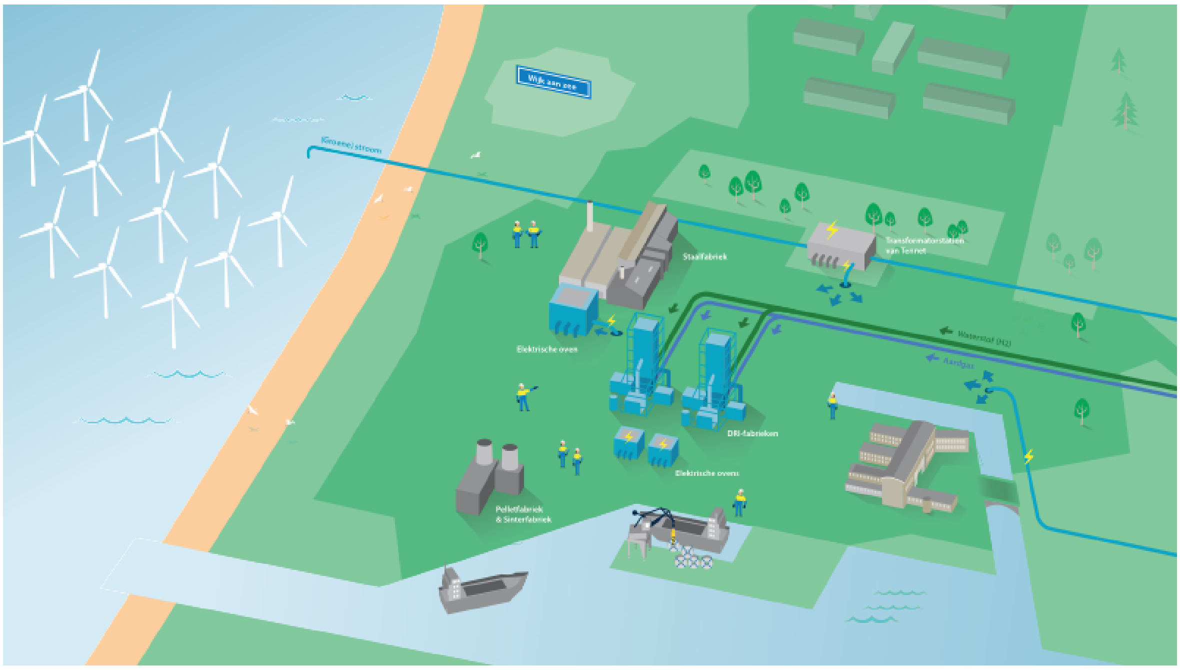
Faculty of Electrical Engineering,Mathematics and Computer Science - Faculty of Technology Policy and Management

Master Thesis - Modeling the Energy Transition of an Integrated Steel Site

The Case of Tata Steel's IJmuiden Site



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Acknowledgment

This thesis marks the conclusion of my journey in the Master's program in Sustainable Energy Technology at TU Delft. Deciding to pursue a second master's degree after completing my first integrated master's in Mechanical Engineering in Greece and serving in the army for 14 months was not an easy choice. However, in hindsight, it seems that it was the right decision. The field of sustainable energy, in my opinion, is closely tied to one of the most challenging problems humanity faces for its future. Working and learning in this domain makes me feel that my efforts are meaningful and impactful.

I want to express my gratitude to all the professors in the program who worked tirelessly to share their knowledge and perspectives with us, the students. The supportive environment, excellent facilities, and overall system provided by TU Delft—and the Netherlands as a whole—created an ideal setting for students to focus on their studies in a safe and stable environment. I deeply appreciate the efforts of everyone who contributed to raising the university to this exceptional level.

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At TU Delft, I am especially grateful to Sugandha Chauhan, my daily supervisor. Her consistent support, weekly meetings, constructive advice, and encouragement throughout the thesis process were invaluable. I deeply appreciate her dedication and wish her all the best in her Ph.D. journey.

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Turning to Tata Steel Netherlands, where I carried out this thesis while completing an internship, I thoroughly enjoyed the opportunity to work in such a large industry and at such a remarkable site. The processes and plants I observed were truly once-in-a-lifetime experiences. I am especially grateful to my daily supervisor from the R&D Department, Thermal Processes Division, Seyed Hossein Jamali, for his dedication and guidance throughout this project. He spent countless hours assisting me, teaching me, providing relevant information, and connecting me with the right people to broaden my knowledge and further develop my work. While we had many discussions, debates, and challenges along the way, we ultimately achieved the goals we set out to accomplish.

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Lastly, I would like to express my deepest gratitude to my parents for their endless support and encouragement throughout this journey. I also want to thank my brother, who is also pursuing a master's degree in the same field at DTU in Denmark; we have supported each other throughout this shared experience.

Finally, I extend my heartfelt thanks to my climbing partners and friends. Climbing together provided a much-needed break from studying and a life lesson: to never stop trying, even after falling.

Ioannis Athanasiadis
Delft, The Netherlands

February 17, 2025

«Αεί ο Θεός ο Μέγας γεωμετρεῖ.»

3.14159

"The Great God always geometrizes."

— *Attributed to Plato*

Confidentiality Statement

This public version of my thesis excludes specific numerical values and plots that contain sensitive operational data from the site or model outputs related to confidential cost information. In particular, details regarding steel production costs, current and future configurations, and proprietary price input projections are redacted due to confidentiality restrictions.

Regarding price inputs provided by Tata Steel, their validity and officiality have been thoroughly reviewed and confirmed by the thesis committee and myself. However, the original source of these price projections, as well as Tata Steel's methodology for estimating future commodity prices, cannot be disclosed in this public version.

Where necessary, sensitive data points have been redacted by leaving certain values blank, obscuring specific plots, or replacing detailed figures with generalized information. Despite these redactions, the reader will still be able to fully understand the methodology and conclusions of this work without access to exact confidential numbers.

It is also important to clarify that all results and conclusions presented in this thesis—after redaction—are solely outputs of my model and my work. These values should not be interpreted as precise representations of the current or future state of the Tata Steel IJmuiden site. While the model is based on the site's operations, numerous assumptions were made throughout my research. As a result, figures related to emissions, energy consumption, and steel production costs are approximate and should not be considered exact for the current configuration. For future scenarios, these values involve even more assumptions as they project further into uncertain conditions.

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Executive Summary

The steel industry is among the most energy-intensive and polluting industrial sectors globally, accounting for nearly 10% of total greenhouse gas (GHG) emissions. Characterized by large-scale infrastructure, long investment cycles, high capital costs, and low profit margins, it is considered a hard-to-abate sector. However, rising CO_2 costs and growing demand for steel—driven by developing economies and the global energy transition—are compelling the industry to adopt decarbonization pathways. This study provides a comprehensive optimization model for Tata Steel's integrated steelmaking site in IJmuiden, Netherlands. The model examines the site's current configuration, proposes a transition pathway towards green steel production, and evaluates the economic and operational impacts of decarbonization strategies within the broader context of the DEMOSES project, which aims to align the Netherlands' energy system for a sustainable future.

Research Objectives

This study addresses the following research questions:

1. **Model Development:** How can Tata Steel's current configuration be optimized to reflect key energy and material flows in a cost-minimization framework adaptable for future configurations?
2. **Transition Pathways:** What are the most feasible pathways for transforming Tata Steel into a green steel producer, considering operational constraints and available technologies?
3. **External Influences:** How will electricity prices, the hydrogen ecosystem, and energy policies impact operational conditions and the marginal cost of green steel production?

The overarching research question is: *What is the impact of different investment decisions regarding the energy transition on achieving Tata Steel IJmuiden's decarbonization goals?*

Methodology

An optimization model was developed to simulate the steelmaking site's operations, using 2022 operational data to define plant capacities, operational ranges, conversion factors, and ramp limits. The model integrates key systems such as gas and steam networks, electricity generation from process gases, and emissions sources. It optimizes site operations to meet annual steel production targets while minimizing costs. The model was validated against real data and tested under four future price scenarios covering electricity, natural gas, coal, hydrogen, and emissions costs.

A transition pathway from 2030 to 2050 was modeled, comprising three progressive configurations:

- **Phase 1 (2030-2037):** Transition from the emission-intensive BF-BOF route to a hybrid configuration combining BF-BOF with a natural gas-based DRP-EAF.
- **Phase 2 (2037-2045):** Increased reliance on DRP-EAF and DRP-SAF-BOF routes, progressively incorporating more hydrogen.
- **Phase 3 (2045-2050):** Full transition to hydrogen-based DRP plants for decarbonized steel production.

Results

The optimization model provides critical insights into Tata Steel's transition to green steel:

- **Cost of Steel:** The cost of steel is expected to rise under future configurations due to increased reliance on electricity and hydrogen, coupled with reduced availability of work-arising gases (WAGs) for on-site electricity generation.
- **Energy Breakdown:** Electricity consumption increases significantly post-Phase 1, making the site more exposed to market volatility. However, the inclusion of EAFs and its surrounding system with larger storage capacities for DRI introduces operational flexibility, enabling price-responsive adjustments.
- **Network Costs:** Oversizing EAFs for cost savings is constrained by the current network cost structure, which penalizes high peak electricity consumption.
- **Hydrogen Dependency:** Hydrogen becomes the primary energy carrier under future configurations. Its cost and availability are critical determinants of economic feasibility, highlighting the need for robust hydrogen supply chains and strategic investments in on-site electrolysis under favorable conditions.

- **Natural Gas as a Transitional Fuel:** Natural gas will serve as an intermediate energy carrier during the transition, bridging the shift from coal to hydrogen.

Conclusion and Recommendations

The study demonstrates that Tata Steel's decarbonization is achievable but requires strategic investments and operational flexibility to mitigate rising costs. Key recommendations include:

1. **Optimization of Investments:** Use the model to balance capital expenditure and operational savings for new components like the EAF.
2. **Energy Flexibility:** Leverage the price-responsive nature of EAFs to adjust production based on real-time electricity prices, minimizing energy costs.
3. **Hydrogen Ecosystem:** Accelerate the development of hydrogen infrastructure, including storage and supply chains, and collaborate with stakeholders to establish favorable policy and market conditions.
4. **Policy Engagement:** Advocate for reforms to network cost structures and renewable energy policies to support decarbonization while maintaining competitiveness.
5. **Integration with Renewable Energy:** Explore on-site renewable energy generation and storage to reduce dependency on grid electricity and enhance resilience.

By implementing these strategies, Tata Steel can achieve its decarbonization goals while positioning itself as a leader in sustainable steel production. The insights from this model also provide a framework for broader industrial decarbonization efforts across the Netherlands.

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Abbreviations and Acronyms

BF: Blast Furnace

BFG: Blast Furnace Gas

BOF : Basic Oxygen Furnace

BOFG : Basic Oxygen Furnace Gas

COG : Coke Oven Gas

DRI : Direct Reduced Iron

DRP : Direct Reducing Plant

DSP : Direct Sheet Plant

EAF : Electric Arc Furnace

HSM : Hot Strip Mill

IJ01 : IJmond 01 generator

PyPSA: Python for Power System Analysis

SAF: Submerged Arc Furnace

VN24: Velsen Noord 24 Generator

VN25: Velsen Noord 25 Generator

WAGs: Work Arising Gases

1 Introduction

The environmental crisis, regulatory frameworks addressing pollution, social reactions against polluters, and global competition are all driving forces pushing companies and industries across all sectors to focus on decarbonizing their processes. In the industrial sector, it is especially critical for the so-called "hard-to-abate" industries, such as steel and cement, to develop plans for converting their processes to be more efficient, sustainable, and environmentally friendly, while simultaneously maintaining competitiveness in their markets.

Competition in these sectors is often distorted by varying environmental regulations worldwide. The EU has implemented measures to prevent carbon leakage, particularly in the iron and steel industry, through schemes like the EU Emissions Trading System (ETS) and the newly introduced Carbon Border Adjustment Mechanism (CBAM). The primary goal of these schemes is to compel industries to reduce pollution by introducing costs for emissions within Europe while also discouraging the import of goods produced in regions with less stringent regulations, unless the emission costs are appropriately accounted for.

Despite these efforts to foster a more sustainable industrial sector as part of the broader energy system, several challenges remain. Path dependencies and lock-ins associated with existing industrial configurations and infrastructures, along with the high costs of sustainable investments, can create significant bottlenecks for the energy transition within specific sectors. This is particularly true for the steel industry, which is the focus of this project.

This project is part of the larger DEMOSES (Designing and Modelling Future Systems of Energy Systems) initiative, funded by the NWO (Nederlandse Organisatie voor Wetenschappelijk Onderzoek - Dutch Research Council). The DEMOSES project represents a breakthrough in energy systems modeling technology, aiming to significantly advance the science of energy systems design and analysis. As energy systems become increasingly complex due to the energy transition and sector coupling, decision-making tools must evolve accordingly. With the energy system becoming more integrated to support electrification and the rapid growth of renewables, current computational modeling lacks the ability to effectively model and analyze various energy carriers, sectors, network levels, and both technical and economic aspects.

Market participants, network operators, and policymakers stand to gain valuable insights into the interactions between different actors and the impact of investment decisions made by each. Without an interactive modeling framework like the one proposed by DEMOSES, decision-making will remain myopic and suboptimal, hindering or even preventing the energy transition.

In this context, this work serves as a bridge between the DEMOSES project and Tata Steel's decarbonization efforts. On one hand, it provides a representative model of Tata Steel's site energy consumption patterns, factoring in energy prices, which is useful for analyzing the energy consumption behavior of one of the largest energy consumers in the Netherlands. This is an essential piece of the larger picture that DEMOSES aims to depict. On the other hand, the model can function as a standalone tool for Tata Steel to assess changes in energy consumption patterns over time, considering external price fluctuations and the specific configuration of the site. Finally, using this model with its distinct characteristics, the research questions for this master's thesis will be explored.

1.1 Literature Review and Academic Knowledge Gap Identification

The iron and steel industry is one of the most energy-intensive and polluting sectors (Hasanbeigi et al., 2013), (Zhang et al., 2019), and transforming it into a more sustainable industry is particularly challenging due to the nature of its processes and the quality requirements of its final products. Despite being energy-intensive, reducing steel production is not considered a viable solution, as steel plays a critical role in today's world and is essential for the energy transition itself. According to (Kim et al., 2022), 71-79% of a wind turbine is made of steel. Tata Steel, a large multinational steel producer, ranks among the ten largest steel producers worldwide, with 30.18 million tons of steel production in 2022 (*worldsteel.org*, 2024). Tata Steel Nederland, with its IJmuiden integrated iron and steel site, is one of the top three largest steel producers in Europe, with a production capacity of 7 million tons of steel per year (*TataSteelIJmuiden*, 2024). Due to the energy-intensive and polluting processes involved in steelmaking, the IJmuiden site emits millions of tons of CO2 annually. Currently, Tata Steel IJmuiden is in the early stages of an energy transition aimed at decarbonizing its processes.

The first step in converting a steel-producing site into a more sustainable one, producing green steel, is to reduce the carbon footprint of the entire steelmaking process. The iron and steel industry is the largest coal consumer and one of the most polluting industries worldwide, consuming about 7% of the total global energy and being responsible for approximately 7 to 9% of global greenhouse gas emissions (Kim et al., 2022).

Many mixed integer linear programming (MILP) models have been developed to optimize integrated steel plants. Dutta et al. (1994) used such a model to optimize the distribution of electricity in the plant under conditions of uncertain electricity availability. The implementation of the model resulted in a benefit of 73 million US dollars for the plant in 1986. Larsson et al. (2006) recognized the interconnection between the processes of an integrated steel plant and used a model to optimize the plant under various objective functions. Zhang et al. (2019) applied an MILP model to optimize the specific energy use of a steel plant in China, leading to a 14% reduction in specific energy consumption. The work by Hasanbeigi et al. (2013) reveals that the Chinese iron and steel industry, which accounts for about 50% of the world's crude steel production, has the potential for electricity savings of up to 251 TWh. To put this into perspective, the Netherlands consumed 121.6 TWh of electricity in 2022 (IEA, 2023). Kim et al. (2022) investigates 86 commercially available, emerging, and experimental innovations for the iron and steel industry. Among these are hydrogen-based direct reduction of iron ore, torrefied biomass, plasma blast furnaces, and others. Despite the advantages of a green steel industry, the authors conclude that barriers such as high capital costs, long investment cycles, the risk of not meeting product standards, and the potential for production disruptions are slowing the transition of this heavy industry. Toktarova et al. (2020) explores different decarbonization pathways for the Swedish steel industry. Pathways such as top gas recycling blast furnaces with carbon capture, biomass for primary production, and Electric Arc Furnaces for secondary production appear to become viable starting from 2030.

After reviewing the key studies related to modeling integrated steel plants and the decarbonization potential of the iron and steel industry, several scientific gaps for this work can be identified. While most studies use energy optimization models to improve the processes and operational planning of integrated steel sites, the focus is often on static and current plant configurations. The results typically show the optimal ways to operate a plant within its current configuration, considering aspects such as planning, process prioritization, cost savings, or operation under uncertainty. There is a noticeable gap in studies related to the transition process itself. For example, how will the replacement of a fundamental process like a blast furnace affect the energy balance of the site? Overall, there is a lack of studies evaluating the impacts of different investment decisions towards creating a more sustainable steel plant. On the other hand, while many theoretical studies investigate the drivers, bottlenecks, and potential of a green steel industry, there are few real-world applications of new sustainable energy technologies and their effects on steel production, as we have already mentioned. This study is based on a model specifically built for Tata Steel's IJmuiden site, considering the unique characteristics of the main plants and their surroundings. Additionally, new configurations are created in phases (snapshots through time), acknowledging that the transition occurs in stages, and each stage is influenced by previous ones. Given this, the future decarbonization pathways are not built from scratch or only depict the final picture but are based on an initial current configuration model, which can be validated using real operational data. Furthermore, the modeling approach uses a user-friendly, modular, component-based tool in Python (PyPSA) (*PyPSA*, 2024), which is a relatively new approach in modeling networks that are not purely electrical, according to the literature I have reviewed. The model in this work was intentionally created as a transition analysis tool specific to Tata Steel IJmuiden's site.

With that said, the main research question that this work will focus on can be phrased as follows:

What would be the impact of different investment decisions regarding energy transition on meeting the decarbonization goals of Tata Steel's integrated steel site in IJmuiden Netherlands ?

1.2 Research approach and sub questions

The goal of this section is to propose a research method suitable for answering the main research question. The answers to the three formulated sub-questions will, when combined, lead to the answer to the main research question. As stated, the main research question can be divided into different parts or segments.

Firstly, to investigate the impacts or define a decarbonization phase for a steel site, a material and energy flow model of the existing configuration must be created for the specific steel site. This model will provide insights into the basic energy consumption, generation, and steel production patterns of the plant, and will help identify the most energy-intensive processes. For the most important plants on the site (such as large energy consumers or significant CO2 emitters), specific constraints for their operation will be added. In addition, the surrounding energy system (such as the electricity and natural gas markets) will be modeled. Finally, and most importantly, the primary goal of a steel-producing site — which is to actually produce steel — will be set, allowing the entire system to be optimized toward achieving this target.

Depending on the researcher's preferences, such a system can be optimized for a variety of objective functions, such as cost minimization, profit maximization, or energy efficiency, among others. In this work, for reasons explained in the following sections, the system is optimized for cost, including the cost of CO2 emissions, in alignment with the ETS system approach.

Based on this, we can formulate the first research sub-question regarding the energy model as follows: **How can the current configuration of the site be optimized as a model that reflects the most important energy and material flows in a cost minimization problem, while also being adaptable for future configurations of the site?**

An energy model, as described in the first research sub-question, forms the foundation and the most significant tool for addressing the two subsequent sub-questions. The second research sub-question is related to investment decisions regarding the energy transition, which is a crucial part of the main research question. Thus, the second research sub-question must define the sustainable energy technologies and their application to create different feasible transition pathways toward a more sustainable, decarbonized, or green steel plant. With that in mind, the second research sub-question can be formulated as follows: **What are the most feasible pathways toward a green steel plant, considering Tata Steel's operational constraints and the different available technologies?**. Finally, the performance of the various investment decisions will be evaluated not only by the model created but also by assessing the impact of external factors on the decision-making process, in order to provide a more complete view of the energy transition for a steel plant. Specifically, how will external factors, such as the availability and development of specific technologies, their associated costs, or the cost of electricity and other energy or material sources, affect the decarbonization pathway of the steel plant? It is important to note that the investment costs of each technology are outside the scope of this work. The configurations will be tested under different pricing scenarios for various energy flows, materials, and emissions (e.g., changes in network costs or high day-ahead electricity prices). Additionally, different design decisions within a configuration will be compared (e.g., using electrolysers on-site to produce hydrogen versus purchasing hydrogen from an external network), with the main focus on the cost of operation and the demand side of the site, rather than on the total investment cost, investment optimization, or generation optimization for the site's demand.

The third research question can be phrased as follows: **What will be the impact of external factors, such as electricity prices, the hydrogen ecosystem, and energy policies, on the operational conditions and the marginal cost of the examined pathways toward green steel production?**

1.3 Research Methods and Research Flow Diagram

An integrated steel plant can include a variety of process routes and configurations, but the most commonly used one is the BF/BOF (Blast Furnace/Basic Oxygen Furnace) route. This is also the route used under the current configuration of Tata Steel's site in IJmuiden. The main plants at the site include the Coking plants, the Sintering Plant, the Pelletizing plant, the Blast Furnaces, and the Basic Oxygen Furnace for crude steel production. After this point, there are other plants and processes, such as the Direct Sheet Plant and the Hot Strip Mill, for further processing the steel according to customer preferences. The main inputs of this configuration are coal, iron ore, natural gas, electricity, and a quantity of imported pellets. The current configuration will be described analytically in the methodology section.

The focus of this study is on the interaction between the most energy-intensive and polluting processes mentioned in the previous paragraph. The exchange of energy, mass, and electricity flows between these processes will be investigated. It is important to note that a significant portion of the energy for this specific site and configuration is contained in the work-arising gases (WAGs) from mainly three plants: the Coking Plants, the Blast Furnaces, and the Basic Oxygen Furnace. These gases are distributed within the gases network and directed to different boilers for heat production or to electricity generators for electricity generation. Therefore, a model capable of depicting and optimizing these flows, while also integrating the constraints of each individual plant (such as capacity, ramp limits, and operational range) and the total system constraints (e.g., storage of hot iron or annual steel targets), will be created and validated using past operational data for the site. A cost minimization method will be applied for both the current configuration and future scenarios. While the transition itself and the changes to the configuration over time will not be optimized, this work will generate a projected configuration for the site until 2050 (in the form of snapshots), and the operation of these configurations will be optimized.

Energy modeling is a continuously developing and challenging field, as energy systems become more complex with the integration of intermittent renewable energy sources. Hilpert et al. (2018) distinguishes between first-generation or closed models and second-generation or open-source models. The benefits of the new-generation open-source models include enhanced collaboration capabilities and greater transparency, among other advantages. For this work, an open-source framework/model/model generator in Python, PyPSA, will be used. PyPSA (Python for Power System Analysis) is an open-source tool that provides a state-of-the-art environment for energy system modeling (*PyPSA*, 2024). PyPSA is primarily used for power system analysis and optimization Hörsch et al. (2018) Parzen et al. (2023), offering time and space resolution capabilities, the modeling of different energy generation technologies, energy consumption nodes, and various energy carriers. In this work, it will be slightly modified from its main goal of simulating electricity grids to simulate and create a cost optimization model for the energy system of an integrated steel site. For this study, PyPSA's capabilities for scaling well with large systems and long time series, as well as its ability to create, store, and substitute plants/components within the model, are highly beneficial for studying the energy transition of an industrial site.

The first step toward answering the research questions of this study will be the creation of an energy and materials flow model of the steel production site in IJmuiden. Data available from Tata Steel Netherlands will be used for the verification and parameterization of this model. This data will indicate the consumption patterns of raw materials, energy, and electricity, as well as the production quantities of steel over time. Such data will be useful for verifying the model and building its constraints. For this particular model, PyPSA will be used to avoid having to build the model and optimization function from scratch. The Linopy library *linopy* (2024) will be used to further adjust the objective function and constraints for more complex formulations of constraints or additional variables. Part of this study will involve evaluating PyPSA's capability as a modeling tool for this purpose. After creating and validating the model with existing data, parts of the current configuration will be replaced (within the model) by new sustainable technologies appropriate for a steel plant, such as a Direct Reduction Plant (DRP) or an Electric Arc Furnace (EAF). The effects of these changes will be addressed and quantified in the model's objective function.

In summary, the first research question focuses on creating an appropriate model capable of describing the energy and material flows of an integrated steel plant. The model must reflect the plant's energy, electricity, and material use over time, as well as steel production over time, with a focus on particular nodes/processors where technology changes can first be applied, and where energy use and carbon footprints are significant. The model must be validated using data provided by Tata Steel. Once validated, the model can be used to answer the second and third sub-research questions. Regarding the second sub-question, the most theoretically feasible sustainable energy technologies that can be applied to this specific steel site will be identified. These technologies will be integrated into the existing model framework to build new, complete configurations/pathways for producing steel with lower CO2 emissions. For the selected alternative technologies that contribute to the decarbonization process of the steel site, external factors, such as electricity prices, energy policies, technology development, and other factors, will be addressed to assess how these factors support or detract from their performance according to the model's results.

These steps will ultimately lead to answering the main research question of this study, as depicted in the following process flow diagram, Figure 1. The project timeline is also shown in Figure 2.

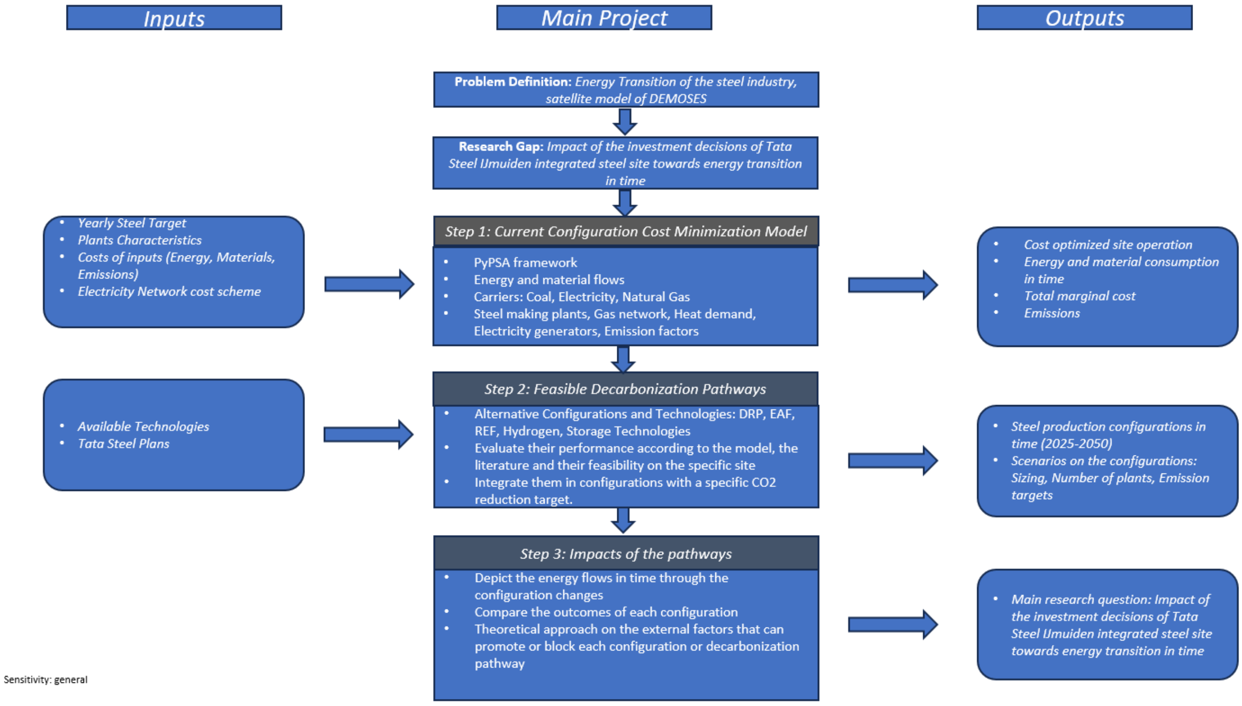

Figure 1: Research flow diagram of the project.

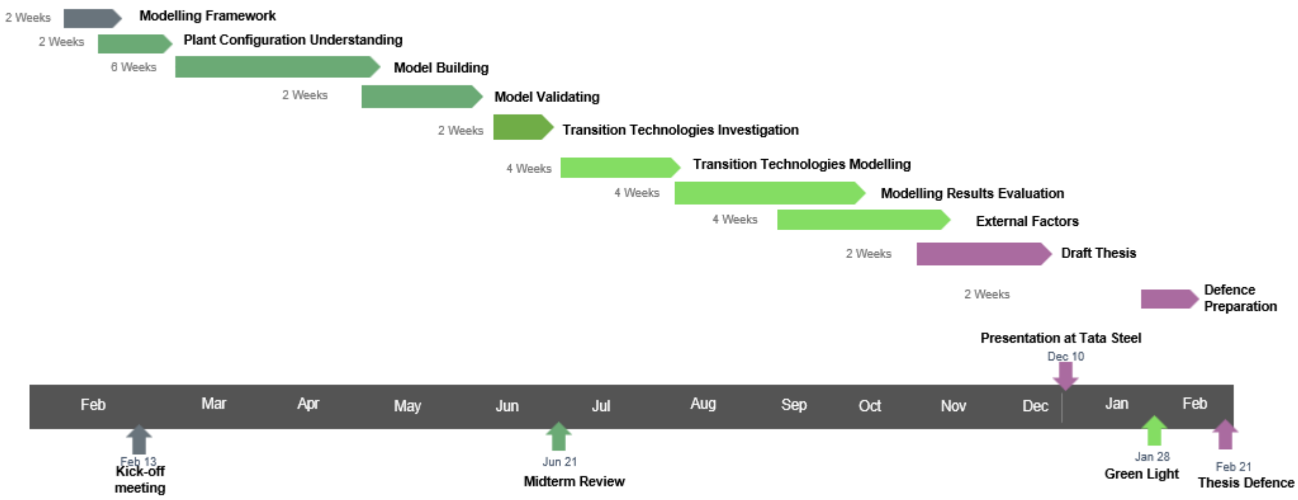

Figure 2: Project development timeline.

1.4 Contributions

1.4.1 SET Relevance

As the title of this project clearly indicates, the primary focus of this master's thesis is the energy transition of the integrated steel industry. Beyond the transition technologies, which lie at the core of the master's program in Sustainable Energy Technologies (SET), the representation of an integrated steel production site as a hybrid energy-process system requires a deep understanding of complex energy systems. This is also highly relevant to many courses within the SET program.

Additionally, formulating and solving large optimization problems, such as the one arising from the model in this project, requires experience and knowledge of fundamental optimization techniques and methods for energy systems, a core component of the SET curriculum. Furthermore, to create scenarios and assess the impacts of the surrounding energy system on decarbonization pathways, one must possess a solid understanding of energy markets, such as the day-ahead electricity market, as well as various network cost schemes. Topics related to hydrogen, electrification, and storage technologies are also integral to studies on the steel industry's transition.

All of these aspects underline the relevance of the SET program to this specific research topic. The courses I completed throughout my studies have been crucial for successfully completing this thesis project.

1.4.2 Social Aspects

The social impact and societal contribution of this work are closely related to the costs and benefits for the people of the Netherlands, particularly those living near the site. The negative health effects of pollution caused by the industry, alongside the potential economic benefits, such as job creation in the area and the broader development of the region, are key considerations in Tata Steel's efforts to decarbonize its processes. To put this into perspective, Tata Steel IJmuiden contributes 6% to the Dutch Gross National Product in the industrial sector and provides a total of 86,000 direct, indirect, and induced jobs. The site's annual steel production capacity is 7 million tons, and its electricity consumption currently amounts to around 3 TWh, representing almost 3% of the total electricity consumption in the Netherlands. Additionally, Tata Steel IJmuiden consumes 45 TWh of energy from coal, accounting for 15% of the country's total energy consumption and 70% of its coal use. Given these figures, the significance of this site and its energy transition is evident—not only for the surrounding communities but also for the national economy, energy system, and citizens. This study is a part of Tata Steel's broader effort to decarbonize its processes and produce steel in a more sustainable and competitive way in the coming years.

1.4.3 Thesis Outline

In the following sections, Chapter 2 provides the theoretical background for the steelmaking industry. Chapter 3 outlines the methodology of this work, detailing the model development, from the model requirements and description to its components, optimization problem, transition configurations, input prices, and model behavior, along with the verification and validation processes. Chapter 4 presents the results and discussion, and Chapter 5 concludes the thesis. Finally, Chapter 6 offers a reflection on the work.

2 Theoretical Background - Steelmaking

This chapter provides further details about the steel industry and its potential decarbonization pathways. Understanding how an integrated steel site operates, as well as the available technologies and pathways for transitioning such a site, is essential for both creating a model and understanding one aimed at achieving this transition. A dedicated section at the end of the chapter will focus specifically on the configuration and transition pathways of Tata Steel, helping readers better comprehend the subsequent steps of this work.

2.1 Steel Industry and Specific Technologies

As previously mentioned, the iron and steel industry is energy-intensive, highly polluting, and responsible for approximately 7-9% of total global greenhouse gas emissions (Kim et al., 2022). The steel industry is also closely linked to coal consumption. Coal is used both as a reducing agent in various chemical reactions involved in iron and steel production and as an energy source for processes across an integrated site. The reliance on coal largely depends on the site's configuration and is particularly significant in the Blast Furnace - Basic Oxygen Furnace (BF-BOF) steelmaking route, which is the most widely used method, accounting for around 65% of global steel production (Kim et al., 2022).

