	140	1	1
Moerdijk	Gas	flexible_eom	Natural gas	0.20	766	77	0.60	3.50	RWE	NL0 9	689	689	140	140	140	1	1

Table E.2: Explanation of Generator Parameter Abbreviations

Abbreviation	Description
EF	Emission Factor (ton CO_2/MWh)
Max P / Min P	Maximum / Minimum Power Output (MW)
Eff.	Electrical Efficiency (%)
Add. Cost	Additional Cost per MWh (€/MWh)
RU / RD	Ramp-Up / Ramp-Down Capacity (MW/hour)
Hot / Warm / Cold	Start-up Costs depending on downtime category (€)
Min. OT / DT	Minimum Operating Time / Minimum Down Time (hours)