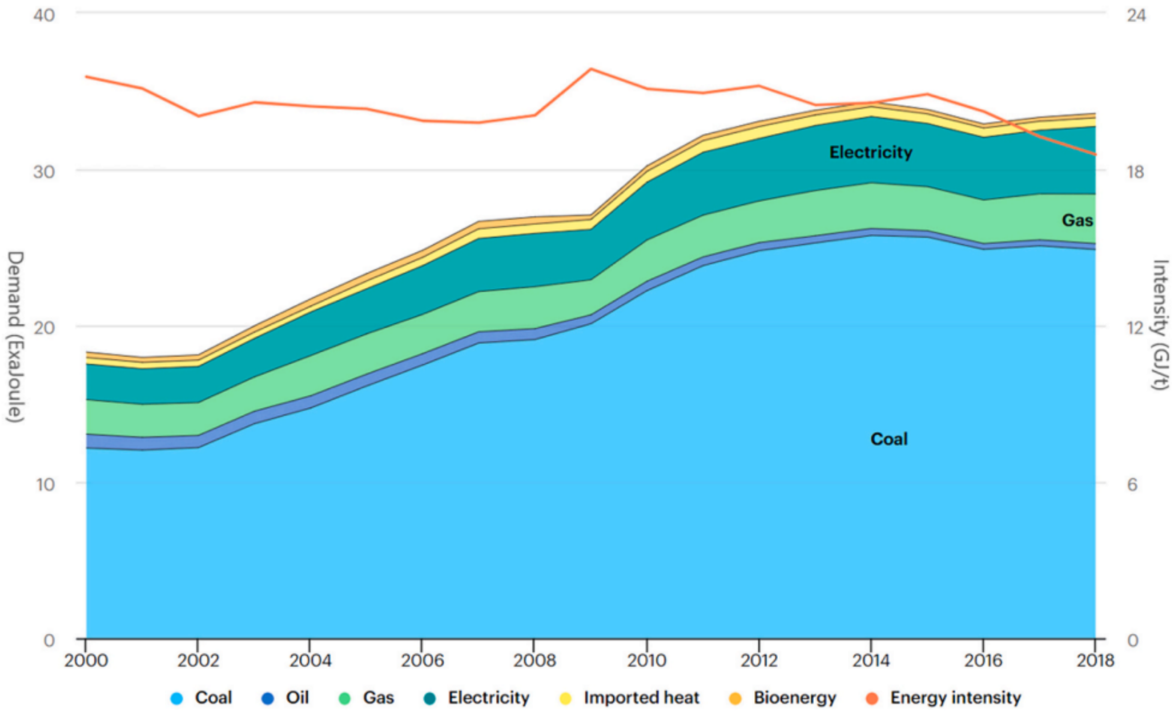

Figure 3: The coal consumption of the global steel industry and the energy intensity of steelmaking (Kim et al., 2022)

Other routes to produce steel include the Direct Reduced Iron - Electric Arc Furnace (DRI/EAF) method, which accounts for about 30% of global steel production, and two alternatives: smelting reduction and the direct melting of scrap (the latter being more aligned with steel recycling). The iron and steel industry is among the sectors that are particularly challenging to decarbonize for several reasons. These include the high heat requirements, primarily for melting iron and steel; the necessity of carbon as an integral component in steel production—although the final amount of carbon in the steel is very small, the initial amount needed in iron is significantly higher; low profit margins in the steel market; high capital intensity; long asset lifespans; and trade-related challenges (Kim et al., 2022).

Additionally, strict environmental regulations in Europe compared to other regions, along with the uncertainty of future energy prices due to the integration of renewables, significantly impact decision-making regarding the energy transition of the steel industry. The combination of high capital investments required for the transition, uncertain profits, and long investment cycles hinders the rapid decarbonization of this sector.

In Figure 4 from (Kim et al., 2022), the scale of China's steel industry compared to the rest of the world is clearly illustrated. The figure also highlights that the age of China's blast furnaces is relatively young compared to their typical operational lifetime. These assets are so expensive and capital-intensive that economic considerations often preclude their decommissioning before the end of their operational lifespan. This demonstrates that even if conditions were favorable for a transition to green steelmaking (which they currently are not), the industry is constrained by its costly infrastructure and the significant investments made before the global need for transition became evident.

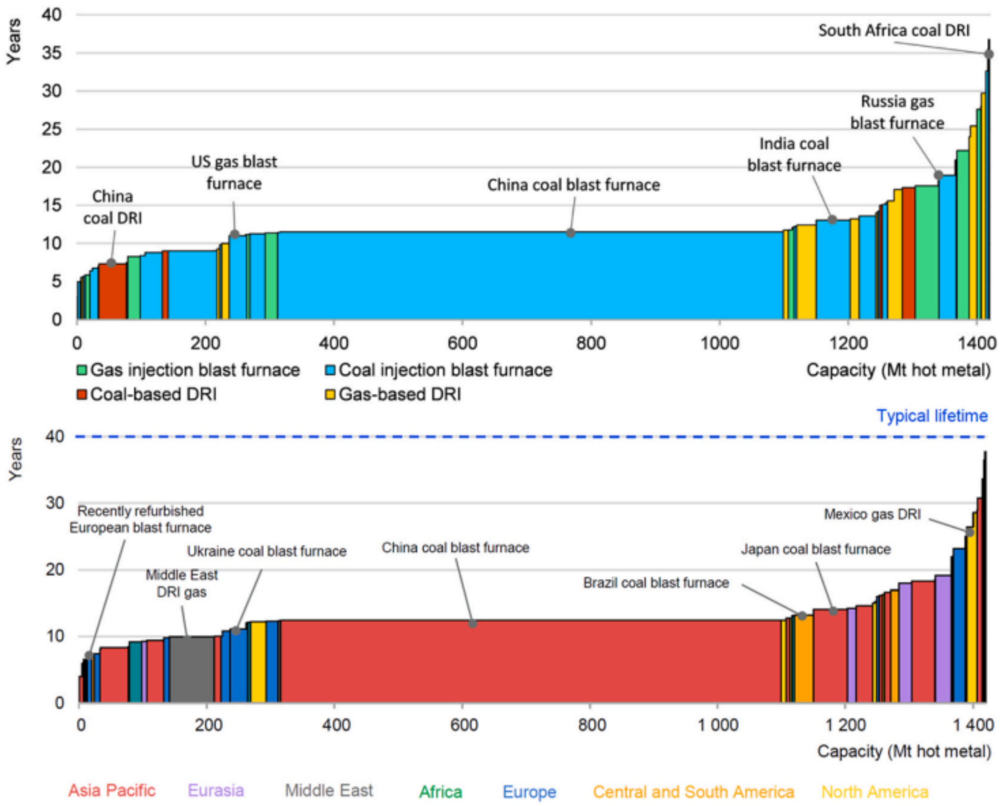

Figure 4: The age of different assets of the steel industry around the world and their capacity (Kim et al., 2022)

For a concise description of the main BF/BOF steelmaking route, which Tata Steel also employs in IJmuiden, as well as the other three primary steelmaking routes, we refer to the following Figure 5 from (Ren et al., 2023). Figure 5 illustrates the four fundamental steelmaking routes.

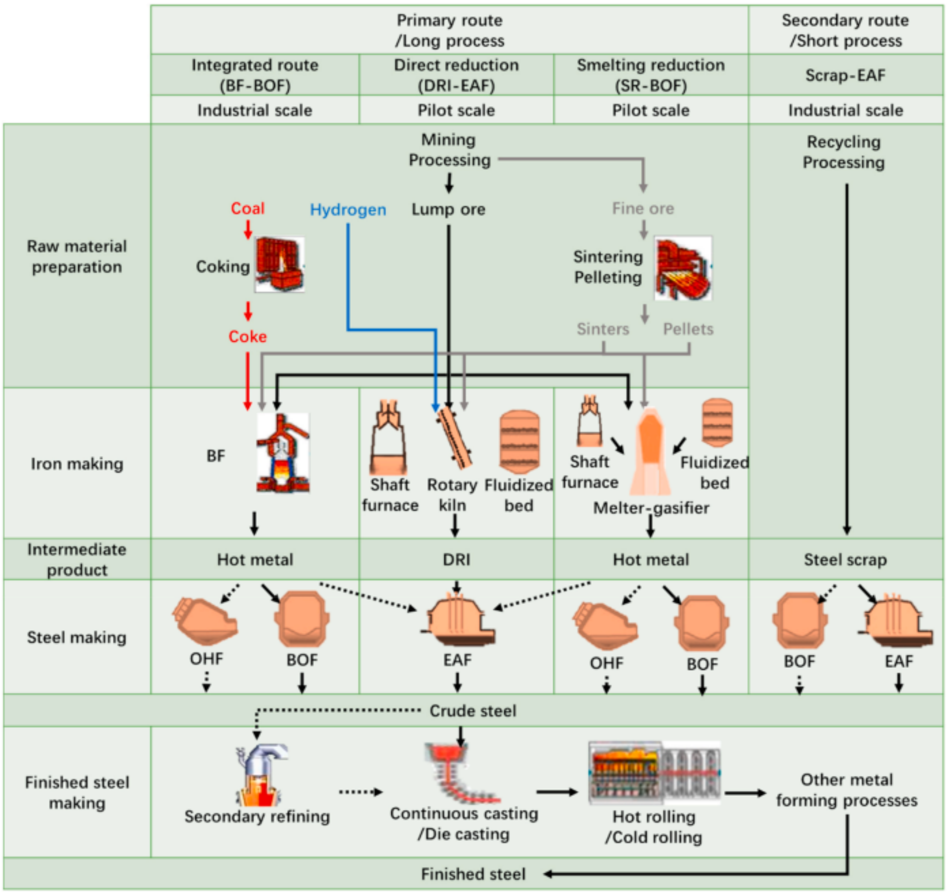

Figure 5: The 4 different steel making routes in a simple diagram by (Ren et al., 2023)

In the first route (BF/BOF), coal is used to produce coke, which is then fed directly into the blast furnaces, along with sinter and pellets. The hot metal from the blast furnaces is sent to the Basic Oxygen Furnace (BOF) or, alternatively, to an Open Hearth Furnace (OHF) to produce crude steel. Further downstream processes, such as Hot Rolling or Cold Rolling, finalize the steel's processing into its required form based on product specifications.

In the second route (DRI/EAF), a specialized reactor replaces the blast furnace, reducing iron ore to produce Direct Reduced Iron (DRI), which is not melted. Subsequently, an Electric Arc Furnace (EAF) is used to melt the iron and reduce its carbon content, transforming it into steel. The final processing steps are similar to those in the BF/BOF route. The DRI production stage allows for the use of alternative fuels, such as natural gas or hydrogen, while the EAF stage provides opportunities for electrification and greater flexibility in steelmaking.

2.2 Decarbonization Pathways and Technologies

We have already mentioned how energy-intensive and hard-to-abate the iron and steel industry is. In 2018, the iron and steel industry consumed approximately 33.5 exajoules (or 9300 TWh) of energy, with energy costs accounting for 20 % to 40 % of the total steelmaking cost (Kim et al., 2022). This highlights the significance of both the environmental and energy aspects of the industry. Considering the scale of steelmaking facilities, their energy intensity, and the substantial role of energy costs in the final cost of steel, it becomes evident how sensitive and exposed the industry is to major changes in energy flows and patterns. These factors contribute to a slower and more uncertain transition.

Nevertheless, several roadmaps for decarbonization have been proposed by various organizations. The International Energy Agency's IEA (2023) roadmap focuses on four major technologies: carbon capture, utilization, and storage (CCUS); hydrogen; direct electrification; and bioenergy (Kim et al., 2022). Similarly, Toktarova et al. (2020) suggest that hydrogen is likely the most feasible pathway for decarbonizing the sector, following an analysis of two alternatives: biomass combined with carbon capture while retaining blast furnaces, and hydrogen-based DRI technology in combination with EAF.

The biomass pathway, paired with carbon capture technology, may be more viable for countries with abundant biomass resources and infrastructure for storing or utilizing large quantities of captured CO2. On the other hand, the hydrogen-DRI pathway faces challenges due to the need for substantial amounts of hydrogen or electricity to produce green hydrogen within a decarbonized power sector. It is worth noting that fully hydrogen-based DRI technologies are expected to reach industrial maturity only after 2040 (Toktarova et al., 2020).

This timeline aligns with the plans of Tata Steel Netherlands, which is why our model incorporates fully hydrogen-based DRI technology only in the transition phase 3. In earlier phases, we utilize Natural Gas Direct Reduction (NG-DRI) or a hybrid Natural Gas and Hydrogen Direct Reduction (NG/H2-DRI), where natural gas is combined with hydrogen for iron reduction.

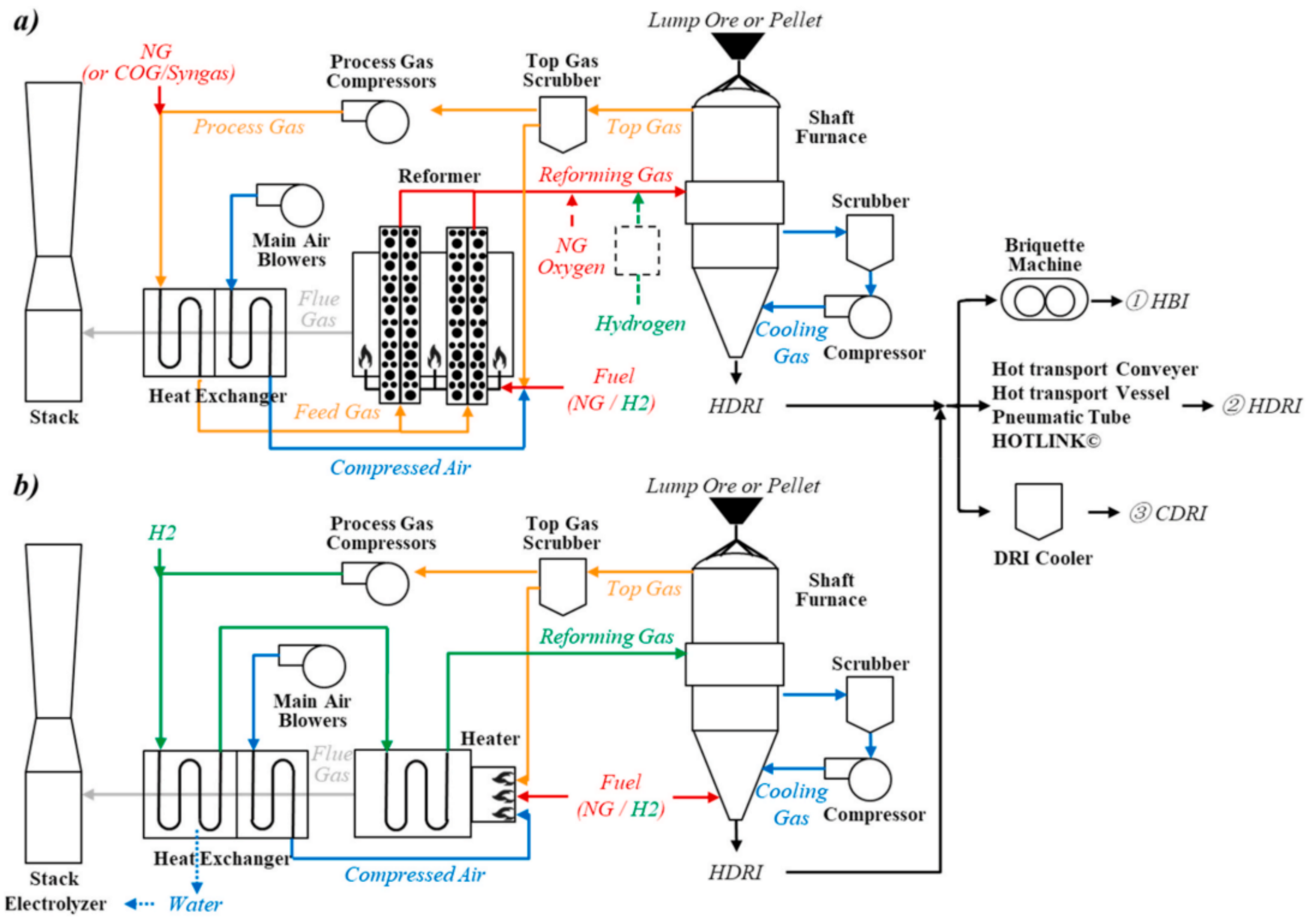

Figure 6: The different types of DR Plants that we are also using in this work by (Ren et al., 2023)

In Figure 6, we present a detailed diagram of the Direct Reduction (DR) process, illustrating how various combinations of natural gas and hydrogen, pure natural gas, or pure hydrogen can be utilized. It is evident that these gases serve two purposes. In a fully natural gas-based DR process, natural gas is used both as a fuel and as a reforming gas. In subsequent stages, hydrogen can be introduced as a fuel while natural gas continues to serve as a reforming gas. At the final stage—still not industrially mature—hydrogen can be used exclusively as both a fuel and a reforming gas, potentially with a small addition of fossil fuel for carbon enrichment of the iron, depending on the desired quality of the DRI.

These processes are still under development (not the DR process itself but its adaptation for hydrogen use), and we will not analyze them in depth in this work. Instead, we utilize these technologies and their associated assumptions regarding conversion factors between energy and material use, as well as the amount of reduced iron produced, depending on the type of DR process. This approach helps us design transition configurations for Tata Steel by combining insights from literature, the company's plans and targets, and the current site configuration's constraints.

When examining the various available or emerging technologies for decarbonizing the steel industry—such as those listed by Kim et al. (2022) in Figure 7—one might initially believe that the potential for decarbonization is significant and that the options are plentiful. However, no single technology can be considered a comprehensive pathway. Due to the long operational lifespans of steel production facilities and the steel market's tight profit margins, the industry already operates close to its thermodynamic limits. Therefore, standalone technologies are unlikely to result in significant improvements in efficiency or emissions reduction.

In this work, we aim to integrate these technologies by focusing on creating configurations rather than investigating the impact of individual technologies. For Tata Steel's site in IJmuiden, we define three transition configurations in addition to the current one. Each configuration is designed to:

1. Achieve a specific emissions target for the designated reference year.

2. Maintain the same steel production capacity as the current configuration.

3. Combine various technologies and plants to meet the above objectives.

Table 6

86 commercially available, emerging, and experimental innovations for the iron and steel industry.

Level of sociotechnical system	Commercially available but not yet widely utilized (as of 2020)	Emerging soon with working prototypes (as of 2020)	Experimental and likely only after 2025
Raw materials	1. Solid recovered fuels for use as reducing agents 2. Heat recovery from sinter cooler 3. Single-chamber-system coking reactors	1. Primary Energy Melter	1. Low-carbon hydrogen-based direct reduction 2. Charcoal in the sintering process 3. Torrefied biomass
Iron and steel making	4. Use of recuperative burners 5. Replacing existing equipment with more efficient ovens, burners, kilns, and furnaces 6. Process modification of kilns 7. Optimization of furnace 8. Waste heat recovery 9. Use of ceramic ladles instead of cast iron pipes 10. Efficient ladle preheating 11. Radiation recuperators for ladle furnace 12. Coal moisture control 13. Coke dry quenching 14. Injection of pulverized coal 15. Top-pressure recovery turbines 16. Recovery of BF/BOF gas 17. Charging carbon composite agglomerates	2. Advanced control of heating walls in coke ovens 3. Hot oxygen injection 4. Tecnored 5. Cyclone converter furnace 6. Continuous horizontal sidewall scrap charging 7. Converting off-gases to fuels (BF) 8. Converting off-gases to chemicals (BF)	4. Plasma blast furnace 5. Off-gas hydrogen enrichment (BF) 6. CO_2 removal for use or storage (BF) 7. Electrolytic H_2 blending (BF) 8. Natural gas-based DRI with high levels of low or zero-carbon electrolytic H_2 blending 9. Natural gas-based DRI with CO_2 capture 10. DRI based solely on low or zero-carbon electrolytic H_2 11. Paired straight hearth furnace 12. Molten oxide electrolysis 13. Suspension hydrogen reduction of iron oxide concentrate 14. Ironmaking using biomass and waste oxides 15. New scrap-based steelmaking process 16. In-situ real-time measurement of melt constituents 17. Continuous steelmaking for EAF
Steel products making and usage	18. Near net shape casting (thin slab) 19. Bottom stirring/stirring gas injection 20. Use of foamy slag practices 21. Use of oxy fuel burners 22. DC arc furnace 23. Scrap preheating and continuous charging 24. Flue gas monitoring and control 25. Eccentric bottom tapping 26. Improved process control 27. Ultra-high-power transformer 28. Twin shell furnace 29. Hot charging 30. Recuperative or regenerative burner 31. Use of ceramic low thermal mass insulators for reheating furnace 32. Controlling oxygen level and variable speed drive on combustion air fans 33. Efficient drives in rolling mill and machining 34. Waste heat recovery (cooling water, annealing, and compressor) 35. Reduced steam use for pickling 36. Automated monitoring and targeting systems 37. Thermal insulation for plating bath 38. Automated bath cover 39. Compressed air network modification 40. Reducing air extraction across heating solution 41. Efficient compressors 42. Optimizing the process solution temperature 43. Use of high-strength steel	9. Energy monitoring and management system in casting 10. Preventative maintenance in steel mills or EAF plants 11. Variable speed drives for flue gas control, pumps, fans in integrated steel mills 12. Cogeneration for the use of untapped coke oven gas, blast furnace gas, and basic oxygen furnace-gas in integrated steel mills 13. Additive manufacturing	18. Smelting reduction with CCUS 19. low or zero-carbon H_2 for high-temperature heat (ancillary processes) 20. Next-generation system for scale-free steel reheating 21. Thermochemical recuperation for steel reheating furnaces 22. Oxygen-rich furnace System 23. Integrating steel production with mineral sequestration
Waste and recycling	44. Rotary hearth furnace dust recycling system 45. Injection of plastic waste	14. Recycling basic oxygen furnace slag 15. Recycling of stainless steel dust 16. Regeneration of hydrochloric acid pickling liquor 17. Recycling of waste oxides in steelmaking furnace	24. Geological sequestration of carbon dioxide using slags

Figure 7: Available or emerging technologies for decarbonizing the steel industry by (Kim et al., 2022)

2.3 Tata Steel's steelmaking configuration and transition plans

The integrated iron and steel site in IJmuiden is certified to produce up to approximately 7 million tons of steel per year, transforming raw inputs such as coal and iron ore into crude steel and subsequently conducting various finishing processes to achieve the desired properties and grade. In this section, we provide concise information about the site's current steelmaking configuration and its future decarbonization plans.

Current Configuration

As previously discussed, Tata Steel currently employs the BF/BOF steelmaking route to produce steel. As shown in the simplified diagram in Figure 8, the primary raw material inputs for the steelmaking process are coal and iron ore. Various processes and plants convert these raw materials into steel. Coking, sintering, and pelletizing provide the necessary inputs for ironmaking in the blast furnaces and steelmaking in the basic oxygen furnace. Subsequently, processes such as rolling and other finishing steps are carried out to bring the steel to its final form for clients.

This entire system both produces and consumes energy in the form of electricity, natural gas, heat, and other sources. Work-arising gases from the various processes are captured and utilized to generate heat in boilers or to produce electricity, which can then be sold back to the electricity market. Additional electricity or heat is supplied directly from the electricity market or generated using natural gas.

Although this system involves numerous plants, sub-processes, and materials—described in greater detail in the following sections—the most significant changes will occur at the core of the site, specifically in the ironmaking process within the blast furnaces. This process is among the most polluting and energy-intensive, both directly, due to substantial CO2 emissions, and indirectly, through the consumption of large amounts of coal and coke, as well as the production of significant quantities of work-arising gases, particularly blast furnace gas (BFG).

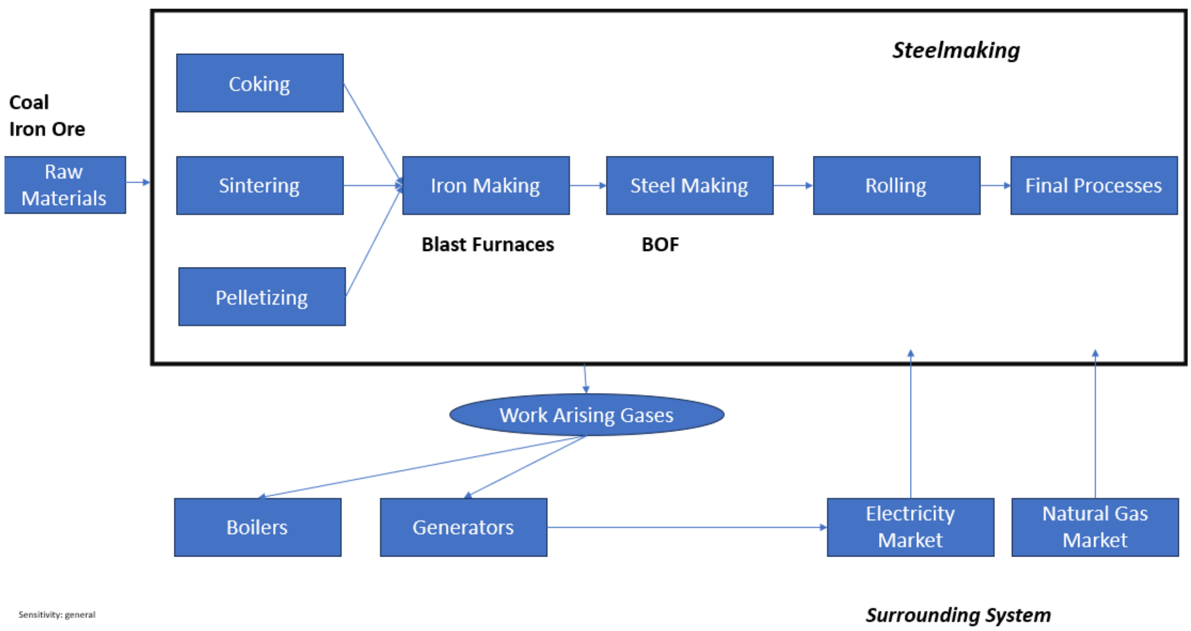

Figure 8: Simple schematic of IJmuiden's steelmaking site

Future Plans

The goal of the site is to gradually decarbonize its steelmaking processes, initially reducing CO2 emissions and ultimately achieving net-zero or green steel production by 2045. In this work, and in alignment with the site's plans, we propose three phases for this transition. The primary changes will focus on the iron and steelmaking processes.

Initially, one of the blast furnaces will be decommissioned, which will also reduce the demand for coke from the coking plants, leading to the shutdown of the first coking plant. To compensate for the lost steelmaking capacity, a Direct Reduction Plant (DRP) and an Electric Arc Furnace (EAF) will be installed. Gradually, the second blast furnace, the second coking plant, and the sintering plant will also be decommissioned. A second DRP will be installed, and a melting furnace will be added to process a portion of the Direct Reduced Iron (DRI) to be used in the Basic Oxygen Furnace (BOF).

In the final stage of the transition, the DRP plants will shift to consuming more hydrogen instead of natural gas, and the boilers will become predominantly electric. To achieve a 100 % reduction in CO2 emissions, carbon capture technologies would need to be implemented. However, modeling these technologies is beyond the scope of this work. Consequently, the recommendations in this work result in an approximate 90 % reduction in CO2 emissions at the site.

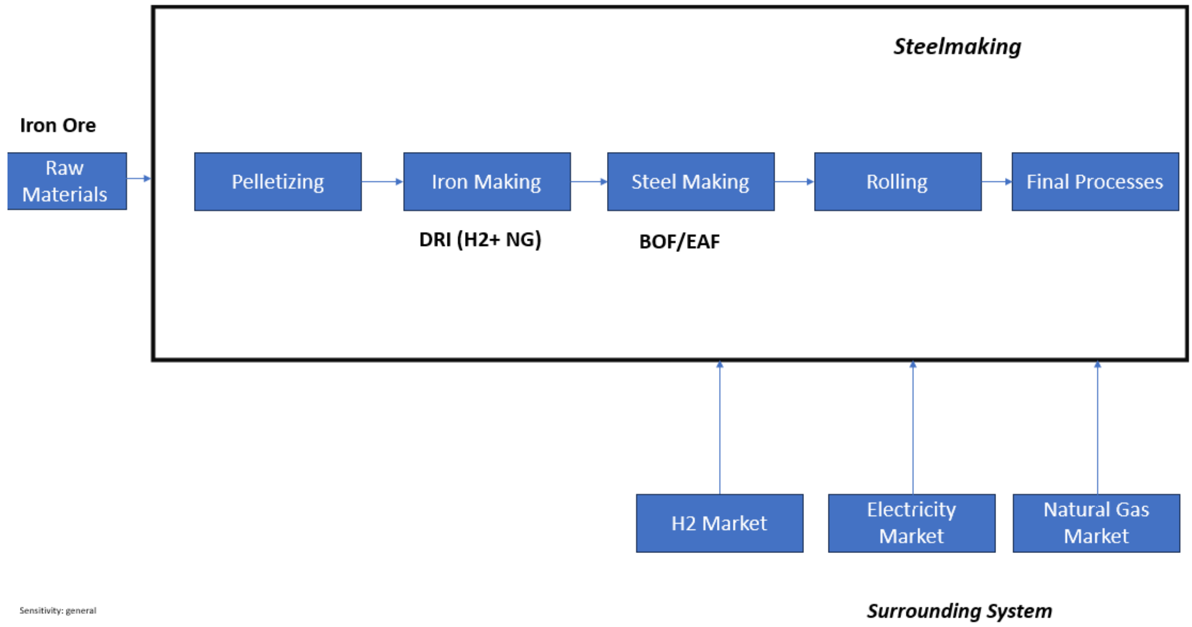

Figure 9: Simple schematic of IJmuiden's steelmaking site future configuration

The key changes are summarized in Figure 9, and the transition configurations will be described in detail in the next chapter.

3 Methodology and Modeling

The primary objective of this study is to investigate the impacts of the energy transition at an integrated steel plant, specifically focusing on Tata Steel's site in IJmuiden, Netherlands. Since "impacts" is a broad term, in this context, it refers to changes in energy consumption patterns—both in terms of quantity and energy sources—carbon dioxide emissions, raw material consumption, and the marginal cost of steel production. Additionally, this study examines these impacts not only in relation to changes in the site's configuration due to the energy transition but also in response to fluctuations in electricity prices, natural gas prices, carbon pricing, and other costs, simulating potential shifts in the energy system as a whole.

Furthermore, this study suggests configurations that are most suitable for decarbonizing the current site. As this research is not purely theoretical, its most valuable outcomes are the specific findings related to the IJmuiden site. To achieve this, a model specifically designed for this case serves as the primary analytical tool.

The model must possess certain essential characteristics to fulfill its purpose, as described above. The Tata-Demoses model, as it is called, is fundamentally a cost-minimization/optimization model. The choice of cost minimization over profit maximization will be explained later. However, the model must function as an optimization model for several reasons. First, the results must reflect an optimized operation of the site to ensure they are realistic and comparable, given that site operations are dynamic and production output over time depends on numerous factors. A static energy model would therefore be insufficient. Second, a cost-optimization model, driven by energy price inputs while adhering to the fundamental operational constraints of steel production processes, is deemed the most suitable tool for assessing the potential impact of energy prices on the operational planning of a heavy steel industry. Third, an optimization model with variable energy price inputs is a fundamental requirement for this model to integrate into the broader DEMOSES project.

This chapter provides a detailed description of the model and its functional requirements. It also explores the PyPSA toolbox and how it was used to develop this model. Additionally, the current configuration and its model components are outlined. The mathematical formulation of the optimization problem is also presented in this section. The components and configurations of the new system are subsequently described. Finally, this chapter discusses the model's constraints concerning plant operations and how these constraints are derived from real data. It also examines the model's behavior through a simulation over a short time period and concludes with the verification and validation of the model.

3.1 Model Requirements and Description

In this section, the Tata-Demoses model will be described in greater detail, and its functional requirements will be outlined in bullet points. The model was developed using Python for Power System Analysis (PyPSA) (*PyPSA*, 2024). The Linopy library was utilized to further refine the optimization problem formulated with PyPSA (*linopy*, 2024). To solve the optimization problem, the High Performance Software for Linear Optimization (HiGHS) solver was employed (*HiGHS*, 2024).

The simulations were conducted on a PC equipped with an 11th-generation Intel(R) Core(TM) i5-1145G7 @ 2.6 GHz processor and 16.0 GB of RAM (15.4 GB usable) running a 64-bit operating system.

Modeling approach specific for a steel site

At this point, it is important to mention that integrated steel sites consist of multiple plants operating together and interacting with one another to produce the final steel products at the required quality and quantity demanded by customers. While each plant typically functions independently, its outputs often serve as inputs for another plant within the steel production process chain. As a result, the operation of each plant influences other processes and is constrained by them, depending on the storage capacities of each intermediate product.

In this study, the steel site is approached as an energy system. However, this does not imply that it operates purely as an energy system that always prioritizes minimizing energy consumption and maximizing energy efficiency. For an integrated steel site, delivering the final product—typically valued much higher than any individual energy or material input—at the required quantity and quality is generally the top priority, taking precedence over any other cost-related factors.

At the same time, energy transition pathways for the steel industry indicate that steel sites will increasingly rely on electricity, natural gas, and hydrogen prices in the future, making them more exposed to external market fluctuations. This contrasts with the current situation, where coal and iron ore—the primary energy and material inputs—have more stable prices and can be stored for long periods (Boldrini, Koolen, Crijns-Graus, & van den Broek, 2024), (Boldrini, Koolen, Crijns-Graus, Worrell, & van den Broek, 2024), (Wang et al., 2020). Additionally, electricity prices currently have a limited impact on the operation of steel sites. This is either because electricity consumption represents a relatively small portion of total energy and cost inputs or because the system remains balanced due to self-generated electricity from work-arising gases (WAGs) produced by various processes, as will be explained later.

Considering these factors, this system is best understood as a hybrid: on one hand, it remains a target-driven industry focused on delivering high-quality steel (reflecting the current situation), and on the other, it must increasingly adapt to external price signals, particularly for energy inputs (reflecting the future scenario). Therefore, a model that integrates both of these aspects was developed.At this point, it is important to mention that integrated steel sites consist of multiple plants operating together and interacting with one another to produce the final steel products at the required quality and quantity demanded by customers. While each plant typically functions independently, its outputs often serve as inputs for another plant within the steel production process chain. As a result, the operation of each plant influences other processes and is constrained by them, depending on the storage capacities of each intermediate product.

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Specific steel production target as the fundamental constraint of the model

The driving force behind the system's operation is a steel production target set at the final stages of the integrated steel site's process chain—specifically, after the Hot Strip Mill and the Direct Sheet Plant, which both produce coiled steel in parallel. This target location was chosen because nearly all the steel produced passes through these processes. After this stage, the coiled steel is directed to various final processing steps depending on the specific characteristics required by customers.

A basic configuration of a typical steel production route used at Tata Steel's IJmuiden site is shown in Figure 10. The model ensures that the steel production target, aligned with Tata Steel's actual production goals over a given period, is met. At the same time, it incorporates cost inputs from various sources, including electricity, natural gas, coal, iron ore, CO2, and other factors, to adjust plant operations as efficiently as possible to achieve this target in a cost-effective manner.

However, this optimization is constrained by the operational limitations of each plant. For example, individual plants cannot instantly scale production up or down solely in response to price signals. Additionally, beyond price fluctuations, the system as a whole must meet the minimum steel production quantity required to align with the site's annual target.

Price signals inputs

Price signals can vary as frequently as the simulation's time step, which is set at one hour, depending on the nature of each input. For example, electricity prices are provided on an hourly basis, aligned with the day-ahead electricity market, while coal and iron ore prices are more stable and typically change on a monthly basis. This approach reflects their relatively steady nature while keeping the computational cost of the simulation manageable.

The price data provided by Tata Steel consists of scenario-based predictions, which will be discussed later in this work. These include hourly power price forecasts for the future, as well as monthly gas, coal, and carbon price projections for the same period.

Other cost inputs for the model, such as iron ore prices, scrap prices, pellet import prices, and future hydrogen prices, must be either assumed or sourced from alternative references. It is important to note that this study specifically focuses on electricity demand. For this reason, hourly electricity prices are the most critical cost input in the model, as the site's electricity consumption is expected to change and influence its overall operation. Since electricity prices fluctuate hourly, they introduce a significant challenge to the system: To what extent can the site adjust its operations in response to electricity price changes?

The emphasis on electricity is particularly relevant because both the DEMOSES project and Tata Steel are interested in accurately representing the site's electrical demand. This model serves as a valuable tool in fulfilling that objective.

Cost minimization optimization problem

Regarding the choice between profit maximization and cost minimization, the problem was formulated as a cost minimization model due to the complexity of the various profit streams associated with the site's multiple steel products. A profit maximization approach would likely suggest reducing the site's steel production output under extreme energy price conditions and focusing only on the most expensive final products. However, in reality, this is not feasible, as it would lead to customer dissatisfaction and fail to meet the diverse product demands of clients. Additionally, even if such an approach were possible, analyzing the cost of not capturing steel demand and developing strategies around this issue falls outside the scope of this study.

For this reason, the problem is structured as a cost minimization model with a fundamental steel production target and multiple operational constraints for individual plants as well as for the overall system. Based on the author's assessment—after discussions with Tata Steel representatives and considering the system's requirements as a master's thesis tool, a DEMOSES satellite model, and a decision-support tool for Tata Steel's future investments—this approach is deemed the most suitable for accurately representing the system.

The current configuration as a base for the model

The model is based on the current configuration of Tata Steel's IJmuiden site, where the Blast Furnace–Basic Oxygen Furnace (BF-BOF) route is used, as will be explained later. Since this study investigates the site's energy transition, alternative configurations aimed at reducing carbon dioxide emissions will also be proposed and modeled.

Building the model around the current configuration offers several advantages. Firstly, the operational characteristics of the plants are well-documented, allowing for accurate constraint setting. Additionally, the model's outputs can be compared with the site's real energy consumption patterns. However, as previously discussed, the site primarily operates as a target-oriented industry rather than an energy-optimized system, whereas the Tata-Demoses model integrates both approaches, enabling the exploration of more price-responsive operational strategies.

It is important to note that the site's actual operations cannot strictly follow the model's suggested patterns due to process control limitations, unforeseen circumstances, maintenance requirements, and other constraints not included in the model. Furthermore, many of the site's plants were built decades ago, prioritizing high production output over operational flexibility.

Despite these limitations, basing the model on the current configuration is justified not only by the availability of operational data and the ability to validate results but also because many elements of the existing setup will remain in future configurations, as will be discussed later. Additionally, no major changes to the current configuration are expected until approximately 2030, meaning the model in its present form will remain relevant for analysis until then.

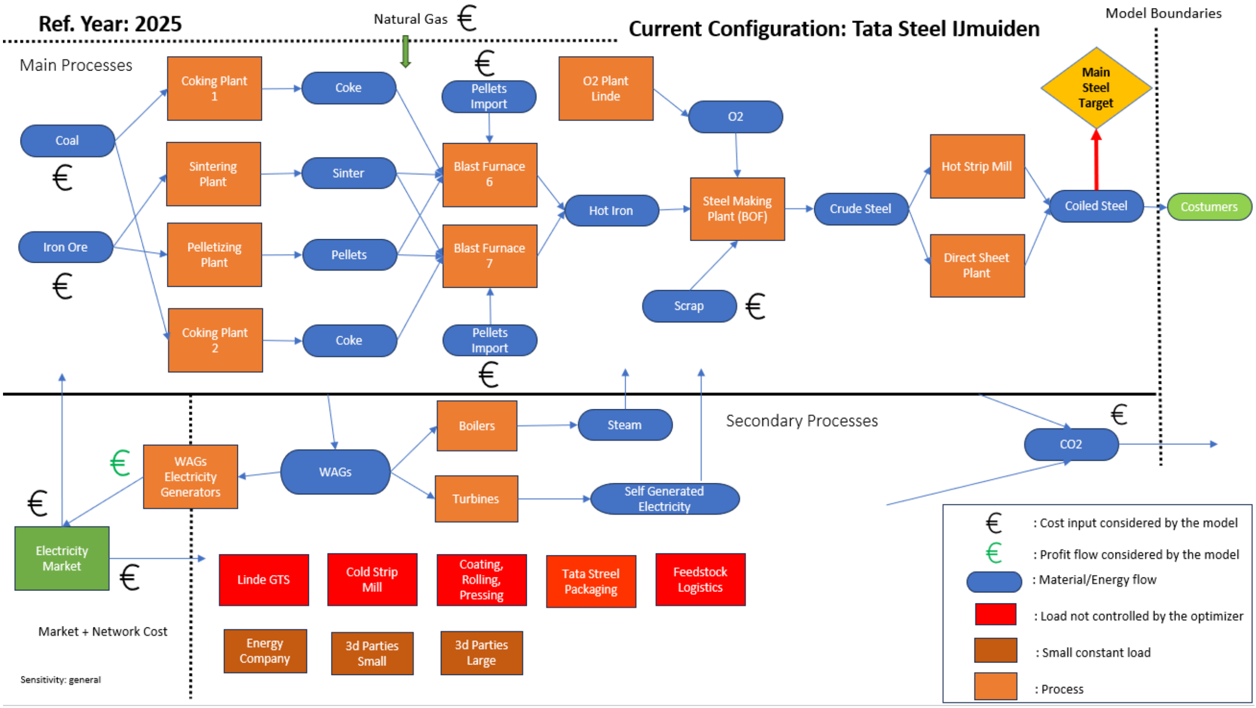

Figure 10: Schematic of the current configuration of Tata Steel's site in IJmuiden as Tata-Demoses model perceives it.

PyPSA Fundamentals - From the site representation to the optimization problem
Figure 10 presents a schematic representation of the modeling approach for Tata Steel's IJmuiden site. The diagram illustrates the main and secondary plants, electricity loads, materials, emissions, and energy flows, among other elements. In this section, we define the fundamental tools from the PyPSA library used in this study to translate a simple diagram—like the one in Figure 10—into a well-structured optimization problem with an objective function, constraints, and variables.

Python for Power System Analysis (PyPSA) *PyPSA* (2024) is an open-source toolbox for simulating and optimizing modern power and energy systems. According to its official description, PyPSA supports:

- Conventional generators with unit commitment
- Variable wind and solar generation
- Storage units
- Coupling between different energy sectors
- Mixed AC and DC networks

According to the PyPSA documentation, the toolbox can perform:

- Static power flow calculations
- Linear optimal power flow
- Security-constrained linear optimal power flow
- Total electricity/energy system least-cost investment optimization, optimizing:
  - Generation
  - Storage dispatch
  - Infrastructure investment

PyPSA is widely used to model complex energy systems, including:

- Large-scale electricity networks, such as the European grid or global energy systems Hörsch et al. (2018); Parzen et al. (2023)
- Hydroelectricity systems with inflow and spillage
- More advanced systems, such as combined heat and power (CHP) units or Power-to-Heat (P2H) systems

The primary users of PyPSA include researchers, planners, and utility companies seeking a transparent tool for power and energy system analysis.

Although PyPSA is primarily designed for electricity networks, it is also well-suited for general energy system optimization when used with appropriate modifications and components. By leveraging PyPSA's:

- Buses
- Links
- Stores
- Loads
- Generators

we translate Tata Steel's industrial operations into an optimization problem.

The methodology followed in this study is presented in a structured and analytical manner to:

- Demonstrate PyPSA's suitability for modeling integrated steel sites
- Ensure the reproducibility of this research by outlining the fundamental principles used
- Provide a clear understanding of the modeling process, from conceptualizing the site's operations to designing a flow diagram of energy and material flows leading to steel production, and finally converting this into an optimization problem using PyPSA

After defining these components, we present a detailed example of a specific process within the site, integrating all of these elements. Throughout this work, references to these components will be made without restating their detailed attributes or functions, so the information provided in this section applies to the entire report.

Buses

The bus serves as the fundamental node in the network to which all other components, such as generators, stores, links, and loads, are attached. Buses can have multiple components connected to them, and their main role is to ensure the conservation of energy and material flows entering and exiting the system.

In this model, buses are defined for all the materials and energy flows we aim to describe. For example, electricity is consumed by various processes within the site, and it can also be produced by internal generators or drawn from the external grid. We define a common electricity bus, where all components that consume, produce, or store electricity are attached. This bus ensures that, for each time step, the electricity production and consumption are balanced, except when a store component is attached. In this case, the bus makes sure the difference between production and consumption is either stored or consumed from the storage component.

Additionally, buses are defined for all the relevant materials and energy flows in the system. For instance, referring back to Figure 10, we define buses for Coal, Iron Ore, Sinter, Pellets, Crude Steel, Coiled Steel, Electricity, Natural Gas, Blast Furnace Gas, etc.

Buses are typically defined at the beginning of the code, which describes the PyPSA network. In PyPSA terminology, a network refers to a system of interacting components. It's important to note that a network cannot exist without buses.

For this study, we create a separate network for each configuration of the site, resulting in a total of four networks: one for the current configuration and three for the transition phases.

A bus is defined by a unique name, and other components refer to this bus by referencing its name as a string within the component's attributes. An example of how buses are defined in the PyPSA environment for the current configuration is shown in Figure 12.

The carrier attribute, which is defined for each bus, is not used in this work. Although it can be utilized in PyPSA to set specific constraints for each carrier, we employ a different approach in this study.

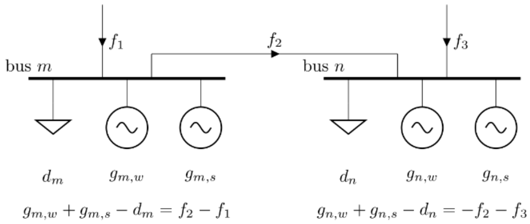

Figure 11: The representation of a system with buses in PyPSA in electricity network terminology *PyPSA* (2024)

```
network.add("Bus", "Coal", carrier="Coal")
network.add("Bus", "Coke", carrier="Coke")
network.add("Bus", "Electricity", carrier="AC")
network.add("Bus", "Blast_Furnace_Gas", carrier="BFG")
network.add("Bus", "Coke_Oven_Gas", carrier="COG")
network.add("Bus", "Pellet", carrier="Pellet")
network.add("Bus", "BOFG", carrier="BOFG")
network.add("Bus", "Iron_Ore", carrier="Iron Ore")
network.add("Bus", "Sinter", carrier="Sinter")
network.add("Bus", "Iron", carrier="Iron")
```

Figure 12: Definition of Buses in a PyPSA network for the current configuration of the site

Links

After defining the buses, another important component for representing the system is the Link component. Links are used to represent electrical connections in grid terminology, typically accounting for losses by defining an efficiency attribute. In this work, we utilize the efficiency attribute to model the processes.

A notable advantage of PyPSA, particularly with Links, is that it allows the modeling of more complex energy systems beyond just pure electricity networks. Specifically, Links can have multiple inputs and outputs, enabling the connection of both materials and energy. This makes Links useful for modeling processes that involve both energy and material conversions. For instance, if we wish to describe a process that consumes coal and produces coke, while also requiring a specific amount of electricity and generating CO2 emissions, we define a link called Coking Plant. This link is connected to the buses for Coal, Coke, Electricity, and CO2, which must already be defined.

Once the link is established, we can set the conversion factors between the main bus and the other buses. In this model, the main bus of each link represents the primary input of the process. For example, in the Coking Plant, the main input is coal, so we define the main bus, or Bus0 in PyPSA terminology, as the Coal bus. All subsequent link settings and conversion factors are based on this primary input.

For example, the capacity of the process is defined in terms of tons of imported coal, and the conversion factor between coal and coke is the ratio of coke produced to coal consumed by the process. Similarly, for the electricity consumption, we define the amount of electricity consumed per ton of coal used in the process.

```python
network.add(
    "Link",
    "Sintering_Plant",
    bus0="Iron_Ore",
    bus1="Sinter",
    bus2="Electricity",
    bus3="Coke_Oven_Gas",
    bus4="CO2",
    bus5="Steam",
    p_nom=MP["Sintering Plant"]["Average Capacity"],
    p_min_pu = MP["Sintering Plant"]["Operational Min"],
    p_max_pu = MP["Sintering Plant"]["Operational Max"],
    ramp_limit_up = MP["Sintering Plant"]["Ramp Up"],
    ramp_limit_down = MP["Sintering Plant"]["Ramp Down"],
    efficiency=MP["Sintering Plant"]["Efficiency_Sinter_to_Iron_Ore"],
    efficiency2=MP["Sintering Plant"]["Efficiency_Electricity_to_Iron_Ore"],
    efficiency3=MP["Sintering Plant"]["Efficiency_COG_to_Iron_Ore"],
    efficiency4=Data_CO2["Sintering Plant"],
    efficiency5=Steam["Sintering Plant"],
)
```

Figure 13: Sintering plant of the current configuration modelled as a Link component in PyPSA

In Figure 13, we can see an example of the Sintering Process or the Sintering Plant represented as a link in PyPSA. According to our modeling approach, the Sintering Plant consumes Iron Ore to produce Sinter, while also consuming electricity, producing Coke Oven Gas, emitting CO2, and consuming steam. Efficiencies play the role of conversion factors, describing the relation between the consumed Bus0 (Iron Ore in this case) and the other buses. These conversion factors are called from Python dictionaries specific to each plant of the site. Consumption or production of a specific bus can be described by setting the conversion factor to a positive or a negative value.

Links have many attributes, but we are mostly using the ones that appear in Figure 13 for our work. The nominal capacity p_nom is also defined in terms of the main input consumption per time step, and the range of operation of the process, expressed as a percentage of this nominal capacity, is set by the p_min_pu and p_max_pu values. For example, if a plant is not allowed to operate below 80% of its nominal capacity, then we set $p\_min\_pu = 0.8$. Similarly, ramp limits are set as a percentage of the nominal capacity of the plant. It is already clear that PyPSA is a user-friendly environment for designing large energy or process systems. By designing a single process smartly and efficiently, one can extend the model to describe many different processes by only changing the name and the attribute names of a link component, for example, and connecting these multiple links with the use of the appropriate buses.

PyPSA offers multiple and generic options relevant for many processes that, if used correctly, can be easily translated into an optimization problem. A link, like the one shown in Figure 13, creates variables and constraints for the optimization problem in the background without the need for the user to manually create them. This is very convenient for large problems but also demands a very good understanding of the system created and the role of all of these variables and constraints. In this work, we are using Links for all of the main plants, the external WAGs generators of Vattenfall, the mixing gas stations, and the boilers of the site, as they will be described in the next sections. This is the approach to model the processes of the site in terms of inputs, outputs, operation range, and ramp limits.

Loads

Load is another component in PyPSA, originating from the concept of an electricity load, which represents an electrical demand that must be met at each timestep of a simulation. In this study, we use loads to model the demand of various site components or processes that are not represented as links or are not part of the decision variables in the optimization problem. For instance, secondary processes such as the Cold Strip Mill plant or Coating, Rolling, and Pressing consume electricity, but their operation is linked to the steel pathway that follows the production of hot-rolled steel. These processes are often not directly relevant to the overall steel output targeted by the model. To minimize complexity and reduce computational time, such processes are modeled as loads.

From the model's perspective, loads are consumers of a specific bus (representing material or energy flows) at each timestep and must be satisfied during every timestep. Loads can represent not only electricity consumption but also natural gas consumption, reflecting secondary processes that consume natural gas but are not part of the main plants, as well as steam consumption, which is modeled in the same manner.

```
network.add(
    "Load",
    "Residual_Electricity_Load",
    bus = "Electricity",
    p_set = Grid["Current Grid"]["Residual Load"],
    )
```

Figure 14: Load component representing the residual electricity consumption of the site in PyPSA

In Figure 14, we can see a load component in PyPSA. Loads have several attributes, but in this work, we are primarily using the bus attribute to connect the load to the appropriate bus, such as electricity, steam, or natural gas. This means that the load is consuming electricity, steam, or natural gas as defined by the value of *p_set*. It is important to note that some loads on the site, such as the green boxes in Figure 10, represent time-series data for electricity demand from these specific processes, based on real consumption data. Other loads, like the yellow boxes, use average values per hour, calculated from total yearly consumption.

Loads are not controlled by the optimizer but are important because they make the system more realistic. By incorporating these loads, the optimizer is required to account for real-world demands in combination with the actual processes. Additionally, they play a crucial role in ensuring that the model outputs align with the total energy consumption of the site.

Generators

Generators play a critical role in the modeling approach used in this work. Through generators, we provide both the initial materials needed as feedstock for the steelmaking process and the energy required. Additionally, we can efficiently incorporate the costs of these materials or energy flows by utilizing the marginal cost attribute of the generators.

An example of using a generator component to model the electricity supply from the electricity market to the site is shown in Figure 15. As with other components, we need to define the bus, and in this case, the relevant bus for the Electricity Market Generator is "Electricity." The maximum power that the site can consume is determined by the available connections and their capacity, which is set using the *p_nom* value.

```
network.add(
    "Generator",
    "Electricity_Market",
    bus="Electricity",
    p_nom=Grid["Current Grid"]["Power"],
    p_nom_extendable=False,
    marginal_cost=Costs_Current["Electricity Cost"],
)
```

Figure 15: Generator component representing the electricity supply of the site in PyPSA from the grid

Declaring that this component is not extendable means that even if it would be optimal for the site to consume more than the nominal capacity of the grid connections (e.g., 500 MW) during specific timesteps of the simulation, this is not allowed due to physical restrictions. In contrast, when modeling coal or iron ore imports to the site—where supply is not restricted and we want to ensure that these materials are always available for the processes—we set their generators with an extendable *p_nom* attribute.

Additionally, we use the marginal cost attribute to define the costs associated with each imported material or energy flow that the site uses to produce steel. The specified value charges the amount set for each unit of material or energy flow that the generator produces or supplies to the site.

In our model for the current configuration of the site, we include seven cost inputs and one profit stream. Coal, iron ore, electricity, natural gas, scrap, and imported pellets (in addition to those produced by the pelletizing plant) are modeled using generators. The CO2 cost is modeled through a Store component, as explained in the next section. Lastly, the profit from using the Work Arising Gases (WAGs) is modeled as a Link with a negative marginal cost attribute.

Stores

The final component used in this work to model the Tata Steel site in IJmuiden is the Store component. Store components are essential because they provide storage for intermediate materials between different steel-making processes. For instance, coke, the main product of the coking plants, can be stored before being used as an input to the blast furnaces. Stores also require a bus as an attribute to specify which material or energy flow they are storing and which processes they are connected to, meaning they can either store outputs or supply inputs to other processes.

An example of a Store component in PyPSA is shown in Figure 16, which represents the storage of hot iron coming from the blast furnaces. We use the cyclic attribute set to 'on' to ensure that at the end of the simulation, the store's level is the same as it was at the beginning. This setting is applied to most of the stores in our model, except for those where the materials accumulate throughout the simulation, such as the CO2 store.

As seen in Figure 16, the size of the storage cannot be extended. This is similar to the *p_nom* attribute of generators, where the limit we set cannot be exceeded, even if it would create an active constraint during the simulation. For example, for the iron store, we define a limit based on the size of the torpedo cars used to transport hot metal from the blast furnaces to the basic oxygen furnace. Since the torpedo cars are of a specific size and the metal is molten, the amount of hot metal stored per timestep cannot exceed this limiting factor. This restriction is not applied to materials that are easier to store, such as coke, sinter, or steel slabs.

```
network.add(
    "Store",
    "Iron_Store",
    bus="Iron",
    e_cyclic=True,
    e_nom_extendable=False,
    e_nom = Stores["Hot_Metal_Storage_Limit"],
)
```

Figure 16: Load component representing the residual electricity consumption of the site in PyPSA

Example of PyPSA use

After explaining the use of the various components in PyPSA, let's now demonstrate how these components are used to model a small part of the site, specifically the coking process in Coking Plant 1. As shown in Figure 17, different colors and shapes are used to represent the various components. We will maintain this color scheme and shape usage throughout the rest of the report when referring to PyPSA terminology.

As previously discussed, every material or energy flow within the system must be defined as a bus so that other components can connect to it. The defined buses for this small system are shown at the top of the figure. Focusing on Coking Plant 1, we can see that the inputs to the plant are coal, a mixture of work arising gases (WAGs) appropriate for Coking Plant 1 (WAGs COK1), electricity, and steam. The outputs include coke, coke oven gas (COG), and CO2.

These various inputs must be supplied by generators or stores (which are filled by other links or generators) or directly by generators. The outputs need to be directed to other links, stores, or loads, which are not relevant to this example. PyPSA converts this system into an objective function, complete with constraints and variables, ensuring that at each time step, the system remains balanced and all constraints are satisfied. The final goal is to produce a specific amount of steel by the end of the simulation period in the most cost-efficient manner.

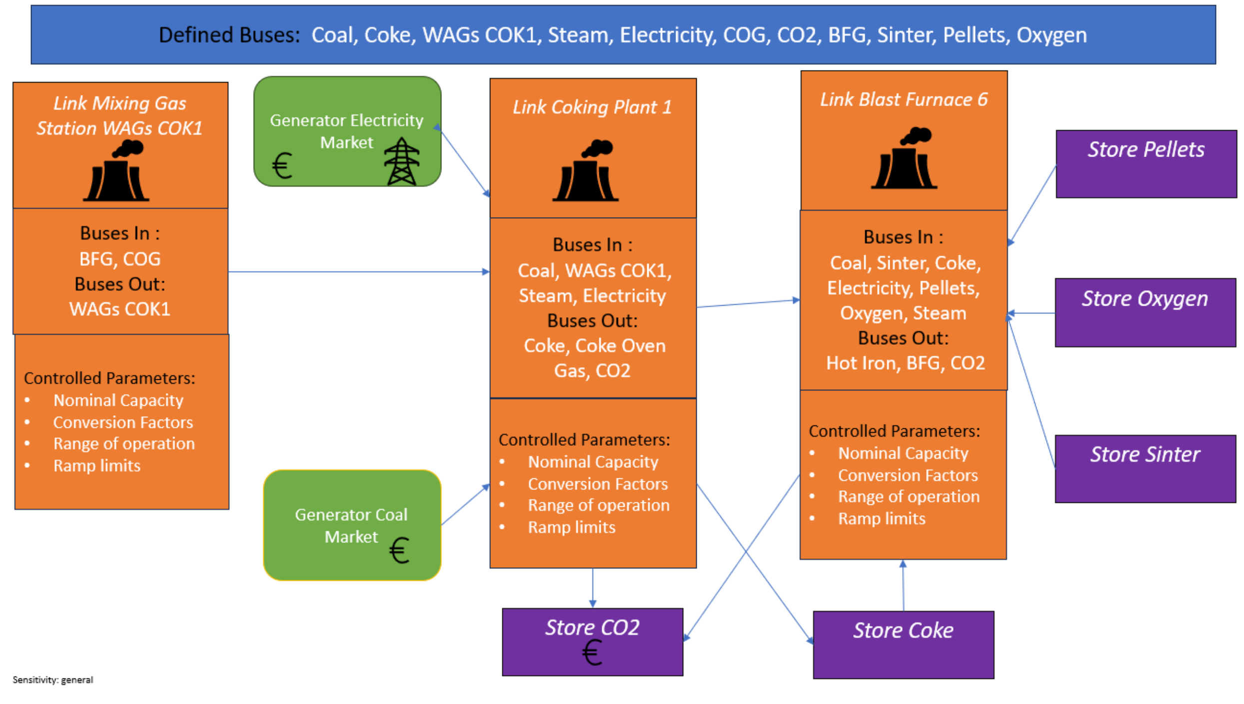

Figure 17: Example of the use of PyPSA components to represent how steel making processes are modeled in this work

To delve deeper into this, specifically, Coking Plant 1 requires coal, which is supplied directly from the coal market generator. This generator adds a specific cost to the system for every ton of coal consumed by the coking plant. WAGs COK1 is a mixture of Blast Furnace Gas and Coke Oven Gas, which is determined by another link called the Mixing Gas Station WAGs COK1. This link receives the gases from the blast furnaces, as well as the coking plant's outputs, with both connected via common buses. Electricity is supplied by the electricity market generator, with the cost depending on the specific timestep.

The outputs of the coking plant are directed to stores (such as CO2 storage) or to coke, which will later be used by other processes or links, such as Blast Furnace 6. PyPSA utilizes these inputs as defined by the designer, with the choice of components translating the system into an optimization problem. For instance, a link creates a decision variable indicating the operational level of the specific process at a given timestep. Through conversion factors, the amounts of the other inputs and outputs for that timestep are determined. This decision forces the generators and stores to supply these amounts, while downstream stores handle the outputs.

The controlled parameters of all links, such as capacity or the range of operation, add constraints to the system. A more detailed mathematical formulation of the optimization problem is provided in section 3.4.

Summary and final remarks regarding PyPSA

- As we have explained, we use different PyPSA components to describe various processes on the site. The choice of a specific component in this model does not imply that the same model cannot be created more efficiently by using a different combination of components or making other modifications.
- The most commonly used component is the link component. Links describe all the main processes on the site, including boilers, mixing gas stations, and external generators from Vattenfall. While it may seem unusual to use links to model generators, the ability of links to handle multiple inputs and

outputs is particularly useful in our case. These generators receive WAGs but produce electricity and CO2, which is easier to model as a link. An interesting addition for future configurations is the new "committable" attribute for the electric furnace's link. This attribute introduces binary variables that allow the link to either operate within its defined range or be turned off. This is not permitted for the main plants in the current configuration, nor for most plants in future configurations, for reasons that will be explained later.

- Stores are used to store materials and restrict the storage capacity for certain materials, such as oxygen or hot iron. In addition, store links serve two crucial purposes in this model. First, a store holding hot rolled steel from the Hot Strip Mill and Direct Sheet Plant is used to define the steel production target of the site. Since PyPSA generates variables for the storage level of stores in a network, we can access the storage level of the Hot Rolled Steel Store and impose a constraint that forces the optimizer to produce at least the specified amount of hot rolled steel. Second, we use a store to represent hypothetical CO2 storage. All processes emitting CO2 have an output bus for CO2, and this quantity is stored in the CO2 Store, as CO2 is not consumed by other processes. By monitoring the CO2 level at the end of the simulation, we can determine the total CO2 emissions for that run. Moreover, we can set a marginal cost for the CO2 Store, allowing us to charge a cost for each ton of CO2 added to the store. This is an effective way to incorporate CO2 costs into the system.

- The flexibility of PyPSA allows the modeler to choose different components depending on the system's requirements. Some processes cannot be described by a single component, but often a combination of components is sufficient to model even the most complex processes. Computational efficiency becomes important at this stage. Which components are most efficient for describing a system? This requires a deep understanding of the system and the ability to model it efficiently, as well as knowledge of how PyPSA generates variables and constraints in the background for each component. For example, tracking the storage level of a component at each timestep can significantly impact computational time, especially when the user is not interested in monitoring this level. However, there are cases where this tracking cannot be avoided.

- Another advantage of PyPSA is that if the variety of components is insufficient to describe a complex system or handle unique constraints, the user can manually create constraints and variables in linopy. PyPSA is compatible with Python libraries such as linopy, pandas, and numpy, enabling users to combine these functionalities with PyPSA's capabilities.

- Finally, we must mention Linny-R by TU Delft and Prof. Pieter Bots (Linny-R, 2022). Linny-R is a graphical specification language designed for MILP, LP problems, and Unit Commitment Problems. In the early stages of this work, I installed and created initial representations of the site in Linny-R. The terminology and design of this software influenced the design of the later PyPSA model. Many components in both tools share similar settings. For example, generators are termed "sources" in Linny-R, while loads are referred to as "sinks." There are also processes in Linny-R, which are equivalent to links in PyPSA. Linny-R is likely more user-friendly and less code-intensive than PyPSA, offering a convenient environment for designing complex systems. However, this work needed to be implemented in Python to ensure compatibility with the DEMOSES project and other ongoing projects at Tata Steel.

Model Functional Description
Below, the basic functions and assumptions of the model will be described:

◇ As previously explained, the processes/plants/components to be modeled are categorized into main processes, which the optimizer can control, and secondary processes, which represent the electricity load and other energy consumption characteristics of certain processes but cannot be controlled by the optimizer. The load of these secondary processes is either constant over time or changes based on historical data series but cannot be adjusted according to external price signals. This separation arises because some of the site's plants are located after the main steel target in the model, as they are related to final steel processes such as coating or galvanizing. Not all of the steel produced goes through these processes, making it technically difficult to control each process in relation to the main steel production processes. For this reason, these plants are represented as loads, as seen in Figure 10. A second reason for this approach is the increase in complexity and computational cost when including all secondary processes as variables in the model. The trade-off between the improvement in the solution and the computational cost does not justify this decision.

- ◇ In addition to the main and secondary processes, the model also handles electricity generation from the work arising gases (WAGs) of various processes, steam generation in boilers from WAGs combined with natural gas to meet the steam demand of the site, and CO2 emissions from each process depending on the level of operation and the distribution of WAGs across different processes/plants.
- ◇ The main and secondary processes in the model represent the majority of the site's energy demand. A residual amount of electricity, energy/steam demand, and CO2 emissions are modeled as residuals via loads, simulating undefined or uncertain demands and emissions based on historical data. These residuals do not participate in the optimization process, but their contribution is important to ensure that the final results reflect the reality of the site more accurately.
- ◇ Each component/process has its own inputs and outputs. The optimizer determines the optimal production plan for each process to meet the final steel demand target by the end of the simulation horizon. A more detailed view of all the inputs and outputs considered in the model is shown in Figure 18. It is important to note that in reality, the materials consumed or produced by each process are far more numerous than those included in the model. In this work, only the main inputs of the different plants, energy-containing gases, CO2 emissions, steam, electricity, and natural gas are considered. The model focuses primarily on energy, using materials in such a way that their quantities and conversion factors create the main constraints for the steel production process.
- ◇ Each main process includes constraints related to its capacity and operational characteristics, which are defined through link components. These constraints, specific to the units of the site, include the nominal production capacity, the minimum and maximum operating levels (both above and below nominal capacity), the duration of the process (for batch processes or via the committable attribute), and the ramp-up and ramp-down limits of the plants.
- ◇ The cost inputs of the model include all materials or energy used to produce steel that have a market cost. The intermediate products produced on the site do not incur an additional cost, as both the initial material from which they were produced and the energy used in their production are already accounted for. The only profit stream in the model is the electricity generated from the site's WAGs and sold to the day-ahead market at the same price as the cost of electricity for each specific timestep, based on Tata Steel's projections.
- ◇ The time step for the simulation is set to 1 hour, which is a typical choice for such applications and allows the model to simulate yearly operations in reasonable timeframes. It is worth mentioning that electricity prices are also provided per hour from the day-ahead electricity market. However, many processes on the site would require much smaller time steps for accurate modeling. For example, a gas storage facility (gas holder tank) can be filled and emptied multiple times within one hour. For the purposes of this work, a 1-hour time step is deemed appropriate.
- ◇ Regarding the code of the model, it is divided into several key parts. Data regarding price inputs, the loads of secondary processes, and residual loads are loaded into the model via Excel files. The characteristics of each plant/process (e.g., nominal capacity or conversion factor) are stored in dictionaries. The site configurations are created using PyPSA tools and components, with the dictionaries being referenced to set the characteristics and constraints, as previously described. The configuration (or "network" in PyPSA terminology) is saved as a specific type of file (.nc). In the final operation of the code, this saved network is loaded and solved, setting the steel target and adding additional constraints and variables to the optimization problem that cannot be conveniently incorporated through PyPSA alone. This is one of the advantages of using PyPSA in combination with Linopy: it allows users to leverage PyPSA's capabilities to build the main optimization problem while also modifying the resulting optimization problem before sending it to the solver.
- ◇ The model does not account for maintenance planning of the plants, which, in reality, introduces additional complexity into the optimization process. For instance, if a plant must be shut down for maintenance, other processes that rely on it must adjust their operations accordingly. The model can still produce realistic results without considering maintenance by incorporating the nominal capacity of the plants, including maintenance periods, by using the plant's yearly production and calculating the average production per hour. The plant is then allowed to operate within a specific range above or below this average.

3.2 Current Configuration

After describing and explaining the main functions and assumptions of the model, as well as how we are using PyPSA components to build it, this section will outline the current configuration of the site.

As shown in the basic schematic of the current configuration (Figure 10) and the more detailed one (Figure 18), the model represents the typical Blast Furnace/Basic Oxygen Furnace (BF/BOF) configuration at the Tata Steel IJmuiden site. In this configuration, the core of the site consists of these two types of plants. First, the blast furnaces, which primarily receive pellets, coke, and sinter to produce hot iron and blast furnace gas (BFG) at their exit. The hot iron is then sent to the Basic Oxygen Furnace, which converts it into crude steel. This crude steel is further processed and coiled by the Hot Strip Mill (HSM) and Direct Sheet Plant (DSP) downstream.

At the exit of these two plants, the steel target is set for the total steel production, depending on the simulation horizon. Over the course of a year, Tata Steel IJmuiden has the capacity and license to produce around 7 million tons of steel. For this model, different targets can be tested (within the maximum capacities of the plants), but the base case target is set at approximately 6.2 million tons of rolled steel per year, in line with the actual production of rolled steel in 2022.

To complete the description of the main plants considered in the model, the Air Separation Unit (ASU) of Linde produces oxygen for both the BOF and the blast furnaces. Additionally, the ASU produces nitrogen for other purposes that are not directly related to Tata Steel, though these nitrogen demands are included as part of the site's overall electricity load.

To produce the materials required for the Blast Furnaces 6 and 7, such as pellets, sinter, and coke, several plants operate: Coking Plant 1 and 2, the Sintering Plant, and the Pelletizing Plant. These plants produce the necessary materials from raw inputs like coal and iron ore.

In Figures 10 and 18, we use specific color patterns to represent the PyPSA components that model the processes and operations of the site as a whole, as described in the previous section. The color scheme helps identify the components and their roles within the model:

- **Orange** represents Links in PyPSA, which are primarily used to describe processes like the main plants, boilers, mixing gas stations, and external generators.
- **Blue** is used for all material and energy flows in the system.
- The **outline color of buses** in Figure 18 distinguishes whether materials are generated or provided as costs using generator components (green outline) or are simply products of the processes (no outline).
- **Purple** outlines represent buses that correspond to materials or energy flows that can be stored, as they are connected to store components.
- **Red** is used to represent all residual loads of the site, such as residual steam, natural gas, and electricity. Residual CO_2 is represented as **green**, as it is added to the system using a generator component. This CO_2, along with the CO_2 produced by the processes, is stored and charged with a cost at a store component connected to the CO_2 bus, as previously explained.

Beyond the main processes, the model also tracks the gases produced and distributed across the site. Specifically, Coke Oven Gas (COG) produced by the coking plants, Blast Furnace Gas (BFG) from the blast furnaces, and Basic Oxygen Furnace Gas (BOFG) from the Basic Oxygen Furnace are considered in the model. These gases are tracked from their production points to their consumption points, which include the main plants, various boilers for steam generation, or the electricity generators of Vattenfall (IJmond01, Velsen-Noord 24, and Velsen-Noord 25).

It is important to note that the gas network system on site is complex. Mixing gas stations are configured to mix gases according to their actual Wobbe index, which is monitored in real time. Detailed specifications of the gas consumers (e.g., boilers, generators) are included, though the time step of the simulation (one hour) is not sufficient to fully track the gas system, as its dynamics are faster in reality. Since the focus of the model is not on optimizing the gas network itself but rather on tracking the basic flows, energy contained in these gases, and their economic impact, the gas network is simplified, as explained in another section.

As mentioned earlier, there are residual loads that are not included in the main processes and cannot be controlled by the optimizer. These residuals provide a more comprehensive view of the site's consumption and a better representation of the total marginal cost of steel production. These loads can be seen in the

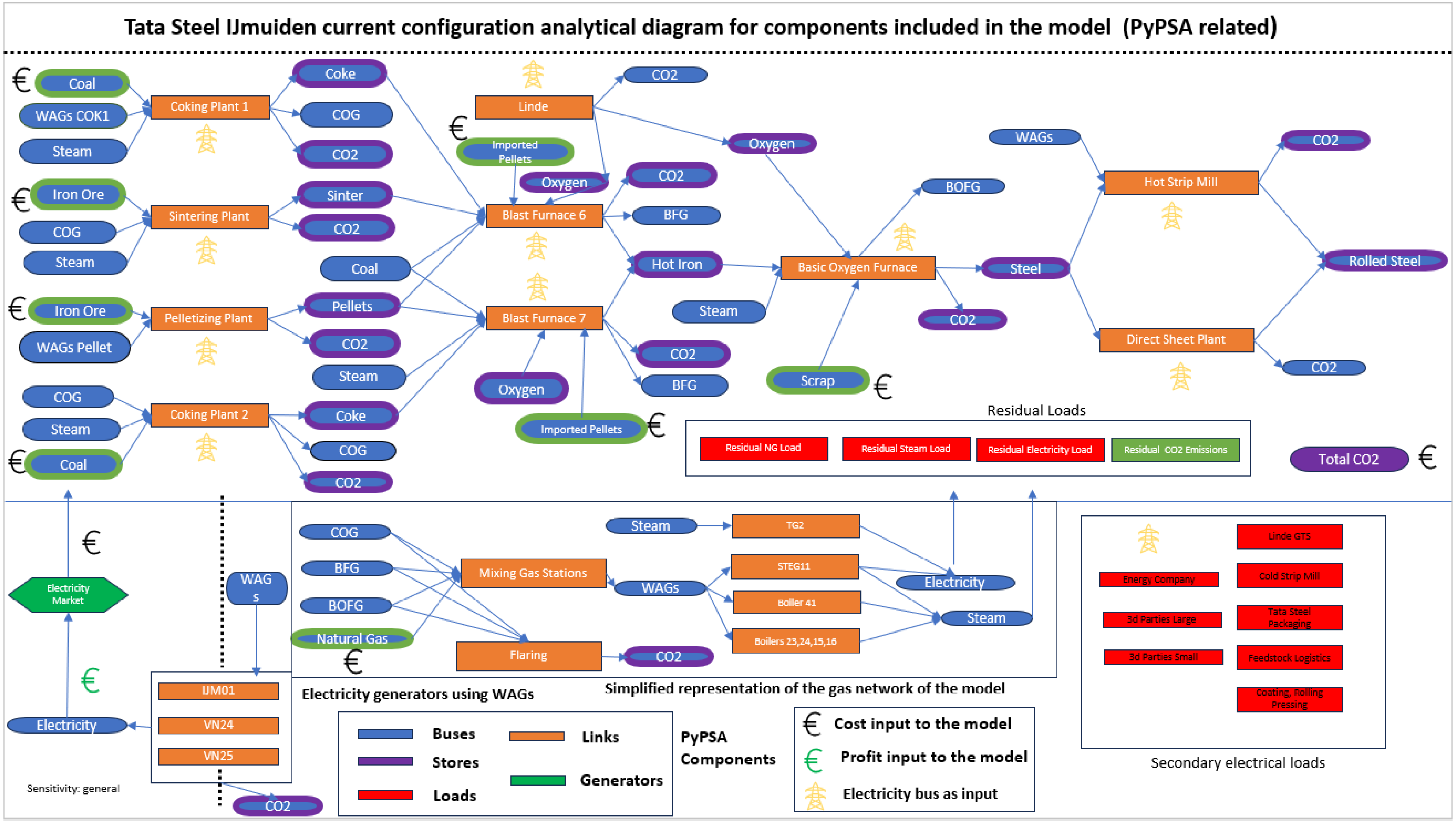

Figure 18: Schematic of the current configuration of Tata Steel's site in IJmuiden as Tata-Demoses model perceives it and represents it in PyPSA terminology.

lower right corner of Figure 18. CO2 emissions, an important aspect of the model and transition, are modeled as outputs from each main process, dependent on their operation level, using emission factor data for each plant. For secondary processes, residual CO2 emissions are applied based on real data from Tata Steel. Similarly, unspecified electricity and steam loads, not coming from the main processes, are treated as residual loads.

The cost inputs to the model, easily identifiable in Figures 10 and 18, include coal, iron ore, scrap, imported pellets (as the Pelletizing Plant capacity cannot meet the Blast Furnace demand), electricity, CO2 emissions, and natural gas. The gases directed toward Vattenfall's electricity generators create a profit stream for Tata Steel. This is considered in the model as the electricity generated from these gases, sold at the day-ahead market price, which is also assumed for the site's electricity consumption.

The site's heat demand is met by boilers, which produce steam using Work Arising Gases (WAGs), namely COG, BOFG, and BFG, in combination with natural gas. The model also includes the flaring of gases, which occurs when gas production exceeds the available consumption points. Flaring is considered a cost input to the model through the price of CO2. At certain time steps, flaring is unavoidable. In yearly simulations, since the optimizer has perfect knowledge of yearly prices, it may increase steel production during cheaper periods, resulting in higher WAG production that needs to be flared. This approach is still cheaper than reducing production without flaring. In reality, flaring typically occurs due to unforeseen circumstances, not as a strategic decision, as the model suggests. It is also important to note that while flaring is modeled as a cost, it is avoided in reality for other reasons, including social and environmental concerns.

To summarize the general description of the current configuration of the model, the system is built around the basic steps of the steel production process. With the steel target set and all plants operating within specific constraints to achieve this target in the most cost-effective way, the core of the system is defined. These processes consume energy (electricity, natural gas, WAGs) and emit CO2 based on their operational levels. The optimizer incorporates the costs of these inputs (energy, materials, and emissions) to find the optimal (cost-minimizing) solution for meeting the steel target while satisfying the constraints of the plants and the system.

3.3 Model Components

In this section, we describe the model components that represent various processes and plants in the real-world configuration, which were created using PyPSA. These components simulate the main processes relevant to the current configuration of Tata Steel's integrated steel plant, which this work is based on. By combining and linking the appropriate model components, a specific configuration can be created and analyzed by solving the associated optimization problem.

The main plants and networks, as shown in Figures 10 and 18, will be described in more detail in this section. First, we will focus on the main plants and their corresponding components. Additionally, we will explain the approach used to model the gas network, including the production and consumption of Work Arising Gases (WAGs) across the site and within the electricity generators of Vattenfall. Finally, the treatment of CO2 emissions, the concept of residual loads, cost inputs, and store components will be discussed in greater detail.

3.3.1 Main Plants

In this subsection, the ten main processes that the model considers will be described using PyPSA terminology, following the definitions provided in section 3.1. Specifically, we will describe the coking plants, sintering plant, pelletizing plant, blast furnaces, basic oxygen furnace, hot strip mill, direct sheet plant, and the Linde plant as Links in PyPSA terminology. Their inputs, outputs, and the types of parameters that are defined for each plant will be discussed here. Please note that the exact operational capacities, ramp limits, and conversion factors for each plant are sensitive and confidential data, which will only be shared with the thesis committee and cannot be published.

In PyPSA notation, the fundamental component used to design the main plants and include them in the model is the Link. A Link can have multiple inputs and outputs, which are referred to as Buses (a term borrowed from electricity grids terminology, as previously explained in section 3.1). In this work, we focus on the primary inputs and outputs of each plant, modeling them to operate in a manner similar to their real-world counterparts. This is achieved by using conversion factors to connect the main inputs (e.g., coal for the coking plants) with the outputs and secondary inputs (e.g., electricity).

In addition to the Buses representing the main inputs and outputs, and the conversion factors that connect them, PyPSA allows the definition of constraints regarding the conversion of inputs into outputs. For this model, we define the nominal capacity for each plant, which determines the rate at which the main input for a process can be consumed, and consequently, the rate at which outputs and secondary inputs can be produced or consumed through the conversion factors. In reality, the nominal capacity represents the average consumption rate of the main input for a specific plant.

Beyond nominal capacity, we also analyze operational data, such as electricity consumption patterns, to define an operating range within which the plant can operate. This range is typically derived using specific percentiles from the plant's operational data. This process will be explained in greater depth later in the work. By defining a nominal capacity and operational range, we set the operational characteristics for each plant. Additionally, we determine the ramp-up and ramp-down limits for each plant based on the rate at which it can adjust its operational level. These limits are derived from data on each plant's ramping behavior.

These are the basic parameters for all of the main plants in the model. An important feature of this model is its ability to be converted into a Mixed Integer Linear Programming (MILP) optimization problem. This is achieved by introducing binary variables to represent the on/off state of a specific plant, though not all plants require this. For example, the Electric Arc Furnace (EAF) in the new site configuration can be modeled as a plant that can turn on and off depending on electricity prices. This is activated using a True command at the specific link component for the EAF. However, not all plants in the configuration need to be modeled this way, as including binary variables for all links would increase the computational cost unnecessarily.

When binary variables are not used (i.e., the model remains as a linear program), the optimizer can adjust plant operation within the defined range based on production targets and cost constraints. However, the optimizer cannot shut down the plants completely unless zero operation is within the specified range of operation, based on the analysis performed for setting the operational ranges. The model can easily switch from an LP to an MILP, allowing for the inclusion of additional constraints like minimum startup times, minimum on-times, and other relevant parameters related to the startup and shutdown of plants (though these are typically more relevant for generators than for steel production plants).

As for the Electric Arc Furnace (EAF), it is a batch process. The plant processes a specified quantity of direct reduced iron and converts it into steel within about an hour. This requires the model to treat it as a committable unit, introducing binary variables to represent the on/off states, along with the minimum on-time to reflect the batch process duration.

For the current configuration, certain processes exhibit characteristics of batch operations, such as the smaller furnaces in the coking plants or the converters in the basic oxygen furnace. In reality, these devices are numerous, and modeling them as individual batch processes can distort the overall behavior of the plant when aggregated. For example, a coking plant may consist of 50 to 100 small furnaces where coal is converted into coke. Instead of modeling each furnace as a separate batch process, the coking plant is treated as a single process, with certain operational limits that reflect the plant's ability to adjust its total coke production. Similarly, for the basic oxygen furnace, the operators can shut down one of the furnaces, which leads to a reduction in production for that period, aligning with the operation range set for the BOF in the Tata-DEMOSES model.

In the following sections, we will present the different parts of the site and how they are modeled using PyPSA notation, starting with the main plants and progressing to the gas network, CO2 emissions, and other secondary systems. It is important to note that specific operational data for the plants, which are fed into the PyPSA components, cannot be published in this report due to their confidential nature, as they pertain to the real operation of the site. However, the reader can refer to similar values found in the following sources: He et al. (2017), Bieda et al. (2015), and Burchart-Korol (2013), which provide information on many of the core plants involved in the BF/BOF steelmaking route.

Coking Plants

The Tata Steel IJmuiden site operates with two coking plants: Coking Plant 1 and Coking Plant 2. Together, they have a combined production capacity of approximately 1.5 million tons of coke per year. During the site's energy transition, Coking Plant 1 will be decommissioned, leaving only Coking Plant 2 active during Transition Phase 1. After the phasing out of both blast furnaces in Transition Phase 2, both coking plants will be retired.

Coke, the primary output of the coking process, plays a crucial role in the conventional BF-BOF steelmaking route. It is used in downstream processes such as sintering, pelletizing, and ironmaking in the blast furnaces Liu et al. (2017). Coke oven gas (COG) is also an important byproduct of the coking process. Some COG is recycled back into the coking plants, while the remainder is used for electricity generation or heating due to its high calorific value He et al. (2017). In Tata Steel's IJmuiden configuration and within the model (as shown in Figures 19 and 20), Coking Plant 2 uses pure COG as input, whereas Coking Plant 1 uses a mix of work arising gases depending on availability.

While the coking process involves several complex sub-processes, this work focuses on the main mass and energy flows, rather than modeling or analyzing these sub-processes in detail. Specifically, the model aims to capture the realistic operational behavior of the coking plants within the broader Tata Steel system.

For modeling the coking plants in PyPSA, the approach described in the previous section is followed. While the two coking plants differ slightly in their characteristics and nominal capacities, they share many similarities. The model focuses on the main materials and flows: coal (as the primary input), coke, coke oven gas (COG), electricity, steam, CO2, and work arising gases (WAGs). A Link component in PyPSA is used to control the entire coking process, setting the conversion factors, range of operation, nominal capacity (in terms of the coal bus), and ramp limits. Figures 19 and 20 illustrate the design approach for the coking plants, showing the relevant buses, generators, and links. Some of these buses are linked to stores, while others cannot be stored. For a broader view, Figure 18 provides a zoomed-out perspective of the coking plants.

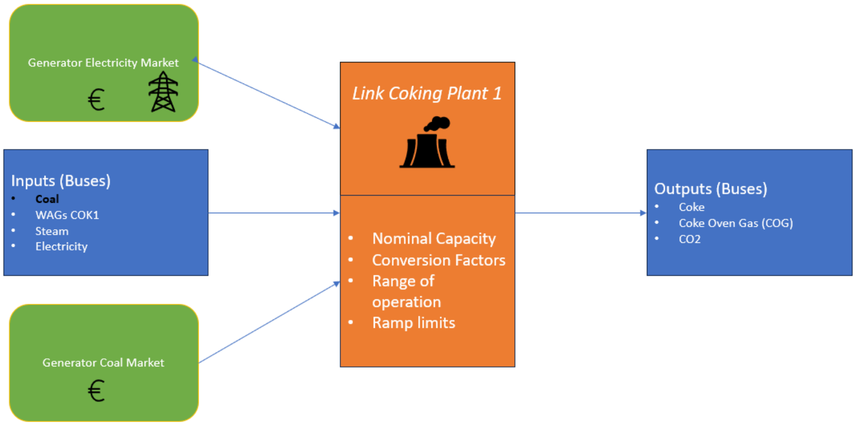

Figure 19: Coking Plant 1 PyPSA modeling approach

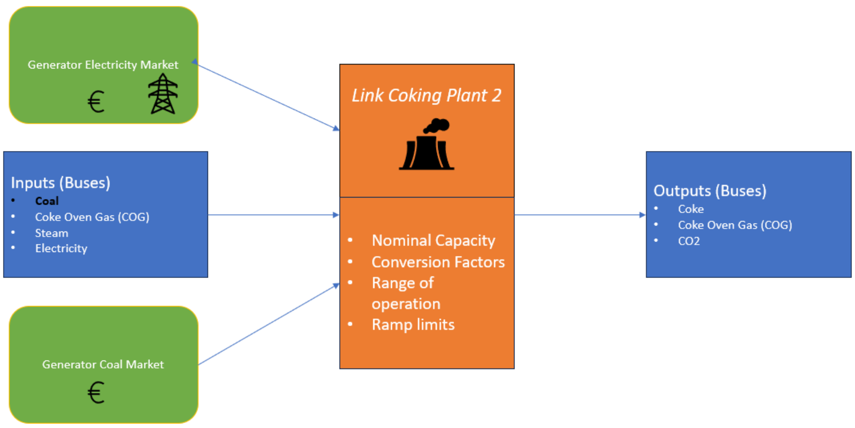

Figure 20: Coking Plant 2 PyPSA modeling approach

Sinter Plant

Following the same approach as for the coking process, a detailed analysis of the sintering process is beyond the scope of this work. The primary function of the sintering process is to convert weakly bonded granules into a partially fused, porous sinter cake that can be used in the blast furnace for ironmaking. Sintering is a complex process involving multiple phases, phenomena, and materials Venkataramana et al. (1998).

The description of the sintering process in PyPSA notation is illustrated in Figure 21. The main inputs considered for this analysis are iron ore (as the primary input, or bus0), electricity, coke oven gas, and steam. Both electricity and iron ore are modeled as Generator components to easily incorporate their marginal costs, as explained earlier. The outputs of the sintering process are sinter and CO2 emissions. Using the Link component, the nominal capacity of the plant is defined in terms of iron ore consumption per hour. Additionally, the range of operation around this nominal capacity is set, reflecting the plant's operational limits. Conversion factors between the main inputs, secondary inputs, and outputs are also specified. Finally, the ramp limits, derived from historical operational data, are incorporated into the Link components.

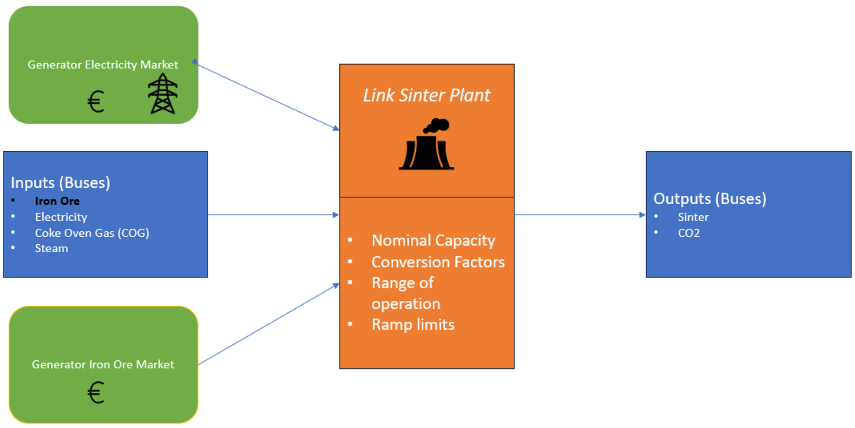

Figure 21: Sinter Plant PyPSA modeling approach

Pelletizing Plant

The pelletizing process is an integral part of the steelmaking operations at the IJmuiden site. Iron pellets, or simply pellets, are used in both the BF-BOF and the alternative DRP/EAF routes for iron-making. During the pelletizing process, iron ore fines are converted into spherical agglomerates known as iron ore pellets, typically a few millimeters in diameter. While the pelletizing process involves numerous sub-processes and inputs, this work focuses only on the key materials that are important for the model. Specifically, we highlight the two primary stages of the process: the initial mixing and grinding stage (referred to as Malerij for the specific plant) and the subsequent firing and indurating stage (Branderij). These stages are differentiated because different types of Work Arising Gases (WAGs) are used at each stage, and this distinction is reflected in the model. The main inputs, outputs, and modeling approach of the pelletizing plant in PyPSA are illustrated in Figure 22.

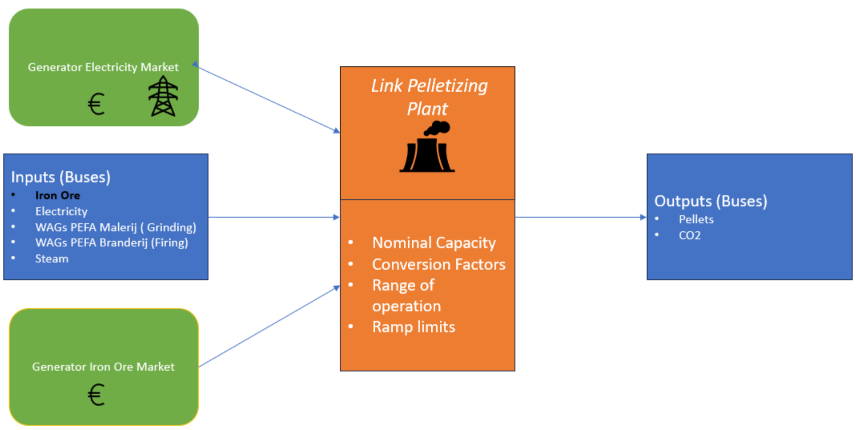

Figure 22: Pelletizing Plant PyPSA modeling approach

Blast Furnaces

Tata Steel's IJmuiden site currently operates two Blast Furnaces: Blast Furnace 6 and Blast Furnace 7. These blast furnaces are central to the BF-BOF steelmaking route, where they convert key materials such as coal, coke, pellets, and sinter into hot iron, which is then transported via torpedo cars to the Basic Oxygen Furnace (BOF) for steel conversion. The blast furnaces are significant contributors to the site's CO2 emissions, not only due to the combustion process but also because of the Blast Furnace Gas (BFG) they produce. This gas is directed either into boilers or electricity generators. Moreover, the upstream processes that supply materials to the blast furnaces—such as coking and sintering—are also major CO2 sources. Should the blast furnaces be decommissioned, these upstream processes will cease to exist as well.

To facilitate the site's decarbonization efforts, Blast Furnace 7, the largest of the two, will be decommissioned first during the initial phase of the transition, followed by the retirement of Blast Furnace 6 in the second phase.

The operation of a blast furnace involves supplying raw materials like coke, pellets, and sinter from the top of the furnace, while a hot blast of air enriched with oxygen is introduced from the bottom. This creates various reactions throughout the furnace. The hot metal and slag are tapped from the bottom, and waste gases (Blast Furnace Gas) exit from the top. The primary reaction within the blast furnace is the chemical reduction of iron oxides by the carbon monoxide from the combustion gases (produced by coke burning) to form elemental iron.

Figures 24 and 25 illustrate the modeling approach of the two blast furnaces at the IJmuiden site in PyPSA. An overview of both furnaces can also be seen in Figure 23.

Figure 23: Blast Furnace 6 (left) and Blast Furnace 7 (right), which is going to be decommissioned first during the transition phase at the site of Tata Steel in IJmuiden, the Netherlands. Combined they can produce more that 650 tons of Hot Iron per hour.

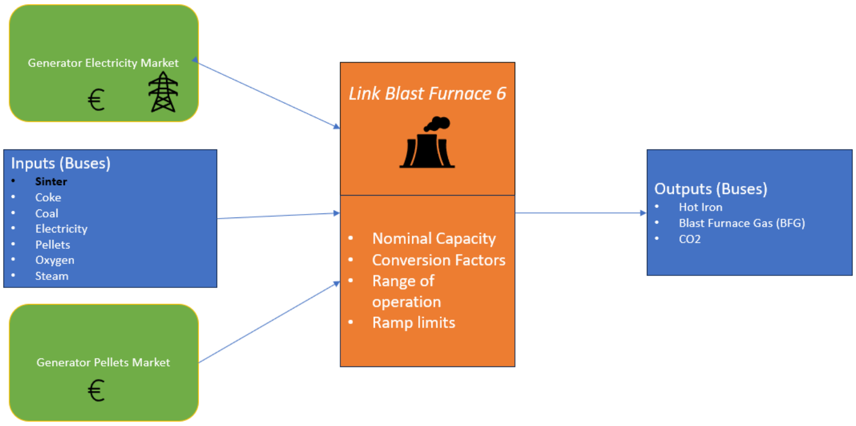

Figure 24: Blast Furnace 6 PyPSA modeling approach

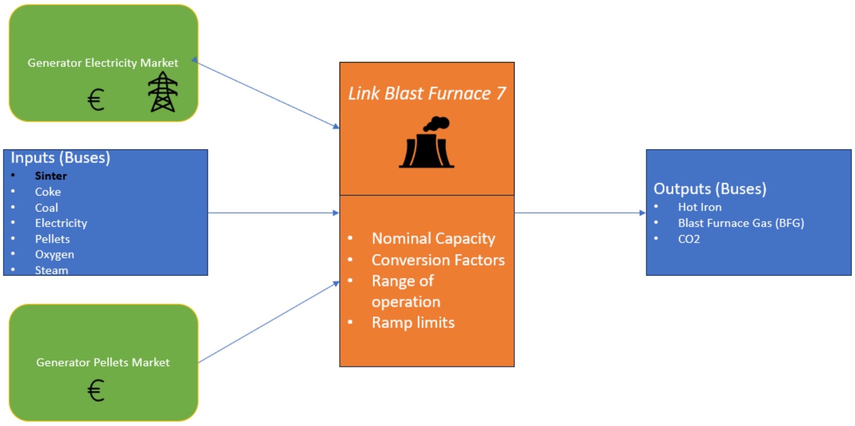

Figure 25: Blast Furnace 7 modeling approach

Basic Oxygen Furnace

The Basic Oxygen Furnace (BOF) is a crucial process in an integrated steel plant like Tata Steel's IJmuiden site. The process, known as basic oxygen steelmaking or Linz-Donawitz steelmaking, aims to convert high-carbon hot iron (or pig iron) from the blast furnaces into low-carbon steel. This is done by blowing pure oxygen at high pressure through a lance over the molten iron alloy inside the converter. The primary chemical reaction in the BOF is the oxidation of carbon in the hot iron to form CO and CO2. This oxidation process generates heat, which also melts the scrap added to the ladle, along with the hot iron. The ratio of hot iron to scrap is critical for the process, but for the purposes of this study, we will assume a typical constant ratio derived from Tata Steel's scrap consumption data.

The modeling approach for the BOF in PyPSA is illustrated in Figure 26. The main input is hot iron, while secondary inputs include oxygen, electricity, steam, and scrap. The outputs of the process are steel, basic oxygen furnace gas (BOFG), and CO2. The Link component in the model is used to represent the plant's constraints and settings, determining the nominal capacity, conversion factors between inputs and outputs, and the range of operation. Additionally, the ramp limits for the plant are based on the historical operational data of the BOF.

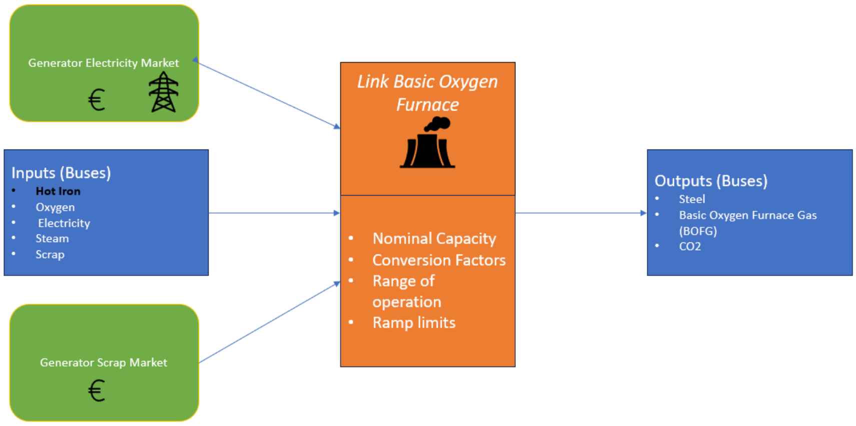

Figure 26: Basic Oxygen Furnace modeling approach

Hot Strip Mill

The hot rolling process in the Hot Strip Mill is a critical step towards the final stages of steel production. Crude steel, which comes from the Basic Oxygen Furnace (BOF) and casters in the form of slabs, ingots, blooms, or billets, enters the Hot Strip Mill. The steel passes through several mills, such as roughing and finishing mills, at high temperatures (above its recrystallization temperature) to shape and reduce its dimensions according to the final product requirements. To achieve the necessary temperature for rolling, the steel slabs are reheated in furnaces to temperatures above 1000°C. This is an energy-intensive process, and efficiently managing the hot steel slabs exiting the casters is crucial for optimizing energy use. The rolling mills themselves also consume significant amounts of energy, primarily in the form of electricity. After shaping, the steel is cooled under controlled conditions, as cooling plays a critical role in determining the steel's properties. At the end of the process, the steel sheets are either coiled or cut, depending on the final product requirements. The inputs and outputs of the Hot Strip Mill in the model are shown in Figure 27.

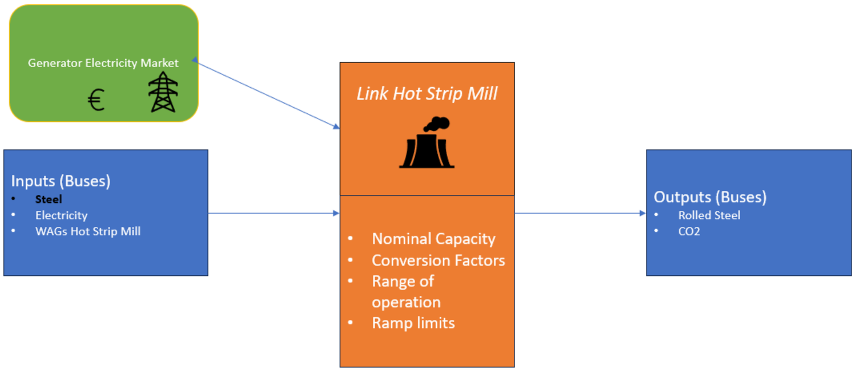

Figure 27: Hot Strip Mill modeling approach

Direct Sheet Plant

A Direct Sheet Plant (DSP) is an alternative and more efficient process for producing hot rolled or cold rolled steel, similar to the Hot Strip Mill. At the IJmuiden site, both the Hot Strip Mill and the DSP produce hot rolled steel, with the DSP contributing approximately 20

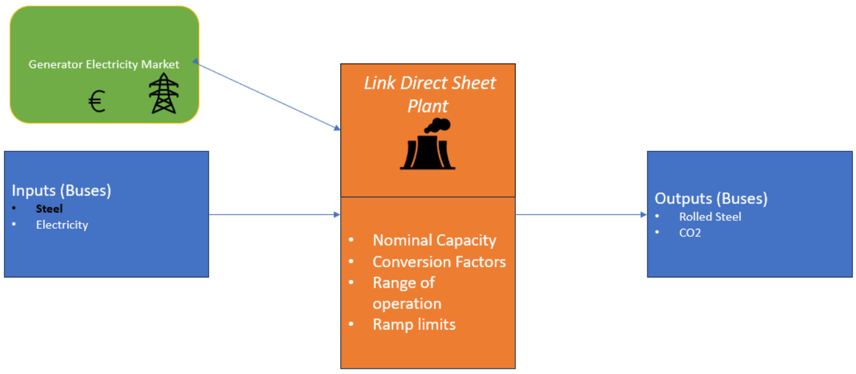

Figure 28: Direct Sheet Plant modeling approach

Linde Oxygen Plant

The Tata Steel site in IJmuiden requires large quantities of purified oxygen, rather than air, for the operation of both the blast furnaces and the Basic Oxygen Furnace (BOF). Pure oxygen enhances the efficiency of the reactions occurring within these plants. The site's oxygen demand is approximately 150 tons per hour, which is why an air separation unit (ASU) by Linde is present at the site. This unit produces pure oxygen by cooling the air to very low temperatures, liquefying the gases, and separating them. Due to the energy-intensive processes involved in compressing and cooling large volumes of gas, the Linde plant is one of the largest electricity consumers at the site.

In the model, we represent the electricity consumption of the Linde plant used for oxygen production, as shown in Figure 29. To maintain consistency with the site's total electricity consumption, we also include the plant's electricity load for non-steel-related processes, such as nitrogen production, which is modeled as a varying electrical load based on historical data. Additionally, for oxygen storage, we assume a storage limit based on the physical infrastructure at the site, which is discussed further in the Stores section.

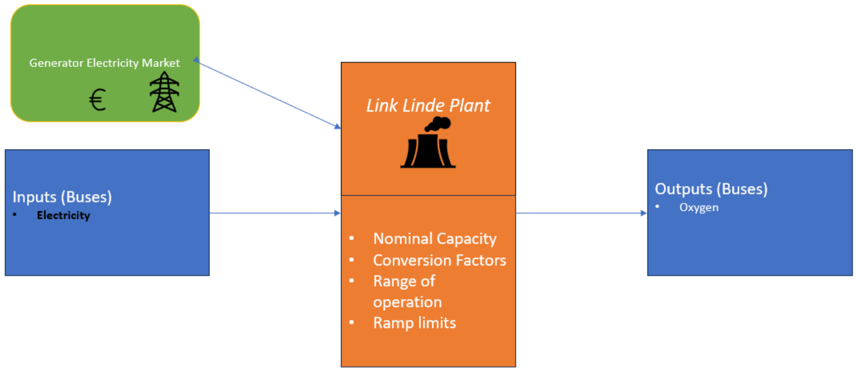

Figure 29: Linde Plant modeling approach

3.3.2 Gas Network

Referring back to Figures subsection 3.2 and Figure 18, it becomes evident that the gas network plays a crucial role both in the real Tata Steel site and in the Tata-DEMOSES model. While a detailed analysis of all gas flows on the site is outside the scope of this work, understanding the primary production and distribution of gases is essential for a comprehensive view of the site as an energy system.

To simplify the gas network in this model, we focus on tracking the production of key gases and their consumption points across the site. The optimization is primarily driven by cost minimization in steel production and the heating value requirements of the consuming processes. While aspects such as Wobbe index requirements, gas heating value fluctuations, maintenance of various boilers, backup operations, and the separation of steam networks under different pressures are not included, the basic concept of optimizing the distribution of gases among boilers, generators, and main plants remains intact. Additionally, the model accounts for gas flaring when consumption points cannot absorb the produced gases at specific time steps.

The gases produced, particularly from the blast furnaces, the oxygen furnace, and the coking plants, are integral to the steel production process. These gases—such as Blast Furnace Gas (BFG), Coke Oven Gas (COG), and Basic Oxygen Furnace Gas (BOFG)—are energy carriers that can be combusted to produce steam in various boilers or electricity through Vattenfall's generators designed for this purpose. By including these gases in the model, we can track CO2 emissions and better understand the impacts of the site's transition. As certain plants that currently produce these gases will be decommissioned in future configurations, this will lead to a reduction in available gases for heat and electricity generation.

This shift is critical in the context of the energy transition. As integrated steel sites move towards decarbonization, they will increasingly depend on external energy markets, such as electricity and natural gas, rather than being self-reliant on coal and iron ore prices. The electrification of processes further amplifies this shift, making the industry more susceptible to fluctuating electricity, natural gas, or even hydrogen prices. This fundamental change in the steel industry, driven by the transition, is a key outcome of this work.

In reality, the gas network at the site is complex. WAGs are continuously produced, with quantities varying based on plant operations. Gas properties, such as the Lower Heating Value (LHV) or Wobbe index, may change depending on input quality (e.g., coal or natural gas) or the site's operation strategy. These properties are monitored in real-time, and gases are mixed in gas stations across the site to meet the specific needs of the consuming processes. For example, the Pelletizing Plant uses BOFG or natural gas for initial grinding of iron ore. Besides being used in primary processes, these gases are also utilized to generate steam in the site's boilers and electricity in external generators.

Optimizing the flow and use of these gases involves balancing the operation of critical steel production processes, generating electricity to sell to the grid, and matching gas production with consumption. Due to limited storage capabilities (and no gas storage in the model), minimizing flaring becomes essential. Flaring occurs when excess gases cannot be utilized and must be burned off. It is an undesirable process because of its environmental impact (CO2 emissions) and the associated costs. Although these gases can generate energy for the site, the challenge lies in aligning production and consumption in real-time, making flaring a common occurrence at industrial sites like this one.

For modeling the gas network, we aim to capture its key functions in a simplified manner. The model includes the production of gases, their mixing based on process requirements, electricity and heat generation, and flaring, but excludes the detailed physical infrastructure such as gas stations and piping systems. Only constraints on the minimum and maximum gas consumption at each point are modeled, as illustrated in Figure 30.

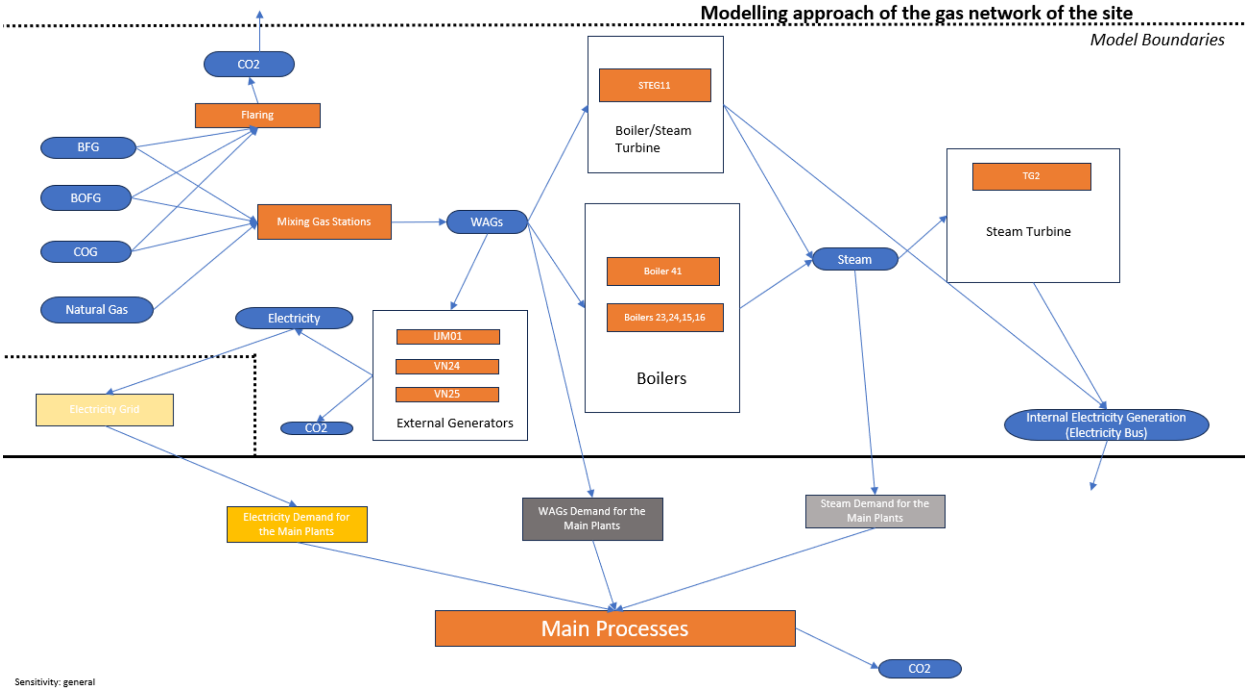

Figure 30: Gas Network of the site as it is modeled in PyPSA

In Figure 30, Work Arising Gases (WAGs) are distributed across various processes, with the primary consumers falling into three categories: external electricity generators, main plants, and internal boilers for steam or electricity generation. Now, let's focus on the approach this model takes to describe how WAGs are distributed among these consumption points.

Work Arising Gases Consumption of the Main Plants

The Work Arising Gases (WAGs) are consumed by several of the site's main plants, adding complexity to the distribution and optimization process. The optimizer and the site's operator must decide whether a certain quantity of produced gas should be consumed at a specific plant, mixed with other gases for electricity generation, or flared. For the main plants that can consume WAGs or natural gas, the schematic of the modeling approach for this decision-making process can be seen in Figure 31.

The plants that can consume either a single type or a mixture of WAGs and natural gas are Coking Plant 1, Hot Strip Mill, and the Pelletizing Plant for its two main subprocesses. In Figure 31, a brief description of the decision-making process for the mixing gas stations of each plant is provided. The PyPSA color coding, as we've designed it, still applies: orange represents link components like the mixing gas stations, and blue represents buses. The heating values of the different WAGs and natural gas used in this model are listed at the top right of the schematic, reflecting the typical heating values used at the site.

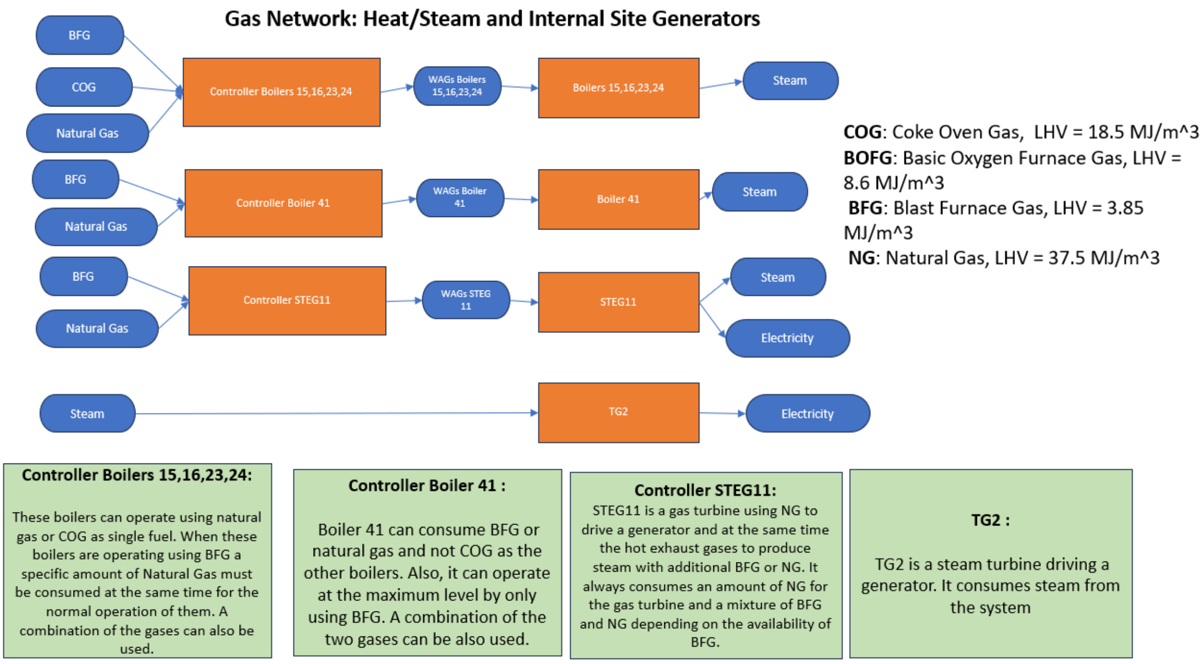

Figure 31: The gas network modeling approach of the consumption of Work Arising Gases by the main plants of the site

In the model, each controller shown in Figure 31 is represented by a link component. In reality, these controllers are constructed in PyPSA using multiple link components, depending on the inputs required for each process. For example, the controller for the Hot Strip Mill is represented by two separate links. One link has Coke Oven Gas (COG) as its input and outputs WAGs for the Hot Strip Mill (WAGs HSM), while the second link has Natural Gas as its input and also outputs WAGs HSM. The conversion factors between the inputs and outputs differ for the two links.

In the first case, the conversion factor between COG and WAGs HSM is 1. In the second case, the conversion factor between Natural Gas and WAGs HSM is 37.5/18.5, reflecting the fact that the heating value of natural gas is higher. This means that to satisfy the Hot Strip Mill's energy demand using Natural Gas, we would need 37.5/18.5 less of it than COG. This approach assumes that the WAGs demand at the Hot Strip Mill is expressed in terms of COG.

This modeling approach is applied to all of the mixing gas stations in the system.

Steam Demand and Boilers

Another key use of the Work Arising Gases (WAGs), in combination with Natural Gas, is their distribution across the site's boilers. These boilers are responsible for ensuring the generation of steam, which is vital for meeting the site's steam demand. The real site features different types of boilers and steam networks, each operating at different pressures. In addition, extra steam production is provided as a backup in case of system failures. To optimize and minimize costs, the boilers are operated based on specific strategies depending on their characteristics and the overall production status of the site.

In the model, we approach the boilers as illustrated in Figure 32. Each main boiler is modeled with its unique characteristics, including capacity and its ability to consume various types of gases. The steam demand is determined by the operational levels of the plants and the residual steam demand of the site, which is assumed to be constant. With this data, the optimizer selects which boilers to operate and at what levels to meet the steam demand.

It is important to note that we do not apply ramp limits for boiler operation in the model. Instead, we assume that one-hour time steps are sufficient for the boilers to ramp up or down within their full operational range.

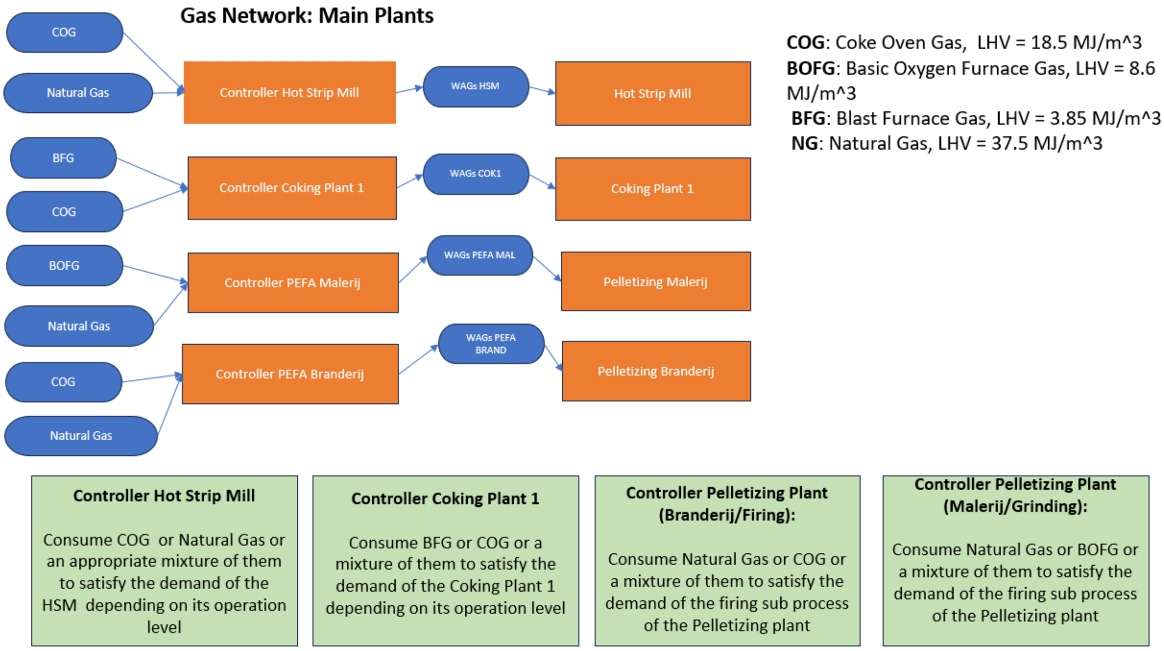

Figure 32: The gas network modeling approach of the consumption of Work Arising Gases by the boilers of the site to satisfy the steam demand of the site

In this subsystem, part of the larger model for the site, we represent links and buses using the same color. The controllers shown here consist of two or three combined links, each converting gas into the appropriate Work Arising Gases (WAGs) mixture. This mixture is adjusted based on the heating values of the gases, resulting in a combined heating value that satisfies the demand of the connected boiler link (e.g., WAGs Boiler 41). The boiler link operates at a specific level to supply the steam required by the various processes on the site, each operating at its designated level to optimize steel production.

This illustrates how the operation of a single boiler is interconnected with the overall optimization of the entire site. A summary of the characteristics of the boilers included in the model can be found in Figure 32.

Electricity Generators Consuming Work Arising Gases

Another key component of the model, and the final major part of this complex gas network, is the gases directed to the external Vattenfall generators. Three generators are located near the IJmuiden site: IJmond01, Velsen-Noord 24, and Velsen Noord 25, with a combined electricity generation capacity of around 1GW. However, Velsen-Noord 24 (VN24) serves as a backup and does not operate under normal conditions. The other two generators, IJmond01 (IJ01) and Velsen Noord 25 (VN25), run depending on the availability of gases, electricity market prices, and the contracts between Tata Steel and Vattenfall.

In this study, we do not investigate the optimal operation of these generators or the details of the contracts between Tata Steel and Vattenfall, such as the responsibility for emissions, the profit from electricity generation, or whether Tata Steel is required to provide a minimum quantity of gases. Instead, we model these generators as part of the system, capable of consuming a specific amount of gases within heating value limitations and generating a profit stream through electricity market prices.

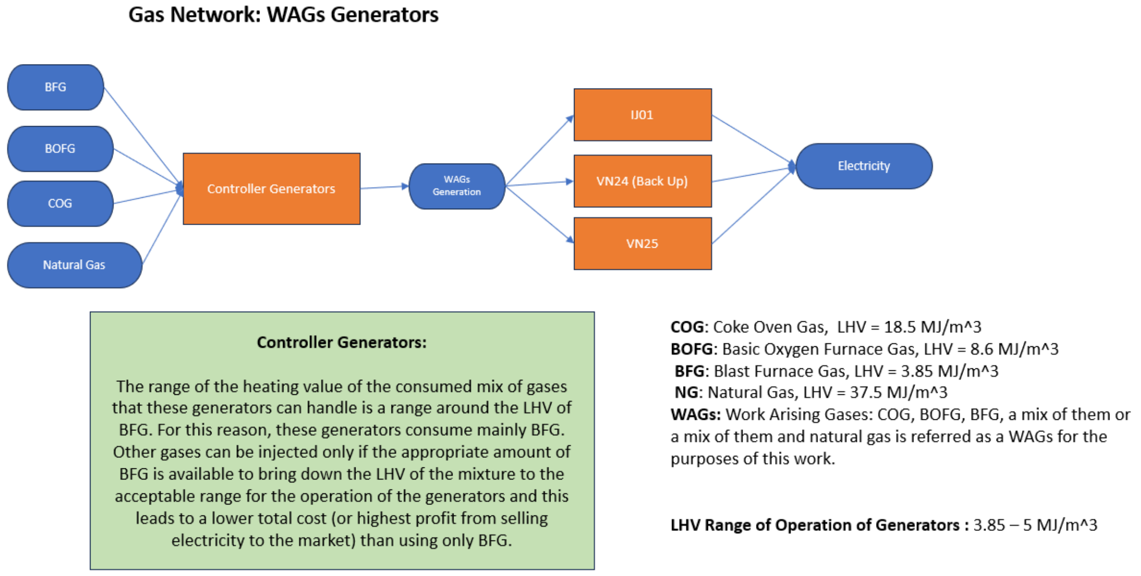

Figure 33: The gas network modeling approach of the consumption of Work Arising Gases by the generators of Vattenfall to generate electricity and provide it to the grid.

A common practice for such generators is that they are designed to run on Work Arising Gases (WAGs) from the steel industry. For this reason, they can operate using gases with characteristics (Heating Value, Wobbe Index) similar to those of Blast Furnace Gas (BFG), which is typically the most abundant gas produced at a steel site. The way we model this process is shown in Figure 33.

In reality, the main controller consists of four links, which convert different gases into a mixture that can be processed by the generator links. For instance, we express the conversion factor between the WAGs mixture and the electricity generated at the generator link in terms of BFG. In this case, the link converting BFG into WAGs has a conversion factor of 1, while the link converting Coke Oven Gas (COG) into WAGs for generation has a conversion factor of 18.5/5. This accounts for the fact that the upper heating value limit of the mixture is 5 MJ/m^3.

This approach is a useful modification to simulate the flexibility of generators in accepting a range of heating values. While BFG's heating value is defined at 3.85 MJ/m^3, when converting other gases into WAGs for generation, we allow the injection of higher heating value gases, up to 5 MJ/m^3. This provides flexibility in the operation of the generators, reflecting their ability to handle gas mixtures with varying heating values.

3.3.3 CO2 Emissions

CO2 emissions are a crucial parameter in the model. It is essential to track these emissions for each configuration of the site in order to gauge the effectiveness of each phase in meeting the emissions reduction goal. As previously explained, the links representing the main plants, as well as secondary processes such as boilers or WAGs generators, always include a bus for CO2 as an output. By using a store PyPSA component to accumulate the CO2 outputs from the various processes and applying a cost for each unit of CO2 emitted, we can represent the total emissions in the model. Additionally, a CO2 generator is included to account for residual emissions from processes that are not modeled as links but still exist, based on data from the site (e.g., emissions from the coal grinding process).

This approach ensures that the CO2 emissions are accurately represented in PyPSA, providing a numeric output of the total CO2 emissions for each configuration. The cost of CO2 emissions is based on the price of carbon under the European Trading System, with projections for future prices derived obtained by Tata Steel.

One of the key performance indicators for the environmental aspects of a steel site configuration is the ratio of CO2 emissions per ton of steel produced. This will be one of the outputs from the model. Another important metric is the cost of CO2 abatement, which reflects the additional cost of steel production per ton of CO2 reduced for each transition configuration. The results for these indicators will be provided in the results section.

In the following Figure..., the representation of CO2 emissions in terms of PyPSA modeling is explained.

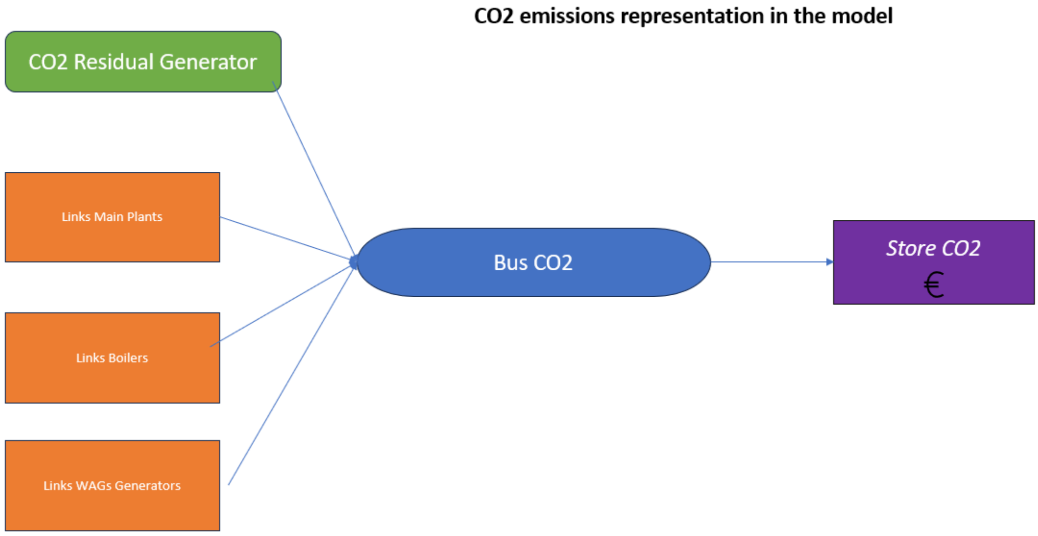

Figure 34: CO2 emissions representation in the model using PyPSA components

3.3.4 Cost Inputs

As previously discussed, the cost inputs of the model are represented by generator components in PyPSA. These generator components simulate the market prices for various flows, assigning a marginal cost to each unit of consumption from the site. For instance, coal is used in the current configuration at both the coking plants and blast furnaces. To model this, we create a generator named Coal Market, which can supply coal to the system at a specified price. By linking processes like the links and connecting them to a specific bus (in this case, a bus called "Coal"), we ensure that each unit of coal passes through the generator and is distributed to the plants consuming it. This distribution is assigned the appropriate marginal cost.

This approach simplifies the tracking of the total marginal cost of operating the entire site, eliminating the need to formulate the marginal cost function at each individual point. We use generator components for electricity, natural gas, iron ore, scrap, imported pellets, coal, and hydrogen in future configurations. The only exception is the CO2 cost, which, as explained in the previous section, is modeled using a store component.

The profit stream from the WAGs generator is introduced into the model by assigning a negative marginal cost to the corresponding link components that represent these generators. This effectively reflects the revenue generated from WAGs in the model.

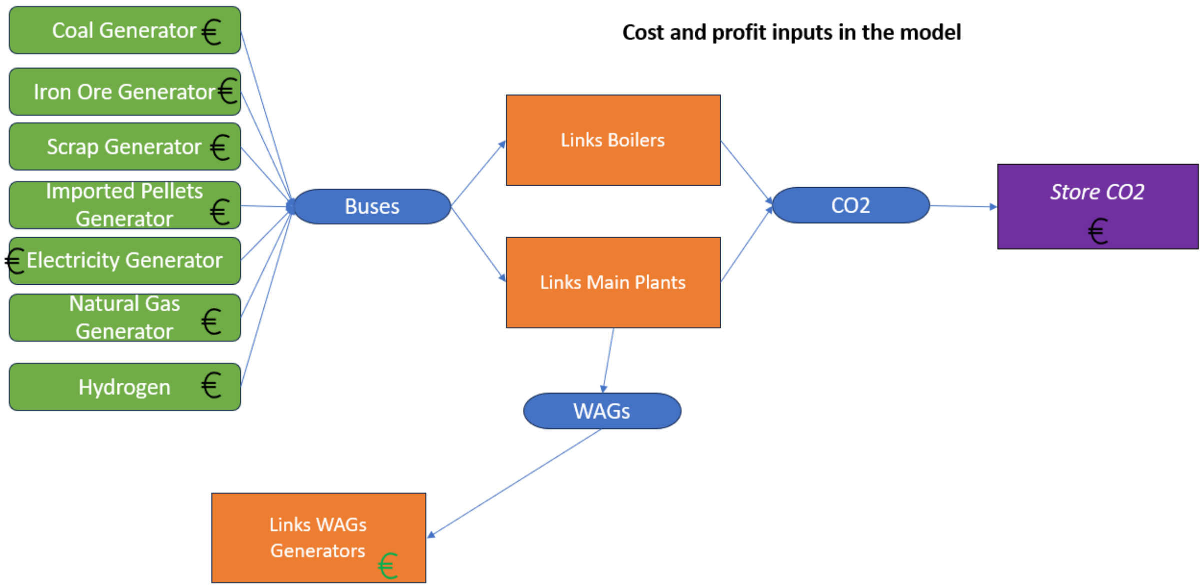

Figure 35: The cost inputs of the model using PyPSA components

The exact values of the costs used in this work cannot be provided in the public version since they are confidential. For the committee version of this report details are presented in the Appendix.

3.3.5 Other Residual Loads

As previously mentioned, load components play a significant role in our model within PyPSA. At the Tata Steel IJmuiden site, there are various consumption points for electricity, steam, and natural gas that are not represented by specific links. There are two key reasons for this:

1. **Complexity and Scope:** Representing every process on such a large site is impractical for a master's thesis project, both in terms of time and computational cost.

2. **Relevance to Optimization:** Including every minor consumption—whether large, small, constant, or varying—would not necessarily influence the main optimization decisions. For example, constant electrical loads like lighting, or natural gas consumption for heating non-production buildings, would not affect steel production and thus do not need to be included as links.

The decision to model a consumption point as a link or as an external load in the optimization problem depends more on the available data and the role of the process in steel production rather than the quantity consumed. For instance, the Linde plant, which consumes around 45 MW of electricity unrelated to steel production, is modeled as an **electricity load**. This means these 45 MW must be supplied by the electricity market generator, contributing to the marginal cost of the optimization. While this electricity use isn't directly related to steel production, accurately representing the site's energy consumption is essential for proper optimization.

A useful rule of thumb for deciding whether to model a process as a link or load is to examine whether the process provides inputs or consumes outputs tied to the main processes. If it does, it's modeled as a link; otherwise, it's represented as a load.

In Figure 18, the different types of residual loads are illustrated:

- **Small boxes** on the bottom right represent electrical loads modeled as constant values for each time-step (typically average yearly values).

- **Larger boxes** represent electrical loads with hourly time-series data available, capturing varying consumption over time.

3.3.6 Store Components and Storage Constraints

Coming to the store components of the model, the logic behind their use has already been explained in Section 3.1, where the role of the store components is described. Store components are typically used for materials to represent the real situation at the site. For example, materials like coke or sinter can be stored infinitely, but hot iron cannot be stored in such a way due to its molten condition and the limiting capacity of the torpedo cars. Store components allow the designer to set limitations on the amount of storage allowed at each time step for each material.

Other storage limitations are used for slabs being stored on-site. Even though the physical space is large and the theoretical storage capacity is undefined, we impose a limitation in the model to avoid unrealistic storage solutions. Additionally, slabs come out hot from the BOF and the casting process, and it is beneficial to have a limitation for storing them in the model, as we do not account for the energy losses due to these slabs cooling, which would result in additional costs. However, the storage limitation for slabs is less strict compared to that for hot iron.

We also use store limitations for the oxygen produced by Linde. A noteworthy case is the storage of WAGs. On-site, there are large storage units for produced WAGs, functioning as buffers to help with the complex distribution system of gases described earlier. However, since the quantities of produced gases are so large, these gas holders can be filled many times within an hour. Given that the time step for the simulation is set to 1 hour, we do not allow the storage of WAGs and thus do not create store components for the different WAGs or the mixture of WAGs buses. These buses must be balanced between consumption and production at each time step.

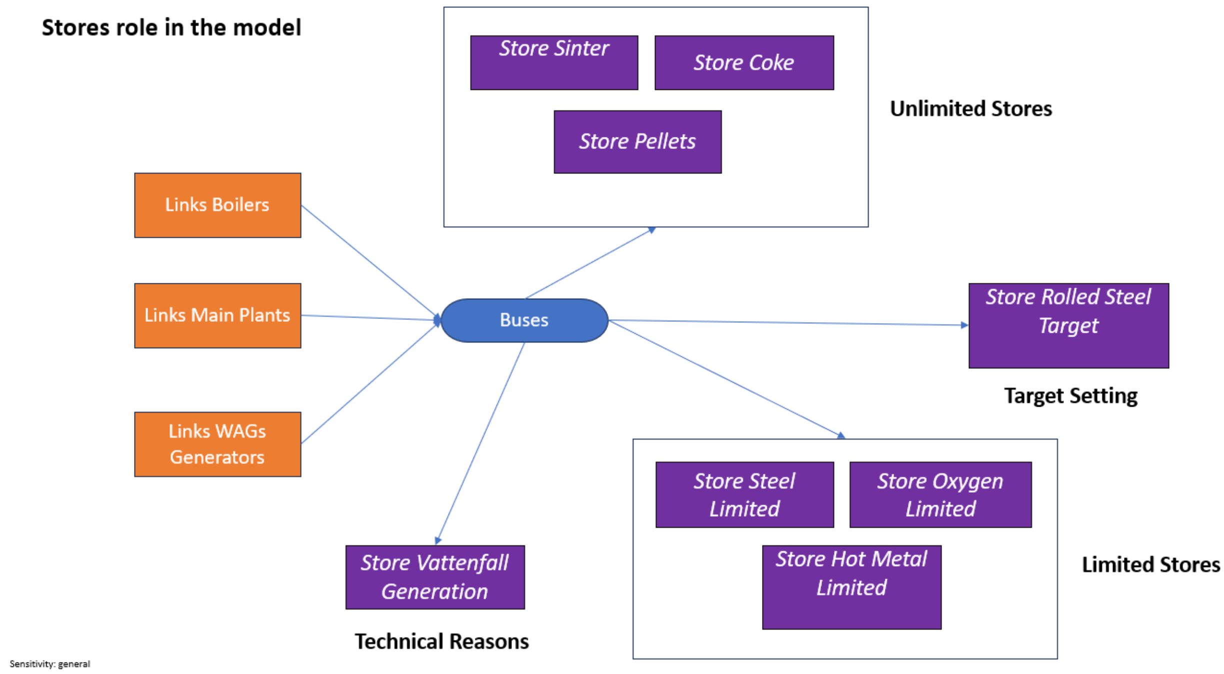

Figure 36: The role of store components of PyPSA in the model

We are using store components for all of the site's materials except the work arising from gases and the materials provided by generator components. For example, there is no need for the coal bus to have a store component connected since the coal generator provides the appropriate amount of coal depending on the demand at each time step. In Figure 36 we can see the model's different uses of the store components. There are materials stored with no restrictions or upper limits and materials stored with specific limitations. A store component is also used to set the final steel target for the simulation. Stores are also used in some instances to direct specific buses that have no other consumption points in this model. For example, the electricity generation from the WAGs generation is stored toinare a specific store since buses need to be balanced and need to be directed somewhere.

Figure 37: One of the Gas Holders of the site in IJmuiden that is used as a buffer for short-time storage of Coke Oven Gas

3.4 Mathematical Formulation of the Optimization Problem

In this section, we revisit the analytical diagram of the model to explain the mathematical formulation of the optimization problem using optimization terminology. PyPSA automatically generates the objective function and constraints of the optimization problem, provided that the user correctly configures the necessary components and connects them to form a feasible optimization setup, as detailed in previous sections.

Since the simulations in this study are primarily conducted on a yearly basis—occasionally on a monthly basis—with an hourly time step, the problem involves a large number of variables for each plant or process on-site. This necessitates careful computational cost management. Binary variables are used only where strictly necessary, as their excessive use significantly slows down the solution process, especially for yearly simulations.

Although PyPSA constructs the main optimization problem, we modify the objective function by incorporating additional constraints and variables through the Linopy library before solving the problem. This allows us to introduce specific functionalities to the model. For instance, factors such as network costs based on the highest monthly and yearly peak power consumption or the steel production target at the end of the simulation period are more efficiently integrated as additional constraints within the objective function rather than being simulated using PyPSA components—an approach that may even be infeasible. This flexibility highlights a key advantage of the selected modeling approach in PyPSA.

Optimization Problem

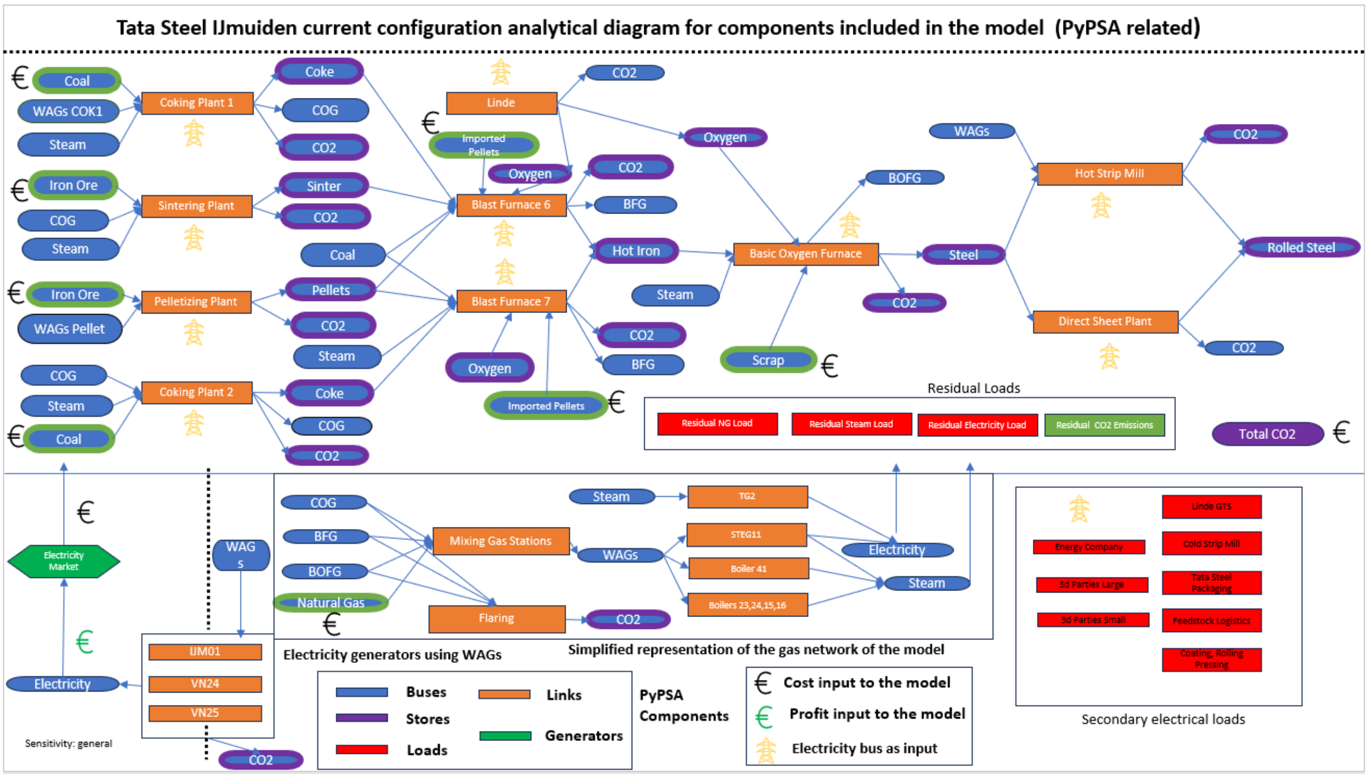

Figure 38: The flow diagram of the current configuration model of the site for explaining the main variables and constraints of the optimization problem.

As we can see in Figure 38 and as we have explained in previous sections, the main decision variables of the problem are the operation level of all the main plants and also of the boilers, turbines, and electricity generators working with WAGs or natural gas; shortly the decision variables are coming from the link components used to represent the different processes of the site. Generators supply inputs to the links at a cost creating the cost multipliers in the objective function, while stores set constraints regarding the quantity of certain materials that can be stored and restrict also the operation of the links depending on the available quantity of a material. Loads are not controlled by the optimization but do set constraints for the operation of the different links, and buses are responsible for maintaining the balance of the whole system and per bus.

The key factor and constraint "pushing" this whole system to operate towards steel production optimally, is the steel target that is set at the end of the main process chain. Hot Rolled Steel produced by the Hot Strip Mill and the Direct Sheet Plant has to be equal or larger than the specific target of the site for the simulation horizon. This target forces the main plants to operate and produce the materials for this final steel target with given constraints and conversion factors for each plant. The operation of the plants produces work arising gases, CO2, and demand for electricity, natural gas, and steam. It is part of the optimization to find the optimal operation pattern of the plants and the other processes of the site like the boilers and the generators to minimize the cost of steel production.

Decision Variables

The optimization problem can be expressed differently depending on the point of view. For example, PyPSA creates variables to track the storage level of a store component for each time step. These variables are not considered decision variables in an optimization problem mathematical terminology since they are not multiplied directly with a cost to create the objective function of the problem. In the way that the model is built in PyPSA, link variables are also not part of the objective function since the only costs are introduced through generator components and only in 2 cases through a link and a store (WAGs generation and CO2 emissions). In this section, we will express the objective function as a sum of processes' operation levels multiplied by specific costs related to these processes to make the problem more clear. However, we need to mention that the real expression of the objective function in PyPSA could be different. Both approaches lead to the same objective value but differ in the definition of the decision variables, since PyPSA calls variables both the parameters and the decision variables of the problem and here these two are distinguished. Here we are defining our main decision variables P_{it} as the operation level of all the link components of the site i and for all of the time steps of the simulation t. We are also defining a cost coefficient for each one of these links C_{it} at the form of a vector derived from the sum of the cost of the input buses of this link per time step.

For example for Coking Plant 1, the main input or bus0 is coal. The only decision variable regarding Coking Plant 1 is the $\mathbf{P_{CokingPlant1t}}$ variable which shows the amount of coal (tons) being consumed by the Coking Plant 1 for a specific time step (hour). All the other inputs or outputs of Coking Plant 1 are connected with this decision variable through the conversion factors set for the link Coking Plant 1. For example, for a specific amount of coal consumed for an hour, a specific amount of coke is going to be produced and a specific amount of CO2 will be emitted. In the same way, the steam demand and the Work Arising Gases demand for this amount of coal consumed are known and also the COG produced and the electricity demand are set once the optimizer has decided on the optimal operation level of the plant. This does not mean that these parameters do not participate in the optimization problem, the optimizer is also considering the parameters and the costs that are related to them via the cost coefficient that we introduced and since all these parameters become a part of the objective function of the problem.

So every process or link controlled by the optimizer has one decision variable. The main processes of this model are the ten main plants colored with orange in Figure 38, also the steam and internal electricity components TG2, STEG11, Boiler 41 and Boilers 23,24,15,16, the mixing gas stations of the model as we have described them in section 3.3.2 that decide on the amount of each gas that is going into the mixture at each time step and also the external electricity generators of Vattenfall IJ01, VN24 and VN25 that the optimizer adjust their operation level depending on the market situation and the availability of gases.

I am not considering the operation level of the Generator components of PyPSA with which I am modeling the cost inputs of the model as decisions variables since the cost coefficients C_{it} which we are using for every link include these cost inputs from the generators. The level of operation of them is determined by the demand of the main processes. The generators are only there to assign the cost at each unit of material consumed by the model as a whole. For example for the coal demand, a PyPSA Generator "Coal Market" having a marginal cost equal to the coal price, is assigning a cost at each unit of coal that is being consumed by whichever process of the model. For the formulation of the mathematical problem is easier to consider the generators' levels of operation as parameters and assign a cost function at each main process depending on its inputs and outputs. To use the same example again, Coking Plant

1, the coal used ,the CO2 produced and the electricity demand are assigned with a cost, so the cost function of this link component will look like:

$$\begin{aligned}\text{Total Cost of Coking Plant 1} = &\left(\text{Cost of Coal}_t \cdot P_{\text{coking1},t}\right)\\ &+ \left(\text{Cost of Electricity}_t \cdot P_{\text{coking1},t} \cdot \text{Conversion Factor}_{\text{coal to electricity}}\right)\\ &+ \left(\text{Cost of CO2}_t \cdot P_{\text{coking1},t} \cdot \text{Conversion Factor}_{\text{coal to CO2}}\right)\end{aligned}$$

Where the cost coefficient is the cost of each material or flow for the specific time step, the P_{it} represents the level of operation of the Coking Plant 1 (decision variable) in terms of coal consumption (bus0) and the conversion factors are the parameters that connect the coal consumption with the electricity demand or the CO2 emissions as we have explained extensively in this work for the link components. The same approach applies for all of the processes that this model considers through link components.

At this point we are defining the decision variables of this optimization problem in the way that we have discussed:

- $\mathbf{P_{it}}$: Operation level of process/link i at time step t.
  i: the plants/processes/links of the site for the production of steel, the boilers and the electricity generators. t: the time step of 1 hour
- $\mathbf{u_{it}}$: Binary variable indicating if plant/link i is on (1) or off (0) at time step t. Binary variables are generally not used in the modeling approach for reasons that are explained in the bullet points regarding model functionalities and also at the constraints explanation section. Binary variables are only used for modeling the Electric Arc Furnace after transition phase 1.

Parameters

As parameters we are considering all of the variables that are part of the optimization problem but are not the decision variables.

- Annual Steel Target: The hot rolled steel target of the site: **AST** (tons)
- Cost function coefficients (vectors) of each main process/link depending on the inputs and the outputs of each process. These cost coefficients contain information about the value of the cost inputs of the model per time step: $\mathbf{C_{it}}$ (€/unit of cost input)
- Nominal capacity of the plant or process or link. The nominal operation level of the process that is the statistical average consumption or production of the plant according to historical data or the actual nominal capacity of a process that historical data are not available, for example boilers. $\mathbf{P_{inom}}$ (unit of main bus)
- Max power of plant or process. The maximum operation level above the nominal capacity of the plant coming from historical data of the plant operation: $\mathbf{P_{imax}}$ (as a percentage of the nominal capacity)
- Min power of plant or process. The minimum operation level below the nominal capacity of the plant coming from historical data of the plant operation: $\mathbf{P_{imin}}$ (as a percentage of the nominal capacity)
- Ramp up limit of the plant i, obtained from historical data: $\mathbf{RU_i}$ (percentage of the nominal capacity of the link)
- Ramp down limit of plant i, obtained from historical data: $\mathbf{RD_i}$ (percentage of the nominal capacity of the link)
- Store levels of materials or gases or other parameters in the model: For the materials that can be stored and specific limitation can apply: $\mathbf{S_{jt}}$ (unit of the bus of the store component) j: the materials for example, coke or sinter.
- Store level change per time step: $\mathbf{S_{pjt}}$ (unit of store bus per time step), can be negative or positive
- Stores maximum limit (Where applicable): $\mathbf{S_{jtmax}}$ (unit of the bus of the store component)

- Conversion factors: The relation between the main input and the other inputs and outputs of a process/plant: $\mathbf{CF_{bus0bus(1:k)}}$ (-), where k is the number of buses that a link has.
- Residual electricity load: $\mathbf{RES_{elt}}$ (MW per time step)
- Residual natural gas demand: $\mathbf{RES_{ngt}}$ (m^3 per time step)
- Residual steam demand: $\mathbf{RES_{stt}}$ (tons per time step)
- Residual CO2 emissions: $\mathbf{RES_{co2t}}$ (tons per time step)
- Generators components level per time step: $\mathbf{G_{it}}$ (unit of generator bus)
- Generators maximum capacity: $\mathbf{G_{itmax}}$ (unit of generator bus), applicable only for the electricity market generator due to the maximum capacity of the connections between the grid and the site. For example $\mathbf{G_{Electricitytmax}} = 500MW$ for the current configuration.

Objective Function

Minimize the total cost of steel production:

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} C_{it} P_{it}$$

Constraints

Ensure that the consumption of each plant does not exceed the stored inputs of it for every time step:

$$P_{it}t \leq S_{jt}, \quad \forall i, t, j$$

related with each process

Ensure that the production of each plant does not exceed the storage limits of its outputs for every time step:

$$P_{it}t \leq S_{jtmax}, \quad \forall i, t, j$$

related with each process

Meet the annual steel target:

$$AST \leq \sum_{t=1}^{T} S_{jt} \leq 1.05 * AST,$$

where j = final rolled steel store at $t = T$. An overproduction of more than 5% is not allowed due to legal restrictions for the total steel production.

Range of operation of the plants:

$$P_{imin} \leq P_{it} \leq P_{imax}, \quad \forall i, t$$

Ramp up limit

$$P_{it+1} - P_{it} \leq RU_i, \quad \forall i, t$$

Ramp down limit

$$P_{it} - P_{it+1} \geq RD_i, \quad \forall i, t$$

Storage Limits

$$S_{jt} \leq S_{jtmax}, \quad \forall j, t$$

for the materials that are subjected to storage limitations like Hot Iron coming out of the BFs due to the torpedoes capacity.

Storage Level Change

$$S_{pjt} \leq S_{jt}, \quad \forall j, t$$

Generator Components Maximum Capacity

$$G_{it} \leq G_{itmax}, \quad \forall i, t$$

applicable only for the electricity generator component

Cyclic Storage Levels

$$S_{jt=0} = S_{jt=T}, \quad \forall j$$

Flows balance via buses

For every bus k:

$$G_{kt} - L_{kt} + P_{kt} + S_{kt} = 0, \quad \forall k, t$$

For every bus of the system the sum of the generation, the consumption in load components, the production or consumption at the links and the storage in the stores should be zero for every time step.

PyPSA/Linopy variables, constraints and objective function

In the following Figures, 39 and 40, we can see how we can access the variables, the constraints, and the objective function of our problem in Python. As we have explained there are differences in the way that Linopy creates the problem based on the components of PyPSA. In this terminology variables or constraints noted with snapshot are variables or constraints per time step so the designer needs to know that adding one of them is adding an extra variable or constraint per time step of the simulation and this can increase the computation time significantly. In Figure 39, the last two constraints are examples of constraints that we have introduced to the problem via Linopy and are not coming from the PyPSA network. They are the constraints for the final steel target.

```
Linopy LP model
===============

Variables:
----------
 * Generator-p_nom (Generator-ext)
 * Store-e_nom (Store-ext)
 * Generator-p (snapshot, Generator)
 * Link-p (snapshot, Link)
 * Store-e (snapshot, Store)
 * Store-p (snapshot, Store)

Constraints:
------------
 * Generator-ext-p_nom-lower (Generator-ext)
 * Generator-ext-p_nom-upper (Generator-ext)
 * Store-ext-e_nom-lower (Store-ext)
 * Store-ext-e_nom-upper (Store-ext)
 * Generator-fix-p-lower (snapshot, Generator-fix)
 * Generator-fix-p-upper (snapshot, Generator-fix)
 * Generator-ext-p-lower (snapshot, Generator-ext)
 * Generator-ext-p-upper (snapshot, Generator-ext)
 * Link-fix-p-lower (snapshot, Link-fix)
 * Link-fix-p-upper (snapshot, Link-fix)
 * Link-fix-p0-ramp_limit_up (snapshot, Link-fix)
 * Link-fix-p0-ramp_limit_down (snapshot, Link-fix)
 * Store-fix-e-lower (snapshot, Store-fix)
 * Store-fix-e-upper (snapshot, Store-fix)
 * Store-ext-e-lower (snapshot, Store-ext)
 * Store-ext-e-upper (snapshot, Store-ext)
 * Bus-nodal_balance (Bus, snapshot)
 * Bus-meshed-nodal_balance (Bus-meshed, snapshot)
 * Store-energy_balance (snapshot, Store)
 * Final_Total (Store)
 * Upper_Bound_Constraint (Store)
```

Figure 39: The variables and the constraints of the problem for the current configuration as Linopy perceives them through PyPSA components.

```
Objective:
----------
LinearExpression: +63.2 Generator-p[2025-01-01 00:00:00, Electricity_Market] + 98.8 Generator-p[2025-01-01 00:00:00, Coal_Ma
rket] + 120 Generator-p[2025-01-01 00:00:00, Iron_Ore_Market] ... +0 Store-e_nom[Hot_Rolled_Steel_Store] + 0 Store-e_nom[Ele
ctricity_Vattenfall_Store] + 0 Store-e_nom[CO2_Store]
Sense: min
```

Figure 40: The objective function of the problem in Python.

The objective function in Linopy is created by multiplying all of the variables (Linopy defined) by a cost and trying to minimize this expression as we can see in Figure 40. To make the optimization problem more clear and follow the way of thinking to build this model, we kept a different definition distinguishing between parameters and decision variables in the previous section. However, both objective functions have the same minimum value at the end.

Network Tariff Modification

Until now, we have not addressed additional costs associated with the site's electricity expenses. Beyond the cost of electricity per MWh from the day-ahead market, significant costs arise from the use of the transmission and distribution network. This work explores the impact of these network tariffs.

Network tariff structures vary across the world, depending on national policies and agreements between network operators and governments. These agreements determine how operators charge electricity consumers for services such as grid expansion, maintenance, and reliability. In the Netherlands, TenneT **?** serves as the Transmission System Operator (TSO) and is responsible for charging large high-voltage consumers network tariffs. Each year, these tariffs are determined through discussions between TenneT and the Dutch energy regulator, ACM.

In general, network tariffs in the Netherlands fall into two main categories:

- **Connection Tariffs** – These cover the costs of initial grid connections or the replacement of existing ones.
- **Transmission Tariffs** – These are based on actual electricity consumption and grid usage. Transmission tariffs include both fixed components, such as administrative costs, and variable components that depend on the consumer's use of the grid.

The specific tariff scheme applied to Tata Steel is explained in the following section. It is worth noting that network tariffs in the Netherlands represent a significant cost for large industries. Moreover, they are among the highest in the region compared to countries like Germany, France, and Belgium, as highlighted in the report by E-Bridge (2024). According to the same source, network tariffs in the Netherlands are expected to rise further due to the need for grid expansion, driven by large offshore wind projects and congestion in many areas of the country.

The pricing scheme for Tata Steel's site is based on a combination of monthly and yearly capacity fees. Each month, the site's peak demand is recorded and charged at a specific tariff rate. Additionally, on a yearly basis, the highest peak demand across the entire year is charged at a higher tariff rate.

This scheme is illustrated in Figure 41, which presents a hypothetical yearly demand curve. In the figure, the peak consumption for each month is highlighted in green. The highest peak demand of the year, which is subject to the higher annual tariff, is marked in red.

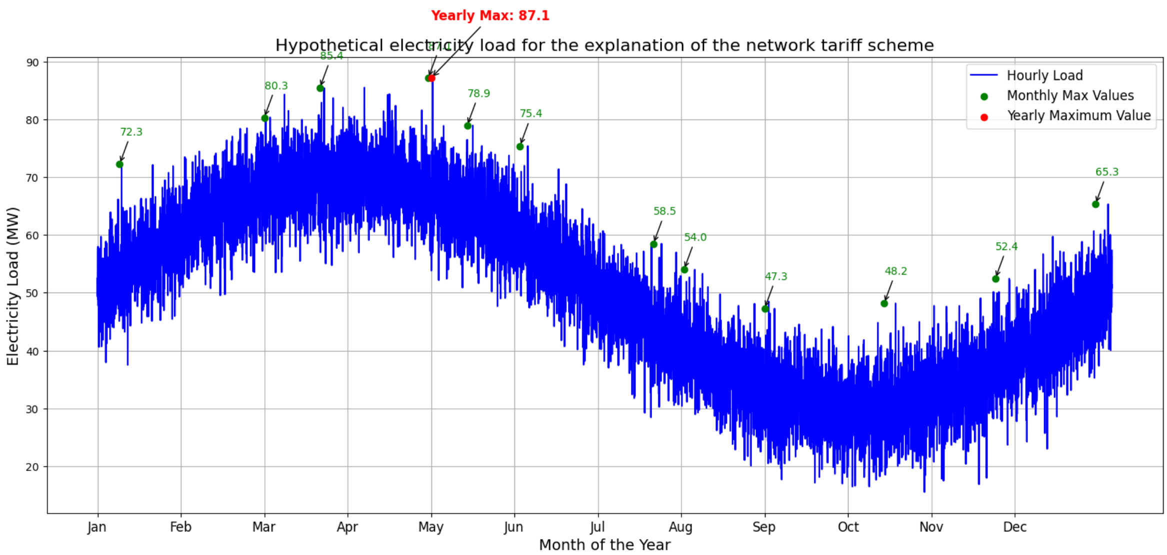

Figure 41: A hypothetical yearly demand curve where monthly and yearly maximums are identified

This network tariff scheme can be mathematically expressed as:

$$\sum_{i=1}^{n=12} a \cdot x_i + b \cdot y$$

where a is the lower tariff coefficient for the monthly maximums, and b is the higher tariff coefficient for the yearly maximum. The variables x_i represent the 12 maximum consumption values for each month, while y represents the yearly maximum consumption.

. Incorporating this equation into our optimization problem is challenging because the maximum values are not known a priori; they are part of the optimization itself. To address this, we intervene in the objective function using Linopy by introducing new variables to store these maximum values.

The process involves iteratively building constraints for every time step in the simulation. At each step, we compare the electricity consumption of the site (or, in terms of PyPSA, the electricity market generator component) with the previously recorded maximum. If the current consumption exceeds the previous value, it is stored as the new maximum. This procedure is repeated monthly to capture the maximum for each month. At the start of a new month, the process resets.

While effective, this approach is computationally intensive, primarily due to the large number of additional constraints it introduces into the optimization problem. However, within the context of this work, the increased computational time is acceptable as it allows us to explore the impact of network tariff costs on the site's behavior and its transition strategies.

Figure 42 illustrates the new created variables and how the network tariff scheme is integrated into the optimization problem using Linopy.

```
Linopy LP model
===============

Variables:
----------
 * Generator-p_nom (Generator-ext)
 * Store-e_nom (Store-ext)
 * Generator-p (snapshot, Generator)
 * Link-p (snapshot, Link)
 * Store-e (snapshot, Store)
 * Store-p (snapshot, Store)
 * max_power_part1
 * max_power_part2
 * max_power_part3
 * max_power_part4
 * max_power_part5
 * max_power_part6
 * max_power_part7
 * max_power_part8
 * max_power_part9
 * max_power_part10
 * max_power_part11
 * max_power_part12
 * overall_max_power
```

Figure 42: The variables of the model after the addition of the network tariff scheme.

Referring back to the objective function introduced in the previous section, the updated objective function incorporating the network tariff scheme can be expressed as follows:

$$\min\left(\sum_{i=1}^{I}\sum_{t=1}^{T} C_{it}P_{it} + \sum_{i=1}^{12} a\cdot x_i + b\cdot y\right)$$

As we have explained, C_{it} are the cost coefficients of each link component. P_{it} are the operation level of each link, a is the low tariff coefficient for monthly maximums and b the higher one. x_i and y represent the monthly and yearly maximums respectively.

Due to confidentiality constraints, we cannot disclose the exact values of the aa and bb coefficients. However, the coefficients used in this study are those currently applicable to Tata Steel. Notably, the ratio between bb and aa is approximately an order of magnitude (10:1).

3.5 Transition Configurations

Until now, we have described the current configuration of the site, its components, and how the model operates based on this configuration. Shifting focus to the decarbonization pathway of the site, this section outlines the proposed transition configurations, which are defined by the CO2 reduction targets they aim to achieve.

There are three transition configurations or phases. The current configuration will remain operational until 2030. Phase 1 will be active from 2030 to 2037, Phase 2 from 2037 to 2045, and Phase 3 will commence in 2045 and continue thereafter.

Details of the three transition configurations are provided below. The CO2 reduction targets for these phases are as follows:

- Phase 1: 30–40 % reduction
- Phase 2: 60–70 % reduction
- Phase 3: 90–100 % reduction (with 100 % achievable only through the use of CCUS).

3.5.1 Phase 1

In this phase, the goal is to reduce CO2 emissions by 30–40 % compared to the current configuration. The reference year for this configuration in the model is set as 2030, although it is more likely that these changes will occur gradually rather than abruptly in a single year. For the purposes of this work, however, the year 2030 is used for energy costs and other predictions.

The key changes in this configuration compared to the current one are as follows:

- Shutdown of Blast Furnace 7 and Coking Plant 1: This will result in reduced Work Arising Gases (WAGs) production, impacting profits from electricity generation and increasing reliance on natural gas for the boilers of the site.
- Introduction of new plants: An Electric Arc Furnace (EAF) and a Direct Reduction Plant (DRP) using natural gas will be installed. These changes will lead to increased electricity and natural gas consumption.
- Market exposure: Dependence on the electricity and natural gas markets becomes more significant due to reduced electricity generation from WAGs and simultaneous increases in electricity and natural gas consumption.
- Final processes: Processes after crude steel production will remain unchanged. However, sintering production will decrease due to reduced demand from the single remaining blast furnace. The pellets consumption previously associated with the decommissioned Blast Furnace 7 will now be replaced by the new DRP plant.

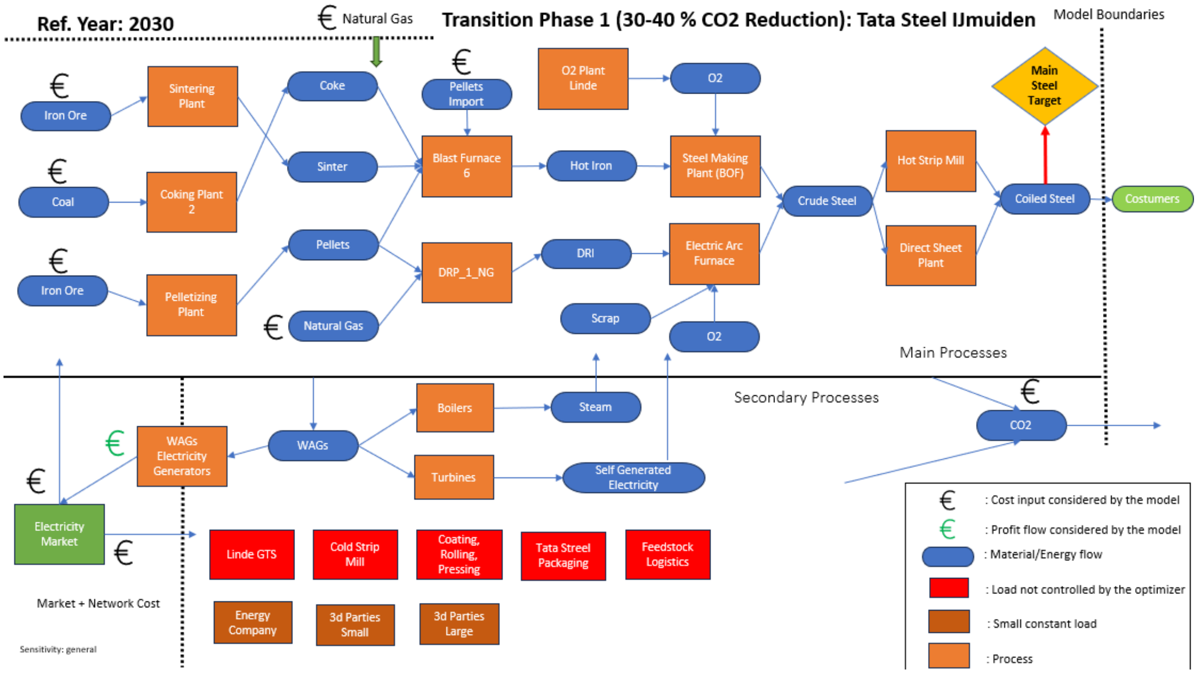

Figure 43: Transition Phase 1

3.5.2 Phase 2

In Phase 2, with the reference year set as 2037, the second blast furnace and the second coking plant will also be shut down, resulting in an approximate CO2 reduction of 70 %. Steel production will proceed through two parallel lines:

- Direct Reduction Plant (DRP) to Smelting Reduction Furnace (SAF) and then to Basic Oxygen Furnace (BOF).
- DRP to Electric Arc Furnace (EAF), continuing from Phase 1.

One DRP will still rely on natural gas, while the other will use a mix of hydrogen and natural gas. This is due to challenges in securing sufficient hydrogen quantities and the maturity limitations of hydrogen DRI technology. Even at the hydrogen DRP plant, a significant amount of natural gas will still be consumed.

Work Arising Gases (WAGs) will be limited to Basic Oxygen Furnace Gas (BOFG) for internal consumption, and the electricity generators will remain unused since the gas volumes, primarily BFG, will no longer be sufficient. Consequently, the site will be fully exposed to the electricity market, as there will no longer be surplus electricity generated for sale to the grid using WAGs.

The remaining small quantities of BOFG and SAFG gases are expected to be used internally, primarily by the main plants such as the Pelletizing Plant. This assumption is reflected in the model.

Steam demand will be reduced since the blast furnaces will no longer be operational. It will be met by boilers using either natural gas or electricity, depending on their relative costs.

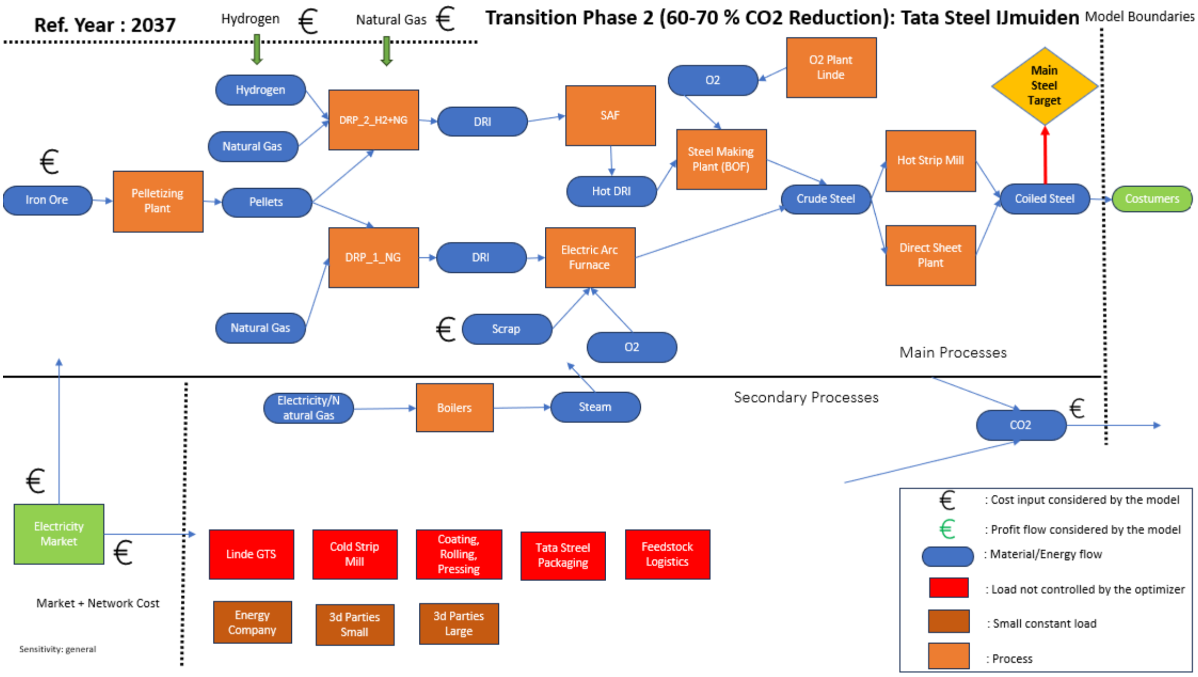

Figure 44: Transition Phase 2

3.5.3 Phase 3

In this third phase, a low-CO2 steelmaking configuration is achieved, with an approximate 90 % reduction in emissions. This configuration is similar to the previous one, but both Direct Reduction Plants (DRPs) operate with a high ratio of hydrogen, and the boilers are fully electric.

Despite these advancements, there remain low levels of CO2 emissions due to the use of natural gas and the operation of certain plants, such as the pelletizing plant. Technologies required to make the site entirely carbon-neutral are not assessed in this work. However, a scenario involving the use of electrolyzers is explored based on this configuration in the concluding sections of this work.

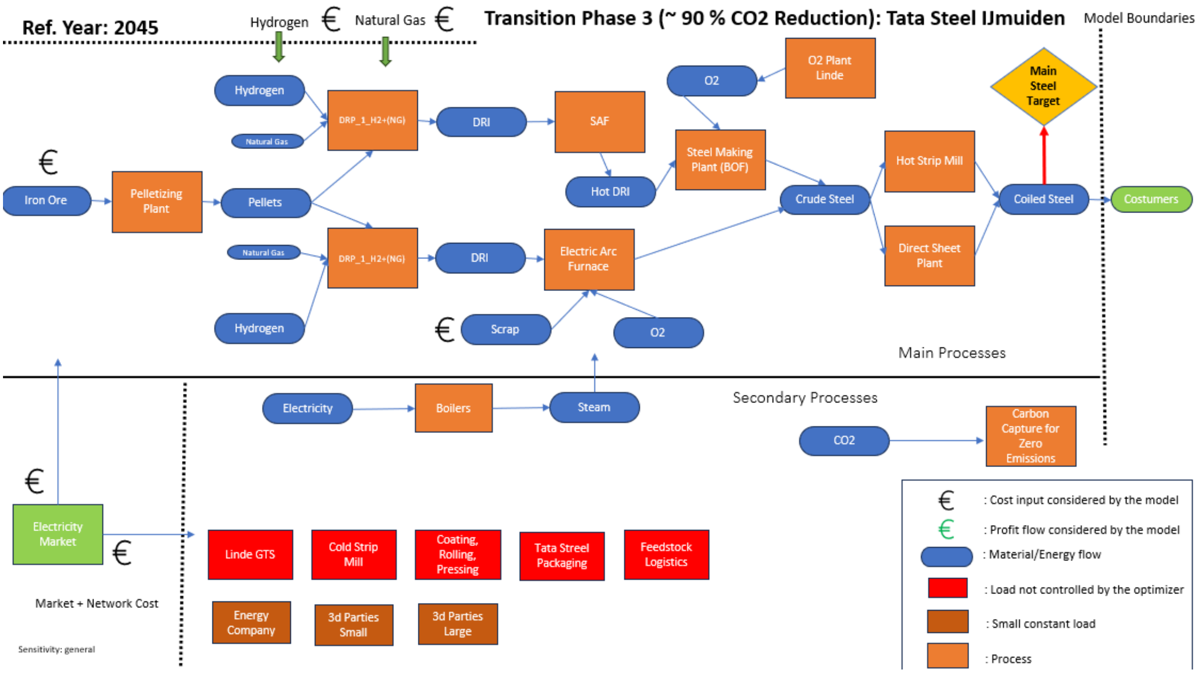

Figure 45: Transition Phase 3

3.5.4 Components of the new configurations

The following components and their modeling approach will be described in the same manner as those for the current configuration in the previous chapters. The new components introduced include the Electric Arc Furnace (EAF), Direct Reduction Plant (DRP) (various types), Submerged Arc Furnace (SAF), and Electrolyzers.

Until now, we have described the components of the current configuration only qualitatively, as the conversion factors and their parameters are classified. For the new components, we will provide some numerical values for comparison purposes with other works assessing the transition of the steel industry. These plants are not yet part of the site, and the parameters have been sourced from the literature.

Electric Arc Furnace (EAF)

The Electric Arc Furnace (EAF) is a critical component in the site's transition configurations. In essence, it is a furnace that primarily uses electrical energy to melt and convert a combination of scrap and direct reduced iron (DRI) into steel. The inputs and outputs of the EAF are illustrated in Figure 46. Table 1 presents several parameters used for modeling the EAF in PyPSA, following the approach shown in Figure 46. Most of these parameters are derived from literature, such as the works of Burchart-Korol (2013) and Ren et al. (2023).

The scrap-to-DRI ratio is determined based on scrap availability, economic considerations, and the desired quality of the produced steel. EAFs can accommodate a wide range of scrap-to-DRI ratios, which in turn affects energy consumption and the quality of the final steel product. For the purposes of this study, we have selected a relatively low scrap-to-DRI ratio, similar to the one currently used in the BOF plant. It is important to note that the model does not include the functionality to automatically adjust energy consumption based on changes in this ratio.

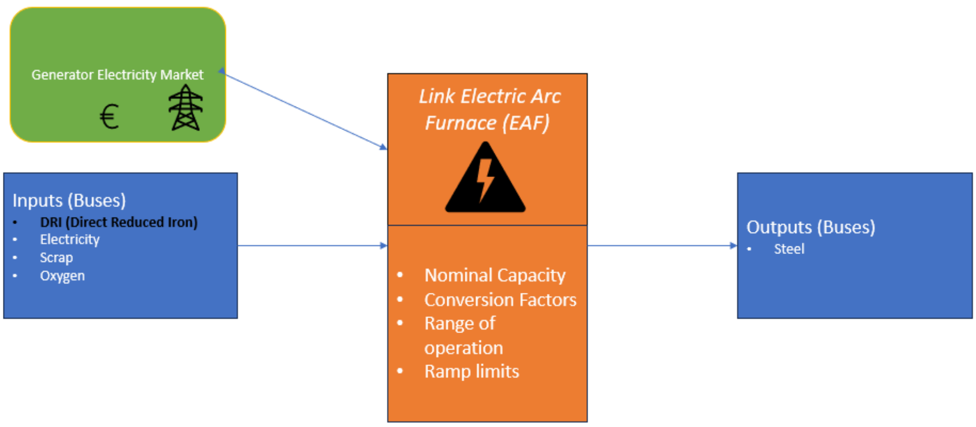

Figure 46: EAF modelling approach

Parameter	Value
Average Capacity	400 tons DRI/hour
Efficiency DRI to Crude Steel	0.95
Electricity Consumption	0.5 MWh/ton of DRI
Scrap Consumption	0.2 tons per ton of DRI
Oxygen Consumption	0.05 tons per ton of DRI
Range of operation	0.9 - 1.1 of the average capacity
Ramp limit up	-
Ramp limit down	-

Table 1: The main parameters of the EAF component used for the future configurations of the site.

The operational range is another assumption commonly applied to the operation of most EAFs. Ramp limits are not defined for the EAF. According to the literature, with the one-hour time step used in the model, most EAFs can transition from zero to their maximum operational level, or to their minimum level, within one hour. In other words, under this modeling approach, the EAF can operate at any level between 90 % and 110 % of its average capacity at each time step or be completely turned off when demand is low, and electricity prices are high.

This component uniquely simulates a large batch process within a single large reactor. For this reason, it is modeled as a MILP component, utilizing binary variables to represent its on and off states.

Direct Reducing Plants (DRPs)

A Direct Reduced Iron (DRI) plant or DRP at a steel site is a facility that produces direct reduced iron by reducing iron ore using a reducing gas, typically composed of hydrogen, carbon monoxide, or a combination of both. This process occurs at lower temperatures than traditional blast furnaces, minimizing carbon emissions. The DRI produced serves as a high-quality feedstock for Electric Arc Furnaces (EAFs), offering a more sustainable and efficient pathway for steel production.

As described earlier in the transition configurations, we employ different types of DRP plants at various phases of the transition. In Phase 1, a single DRP plant operates exclusively on natural gas. In subsequent phases, an additional DRP plant will utilize a combination of natural gas and hydrogen in nearly equal proportions. By Phase 3, when H_2/DRI technology has matured and a hydrogen ecosystem is established to support such plants, a DRP plant will primarily consume hydrogen, with only a small amount of natural gas.

The modeling approaches for these configurations in PyPSA are illustrated in Figures 47, 48, and 49. Tables detailing the main parameters of these components, sourced from the literature, are provided in the following sections.

Natural Gas DRP

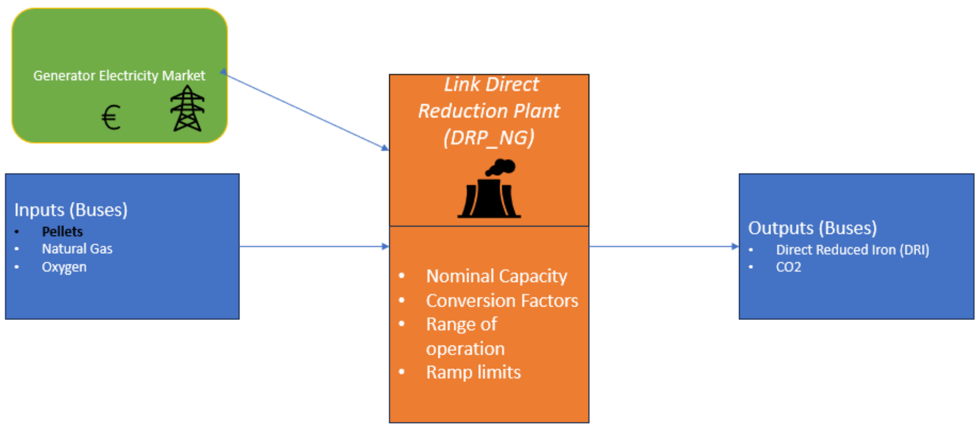

Figure 47: NG DRP modeling approach

Parameter	Value
Average Capacity	500 tons of Pellets/hour
Efficiency Pellets to DRI	0.74
Electricity Consumption	0.1 MWh/ton of Pellets
Natural Gas Consumption	195 m^3/ton of Pellets
CO2 Emissions	0.5 tons per ton of Pellets
Oxygen Consumption	0.1 tons per ton of Pellets
Range of operation	0.7 - 1.1 of the average capacity
Ramp limit up	0.1 of the average capacity per hour
Ramp limit down	0.1 of the average capacity per hour

Table 2: The main parameters of the DRP NG component used for the future configurations of the site.

Natural Gas/Hydrogen DRP

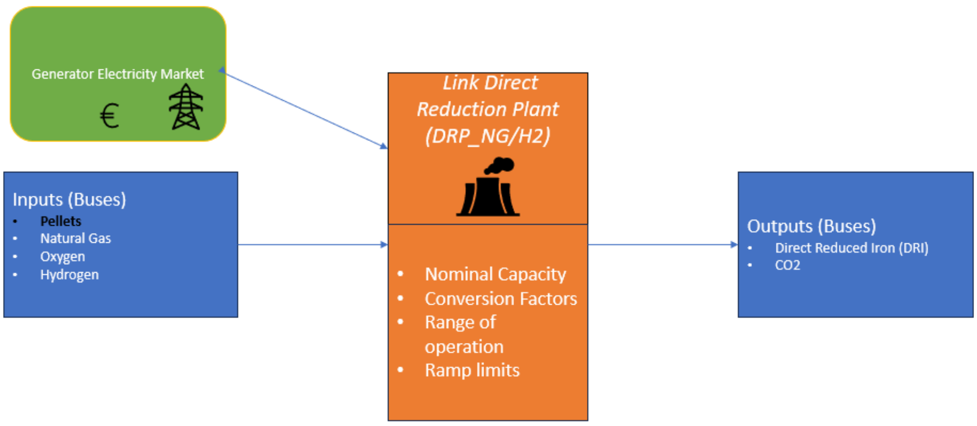

Figure 48: Mixed H2/NG DRP modelling approach

Parameter	Value
Average Capacity	500 tons of Pellets/hour
Efficiency Pellets to DRI	0.74
Electricity Consumption	0.1 MWh/ton of Pellets
Natural Gas Consumption	158 m^3/ton of Pellets
Hydrogen Consumption	0.02 tons of H2/ton of Pellets
CO2 Emissions	0.4 tons per ton of Pellets
Oxygen Consumption	0.05 tons per ton of Pellets
Range of operation	0.7 - 1.1 of the average capacity
Ramp limit up	0.1 of the average capacity per hour
Ramp limit down	0.1 of the average capacity per hour

Table 3: The main parameters of the DRP H2 component used for the future configurations of the site.

Hydrogen DRP

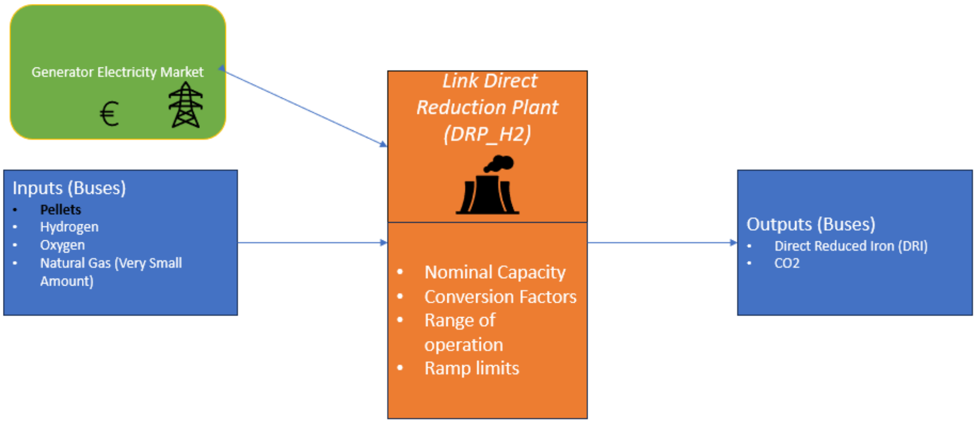

Figure 49: Full H2-DRP modelling approach

Parameter	Value
Average Capacity	500 tons of Pellets/hour
Efficiency Pellets to DRI	0.74
Electricity Consumption	0.1 MWh/ton of Pellets
Natural Gas Consumption	10 m^3/ton of Pellets
Hydrogen Consumption	0.06 tons of H2/ton of Pellets
CO2 Emissions	0.025 tons per ton of Pellets
Oxygen Consumption	0.05 tons per ton of Pellets
Range of operation	0.7 - 1.1 of the average capacity
Ramp limit up	0.1 of the average capacity per hour
Ramp limit down	0.1 of the average capacity per hour

Table 4: The main parameters of the DRP NG component used for the future configurations of the site.

The above data were retrieved from (Ren et al., 2023).

Submerged Arc Furnace (SAF)

The submerged arc furnace (SAF) is a key component in the process of decarbonizing steel production, especially in configurations where direct reduced iron (DRI) from a direct reduction plant (DRP) is utilized. The SAF serves as an intermediary step, melting the DRI to convert it into a form compatible with a basic oxygen furnace (BOF), which requires molten iron rather than the solid output produced by DRP processes.

The BOF is a relatively modern and expensive facility with unique operational characteristics that differ significantly from those of an electric arc furnace (EAF). Given its specialized design and functionality, this configuration provides an efficient means to integrate DRI into existing BOF operations without the need to construct additional EAF capacity. By employing the SAF, the process leverages the advantages of both the DRP and BOF while minimizing capital expenditure and optimizing the use of existing infrastructure.

Unlike the batch operation of some furnaces, the SAF operates as a continuous process. It primarily uses electricity to generate the extreme temperatures necessary to melt the DRI. Additionally, the SAF introduces a controlled amount of carbon into the molten iron to ensure it meets the compositional requirements for subsequent processing in the BOF. The method of carbon addition and the potential role of fossil fuels in this step remain areas for further exploration. However, the SAF process also generates a by-product gas with a heating value comparable to that of basic oxygen furnace gas (BOFG). This gas can potentially be repurposed within the steel production facility. In the current model, for instance, this gas is utilized in the pelletizing plant as a substitute for coke oven gas (COG), promoting internal resource efficiency. The precise applications of this gas remain under investigation, but its integration into the energy system highlights the potential for circular resource use within the facility.

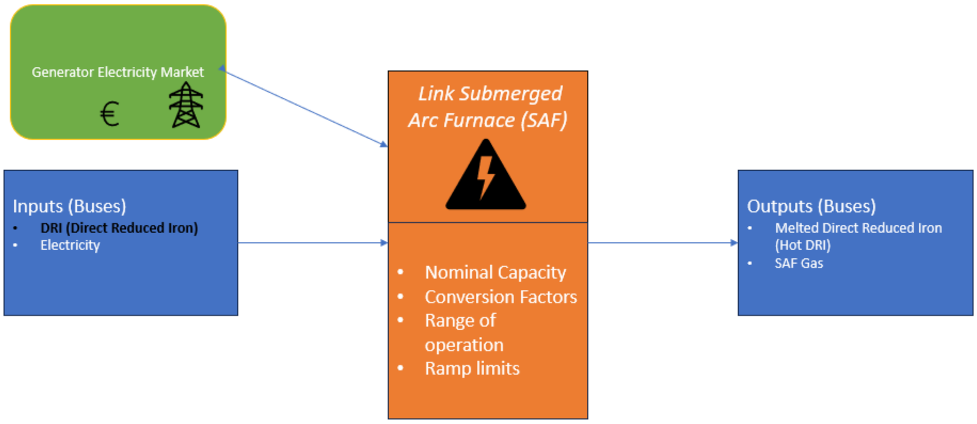

Figure 50: SAF modelling approach

Parameter	**Value**
Average Capacity	400 tons of DRI/hour
Efficiency DRI to Hot DRI	0.95
Electricity Consumption	1 MWh/ton of DRI
SAF Gas Production	50 m^3 per ton of DRI
CO2 Emissions	0.005 tons per ton of Pellets
Oxygen Consumption	0.05 tons per ton of Pellets
Range of operation	0.7 - 1.1 of the average capacity
Ramp limit up	0.1 of the average capacity per hour
Ramp limit down	0.1 of the average capacity per hour

Table 5: The main parameters of the SAF component used for the future configurations of the site.

3.6 Model Behavior

The following sections provide a deeper insight into the model and its functionality.

Constraints and Historical Data

Initially, we describe how the constraints governing the operation of various components, plants, and processes were developed. These constraints were created using historical data collected from past operations. This approach ensures that the model accurately reflects real-world behavior and operational limits, capturing the complexities of the system effectively.

Typical Model Solution

In the next section, a typical solution of the model for the current configuration of the site is presented. This allows the reader to understand the model's outputs, including the identification of site bottlenecks and how constraints manifest in practical scenarios. By analyzing these outputs, we can pinpoint areas where the system's efficiency can be improved and recognize the critical factors influencing production.

Verification through Extreme Cases

The verification section follows, showcasing the model's flexibility by simulating extreme cases and rare occurrences. These scenarios demonstrate the robustness of the model under varying conditions, highlighting its ability to adapt to different operational challenges and uncertainties.

Validation with Real-World Data

Finally, the validation section compares key outputs of the model with actual values obtained from the site. This comparison ensures that the model is reliable and provides confidence in its predictive capabilities. By aligning the model's results with real-world data, we can confirm its accuracy and relevance for decision-making.

3.6.1 Design of Constraints

In the design phase of the model, real data from the main plants were utilized, as explained in the methodology section, to create constraints for each plant's operation. Figure 51 illustrates the hourly operation of a specific plant at the site for 2022. Due to confidentiality reasons, the plant's name cannot be disclosed. Similar patterns were applied across all the main plants included in the model.

By performing straightforward data analysis, the average electricity consumption of each plant was identified. This average serves as the conversion factor linking the plant's production level to its electricity consumption. These relationships are established by correlating electricity consumption data with production metrics, such as the output of hot metal or coke for a given plant. Furthermore, the allowed range of the plant's operation was determined based on this data. Since the data distribution is not always normal, percentiles were employed. For the current configuration, the 90% percentile defines the upper operational limit, while the 10

For example, consider a plant with an average production rate of 100 tons of output per hour. From the electricity consumption data, we determine that the plant's average electricity consumption is 50 MW, with the 90% percentile at 60 MW and the 10% percentile at 40 MW. These values allow us to define the model parameters for this plant. Specifically, the plant's capacity is set at 100 tons per hour (or per time step in the simulation, given the hourly resolution). The conversion factor between the main output and electricity consumption is defined as 50 MW per 100 tons. Using the electricity consumption patterns, which are more readily accessible, we establish the plant's operational range. Based on the 10% and 90% percentiles, the plant is allowed to produce between 80 and 120 tons of output per hour.

This methodology ensures that the model accurately represents the operational constraints and variability of each plant, enabling realistic simulation of their performance.

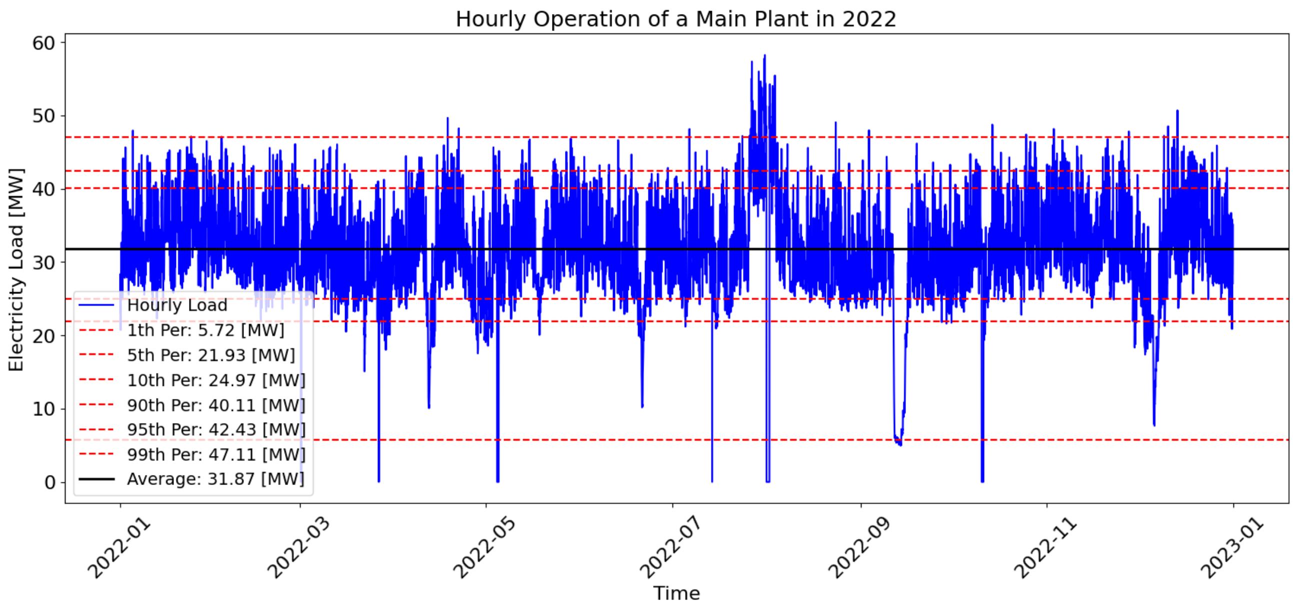

Figure 51: Real hourly operation of a main plant of the site for 2022 as of electricity consumption. The percentiles of its distribution and the average value can be also seen.

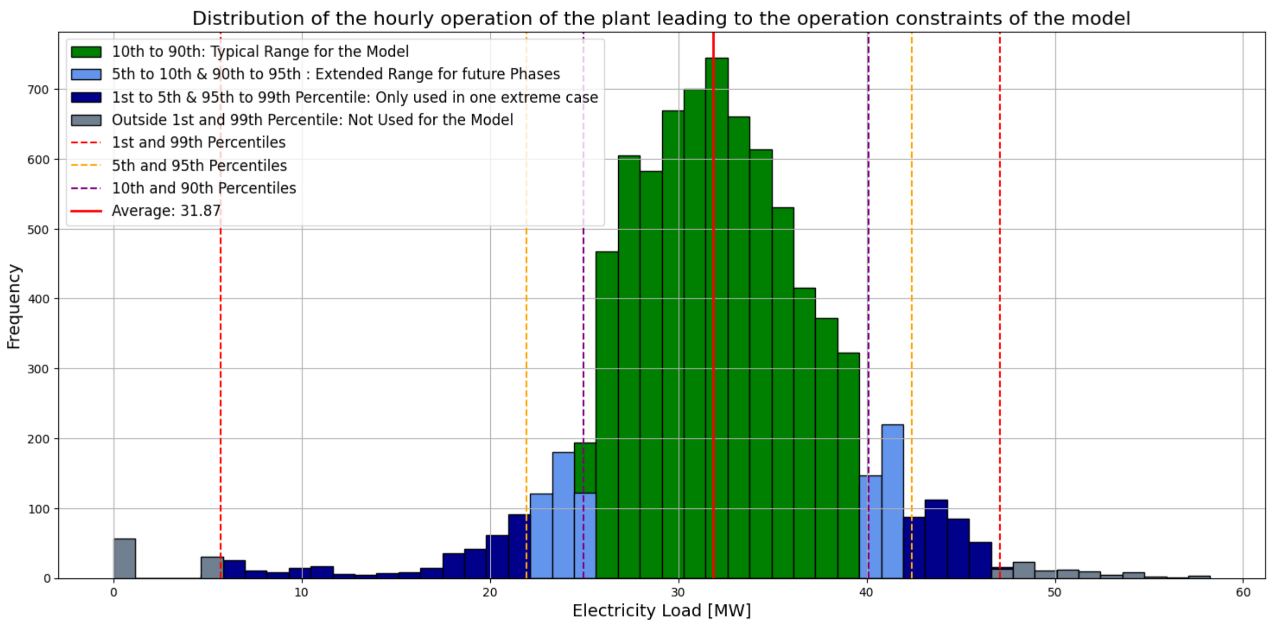

Figure 52: The distribution of the operation of the same plant showing with different colors the different ranges of operation that are used as constraints in the model.

With the same approach, we also define the ramp-up and ramp-down limits of the plant using real data. Figures 53 and 54 demonstrate the analysis used to determine these constraints. We utilize the 90% percentiles for ramp-up and ramp-down values to avoid overestimating the plants' flexibility, which could arise from extreme cases of production disruptions, outages, or other failures. These percentile-based limits reflect the range of level changes observed during 90% of actual operational scenarios. For instance, if a plant typically experiences level changes within a range of 10 tons per hour during most operations, the 90% percentile is used to set a reliable and realistic limit.

This methodology ensures that the model accurately represents the operational constraints, variability, and ramping flexibility of each plant, enabling realistic and robust simulation of their performance.

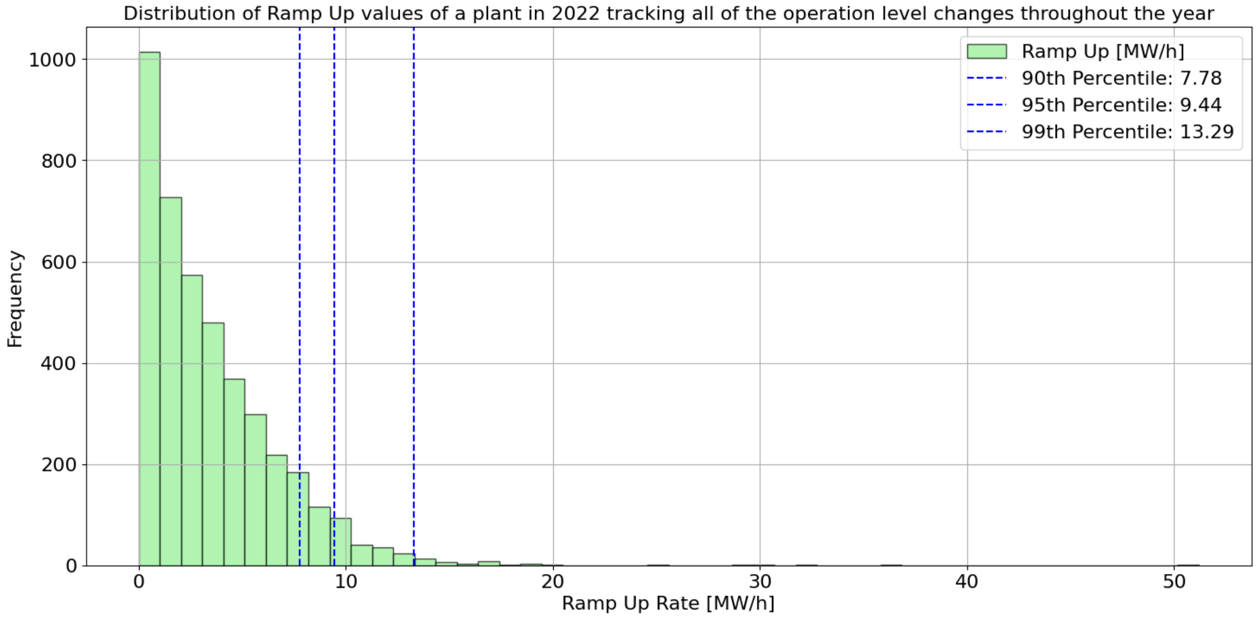

Figure 53: The distribution of the ramp up limits of the same plant and the relevant percentiles for this distribution.

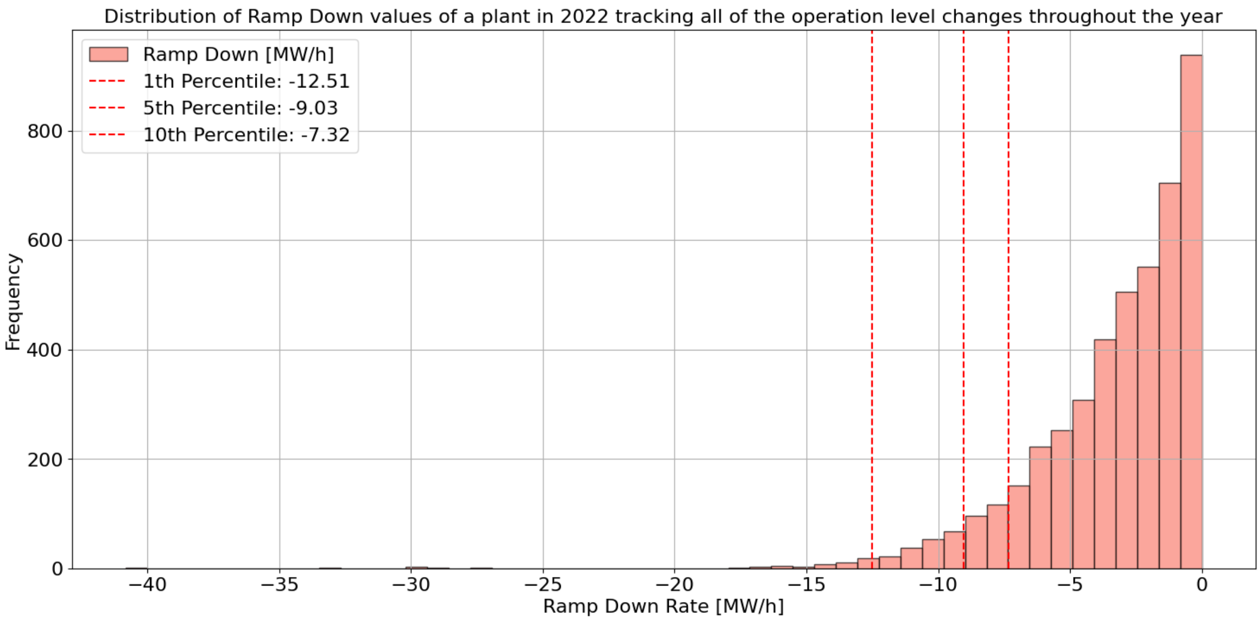

Figure 54: The distribution of the ramp down limits of the same plant and the relevant percentiles for this distribution.

An important assumption in the model is related to the use of hourly electricity consumption data to infer the productivity behavior of the plants. This means that the production levels of materials are assumed to follow the same patterns as electricity consumption. While the model uses average values for the production and consumption of each material and flow—calculated via conversion factors—the range of operation and ramp limits are directly determined using electricity data. This is a significant assumption, as it implies that plants without a linear relationship between electricity consumption and production are not modeled with perfect accuracy. However, for most plants, this assumption aligns closely with reality. Additionally, the outputs and inputs of materials are cross-checked using averages from other sources or datasets to validate the assumptions.

Another key assumption concerns the operational range depicted in Figure 52. The standard operational range used throughout the model is the 10-90 percentile range, as previously explained. However, in some future configurations, it may be necessary to extend this range to achieve feasible solutions. For instance, in plants that remain operational in future configurations, the 5-95 percentile range is sometimes applied. In extreme cases, an even broader range, such as 2.5-97.5 percentiles, may be used. These adjustments account for changes in site configurations and operational demands. For example, after Phase 1, when Blast Furnace 7 is decommissioned, the demand for sinter from the Sintering Plant decreases. To accommodate this change, the operational range of the Sintering Plant must be adjusted. Without such adjustments, forcing the plant to operate above its old minimum limit could lead to excessive sinter production, storage constraint violations, and unfeasible solutions.

This methodology and its assumptions ensure that the model remains flexible and robust while capturing the key operational constraints and dynamics of the site.

3.6.2 A typical model solution explanation

The simulation of the site encompasses numerous processes, plants, constraints, and stored materials, forming a connected system designed to achieve the steel production target for the simulation period in a cost-optimal manner. This optimization is carried out while adhering to various constraints, including the operational requirements of each plant and the storage limits of intermediate products.

The optimizer integrates these parameters and prioritizes energy price fluctuations as a key factor, given their variability, while accounting for more stable material prices. To enhance understanding of this intricate system, this section presents a typical monthly simulation of the current configuration, highlighting its main outputs. We will walk through the process step by step, identifying the parameters that significantly influence the outcomes and deriving key conclusions from them.

This methodology will also be applied in the results chapter to analyze the transitional phases of the site.

Monthly Simulation - January 2025 - Central Prices - Current Configuration

Cost Inputs

Initially, the model receives cost inputs for energy or materials, as previously explained. In Figures 55 and 56, typical examples of the hourly electricity prices and the constant monthly natural gas price are provided for a monthly period, specifically for January. Similarly, price inputs are given for the other cost components of the model, as already referenced in subsubsection 3.3.4.

After running the simulation with a specific steel target for the simulation period and applying all constraints for the plants and processes on the site, the results include numerous plots. These plots detail the stored materials throughout the simulation, the operation of the plants, energy consumption, the total cost of steel production, and the various aspects of the total cost. In Figure 57, the accumulated rolled steel produced as output from the final processes of the Direct Sheet Plant and the Hot Strip Mill is depicted. It is evident how the optimizer adjusts production such that, by the end of the period, the steel target is successfully achieved.

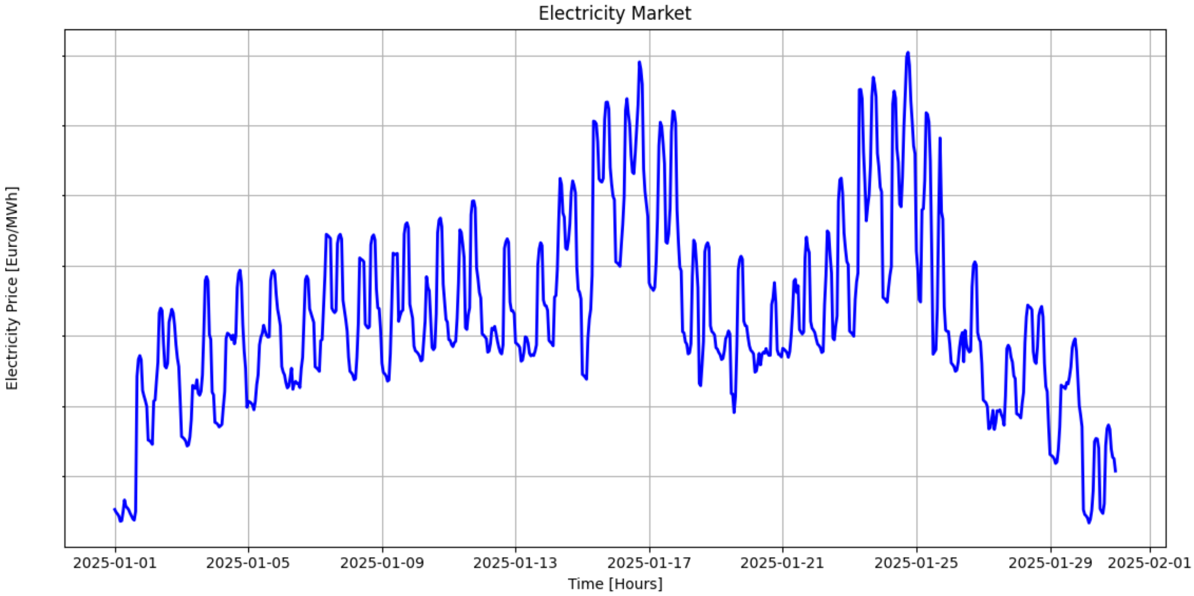

Figure 55: Hourly electricity prices as a cost input

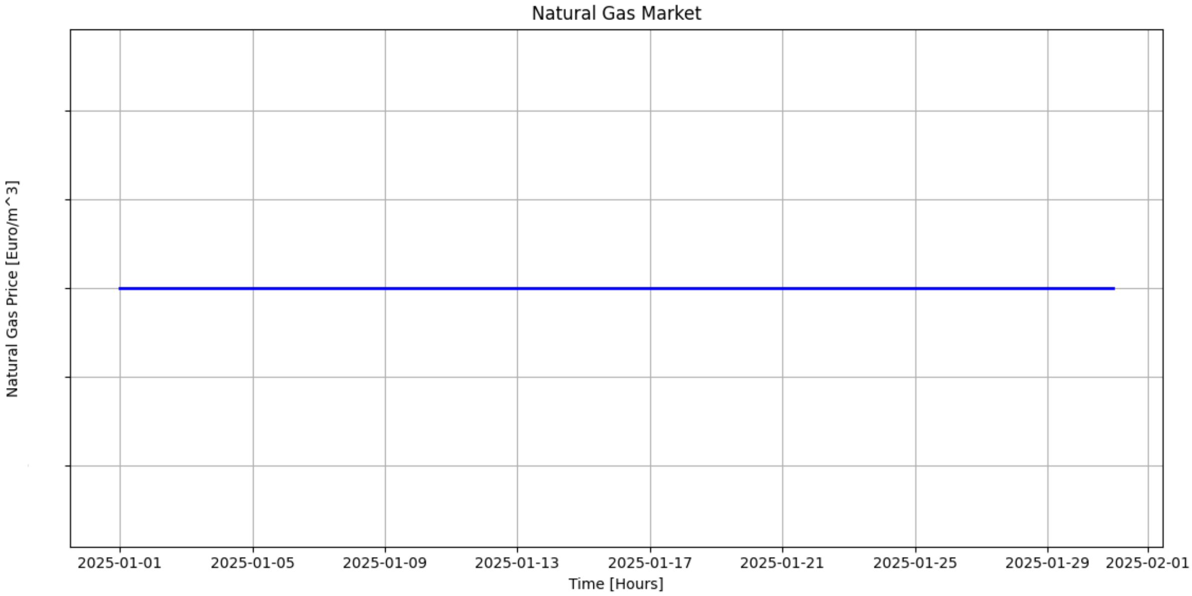

Figure 56: Natural gas constant monthly price as a cost input

Steel Target

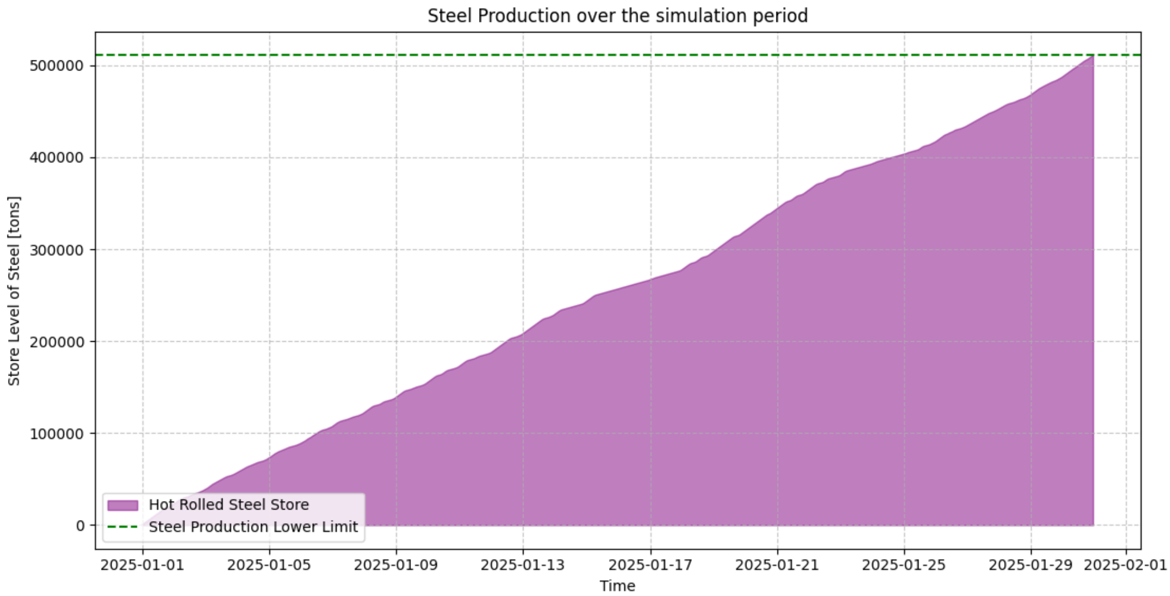

Figure 57: Rolled steel storage throughout the simulation period

Plant's Operation

In the following figures, we present the operation of some of the main plants on the site, plotted alongside their allowed operational ranges, as explained in the previous section. It can be observed that certain plants operate at a lower capacity factor, closer to their lower operational limits, while others operate near the higher end of their range. This serves as an initial indication of potential bottlenecks on the site, which will be discussed further later.

Simultaneously, we observe how the optimizer adjusts the operation of specific plants in response to price signals, primarily the hourly varying electricity prices. These adjustments also consider the ramp-up and ramp-down limits of each plant. The electricity consumption of a plant significantly influences these decisions; for instance, optimizing the operation of a highly electricity-intensive plant may take precedence over a low electricity-consuming plant. The latter might be kept more stable, for example, to ensure a constant flow of WAGs for electricity production during periods of high electricity prices.

Here, we focus on the main plants; however, the model generates such outputs for every component of the site, including boilers, electricity generators, and gas mixing stations.

Another key aspect of plant operation, beyond their constraints, is their integration within the larger system, where components influence each other. For instance, coke produced by the coking plant serves as an input for other downstream processes. If these downstream processes need to operate during a specific period, the coking plant may be forced to run to supply the required amount of coke. This behavior is particularly evident in simulations with perfect knowledge of prices over the entire optimization period.

In Figure 64, we illustrate the coke storage output from the simulation. Coke storage is unrestricted, and it is evident that an accumulation of coke occurs during the early part of the month. This accumulation is driven more by the operation of downstream processes than by the operation of the coking plants themselves.

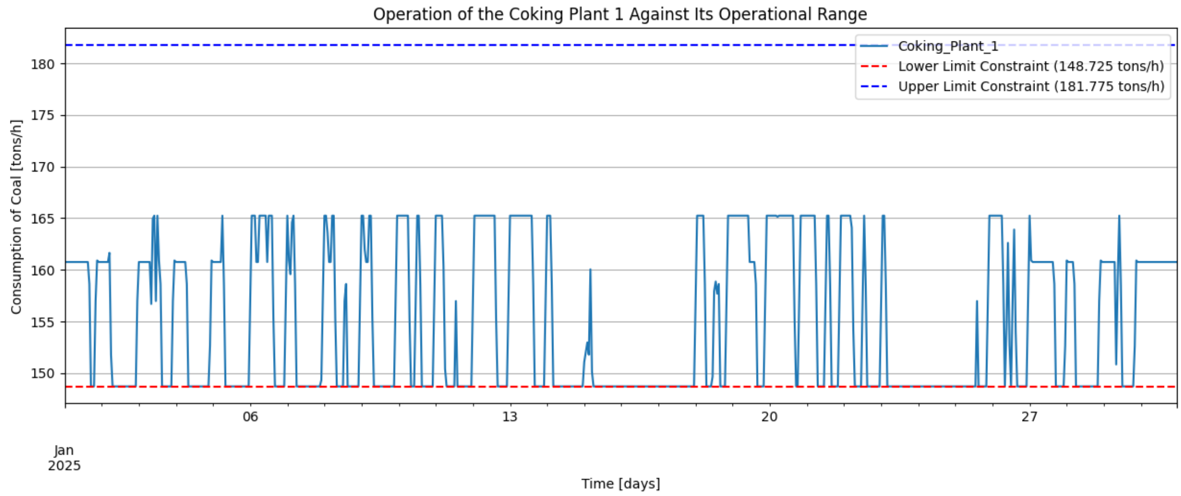

Figure 58: The operation of the Coking Plant 1 throughout the simulation period

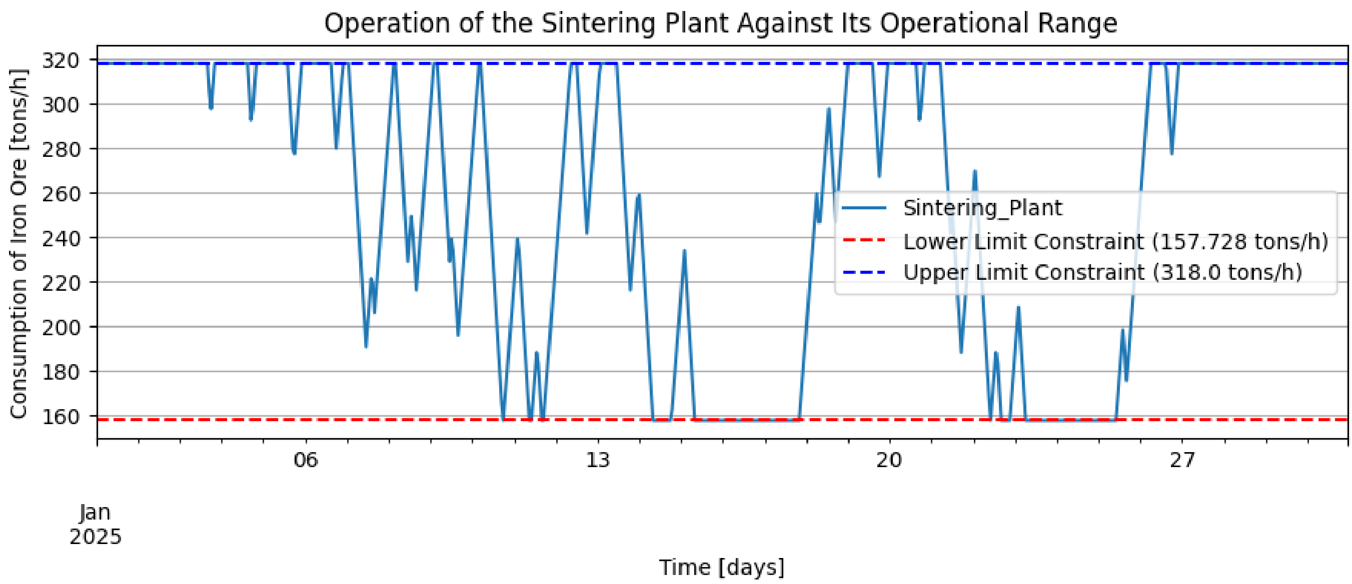

Figure 59: The operation of the Sintering Plant throughout the simulation period

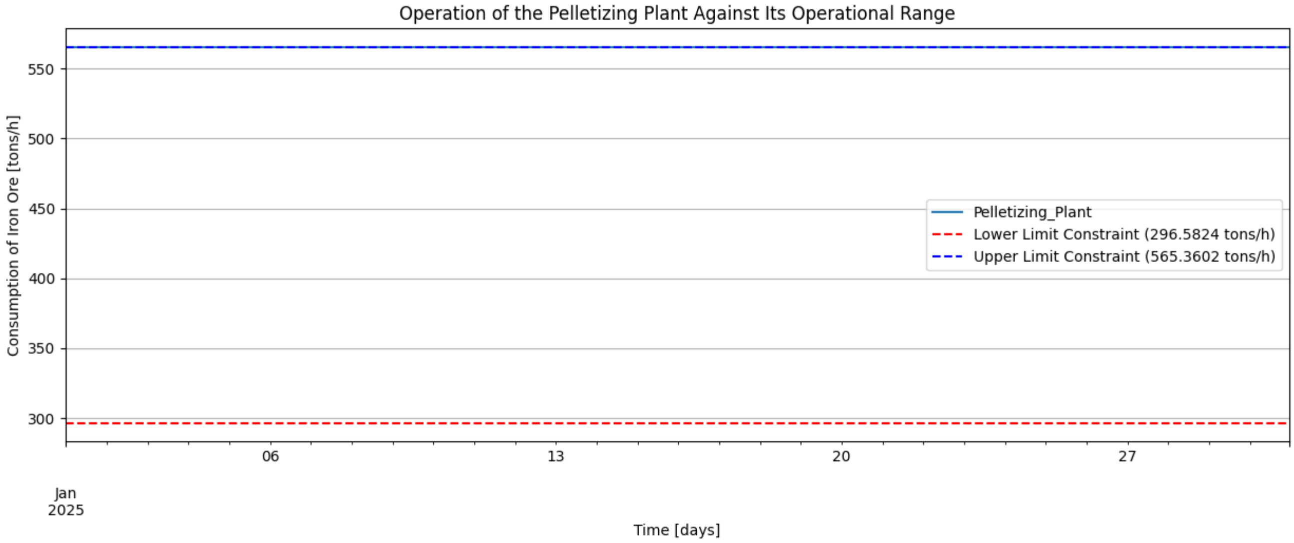

Figure 60: The operation of the Pelletizing Plant throughout the simulation period

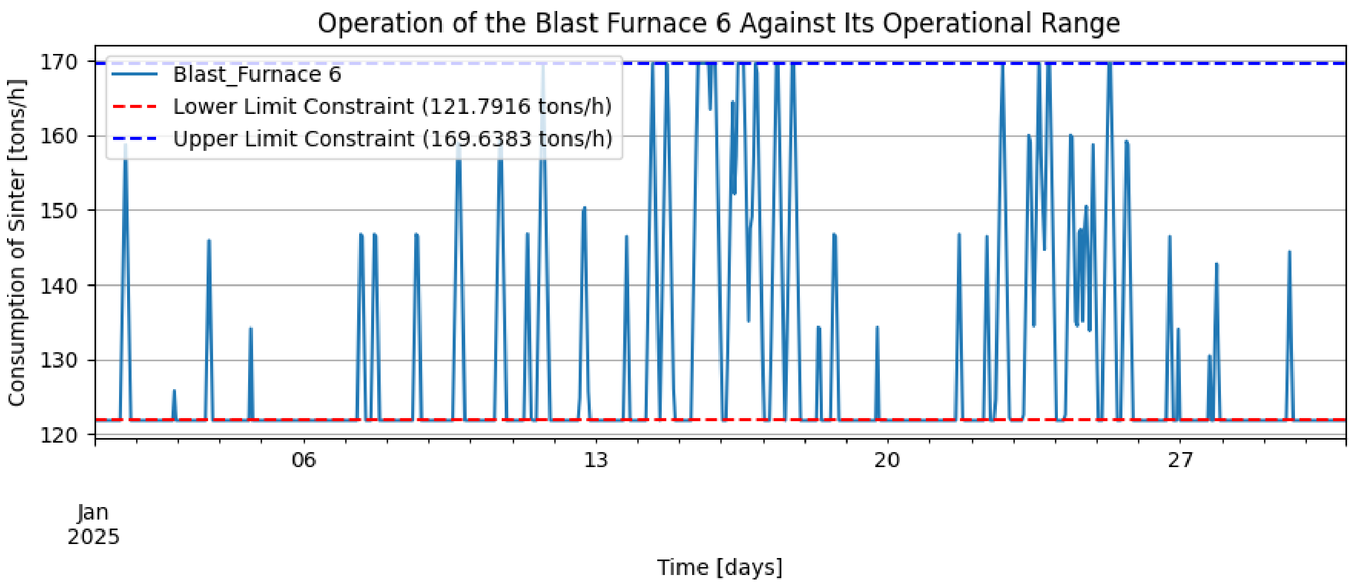

Figure 61: The operation of the Blast Furnace 6 throughout the simulation period

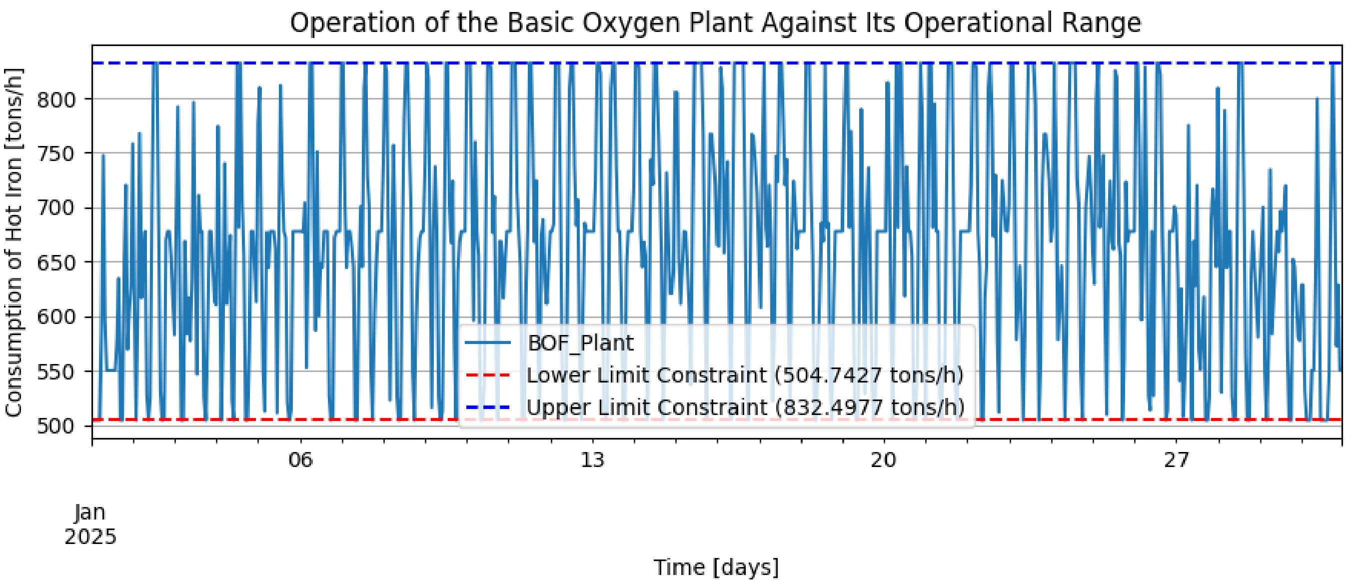

Figure 62: The operation of the Basic Oxygen Furnace throughout the simulation period

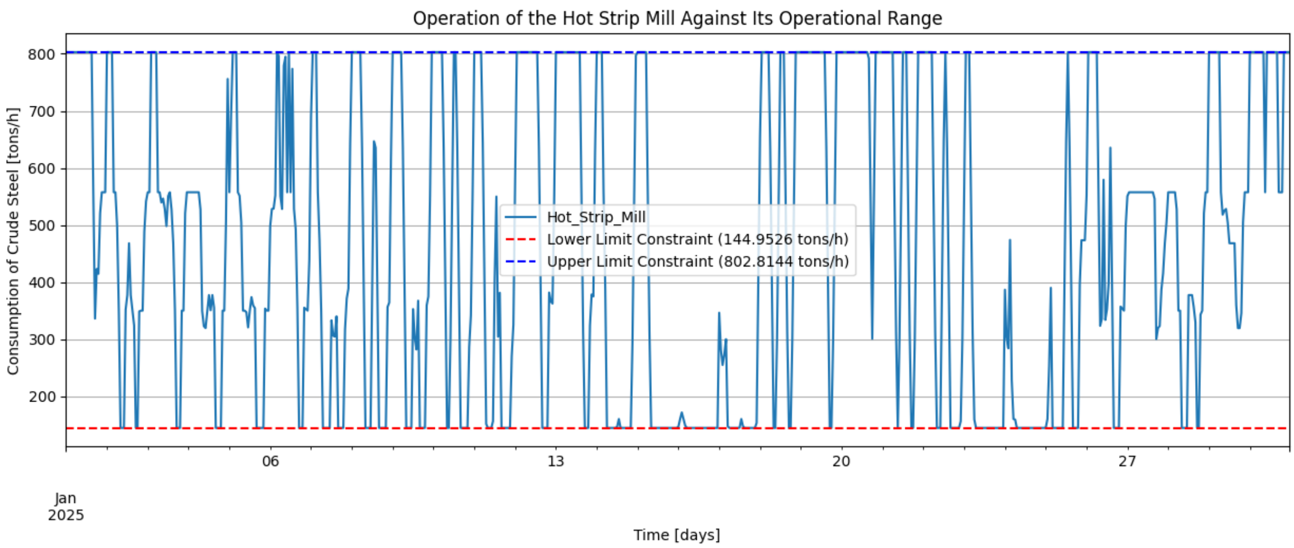

Figure 63: The operation of the Hot Strip Mill throughout the simulation period

Stores

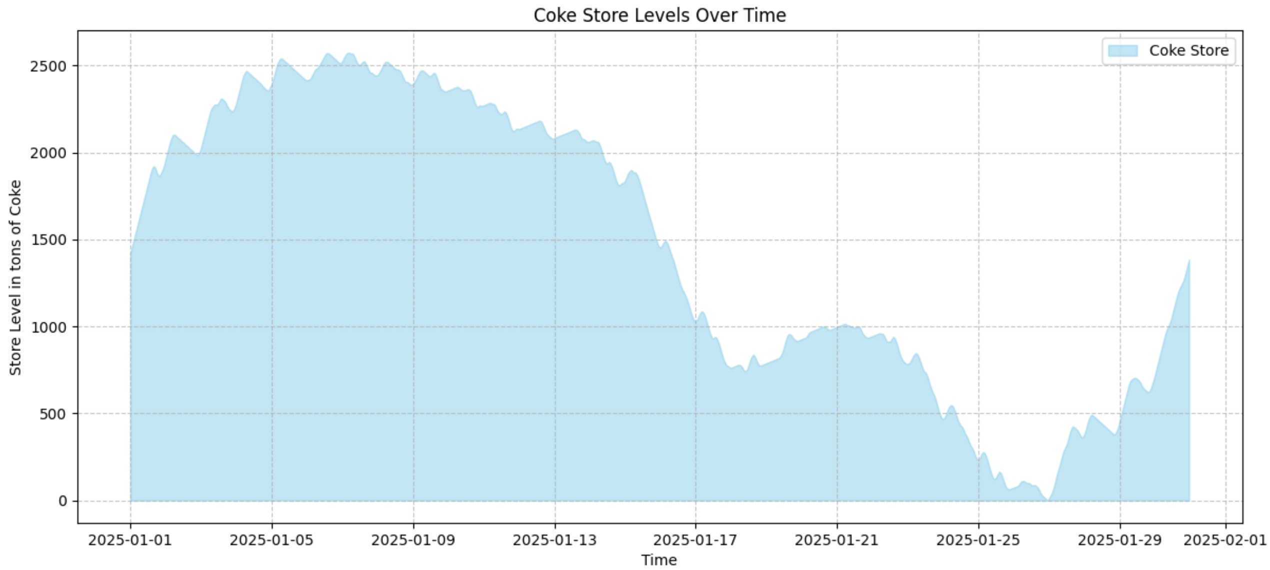

Figure 64: Coke store levels throughout the simulation

In Figures 65, 66, and 67, storage limitations are applied for reasons previously explained. It is evident that the hot metal storage limitation acts as a bottleneck for the system, as the optimizer would frequently benefit from a larger storage capacity throughout the simulation.

A similar observation applies to oxygen storage. Oxygen production is an electricity-intensive process, making it logical for the optimizer to operate the Linde plant during periods of low electricity prices. However, to reflect the real site's current practices—where oxygen is not strategically stored—we enforce a low oxygen storage constraint in the model.

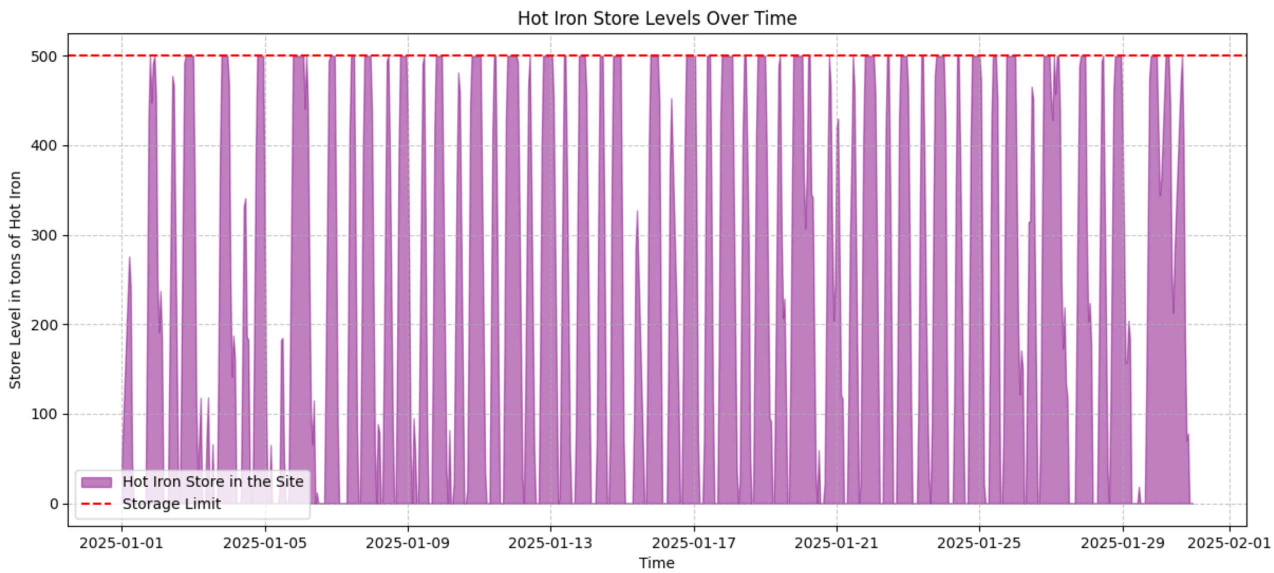

Figure 65: Hot Iron store levels throughout the simulation

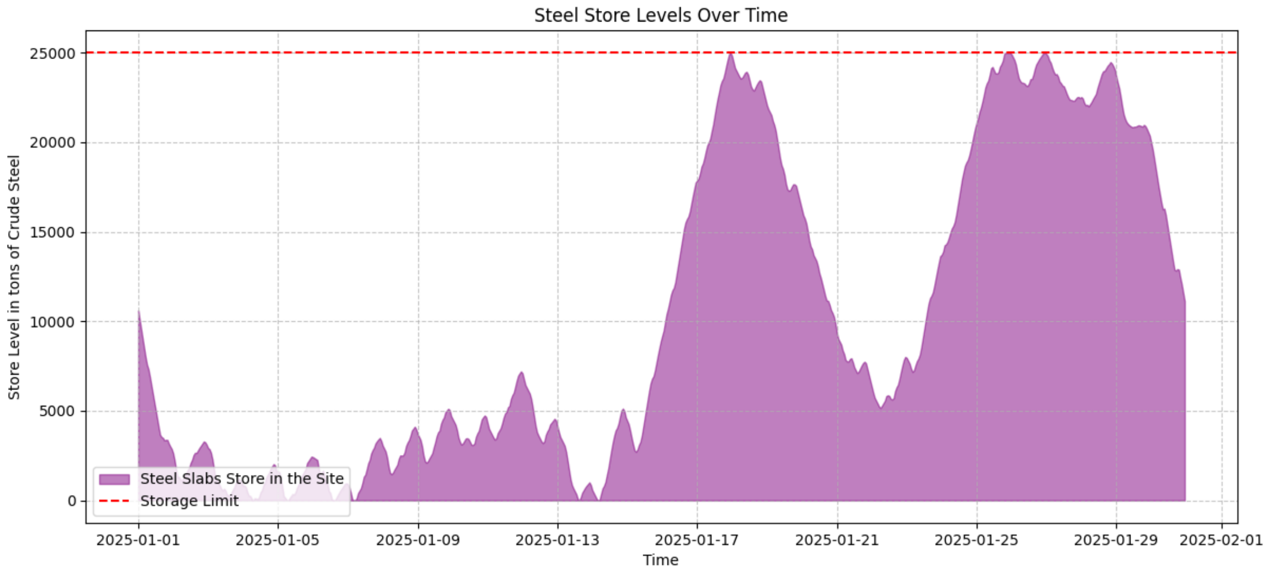

Figure 66: Steel slabs store levels throughout the simulation

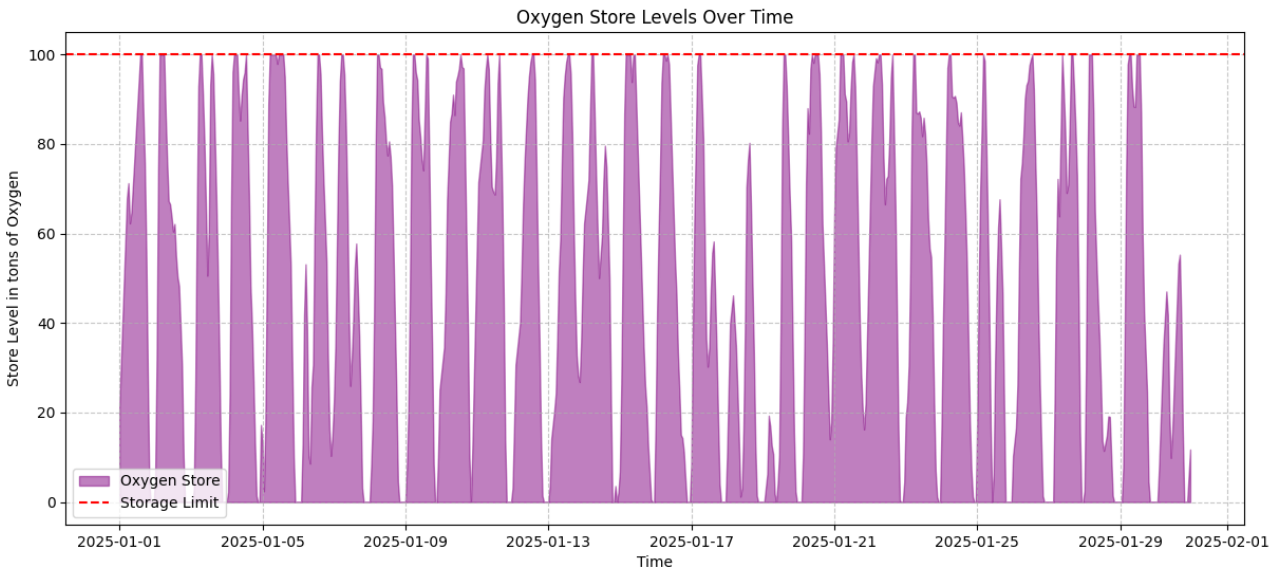

Figure 67: Oxygen store levels throughout the simulation

Final Outputs

To close the presentation of this small monthly simulation example we are presenting some important outputs that are expected from the model. In the following figures we can see how the sum of the operation of the different plants of the site create the total demand output of the whole site and the same for natural gas. In the same way we can obtain the consumption of all of the materials or energy flows of the site. In Table 6, we can see some numerical values of some main results of the simulation.

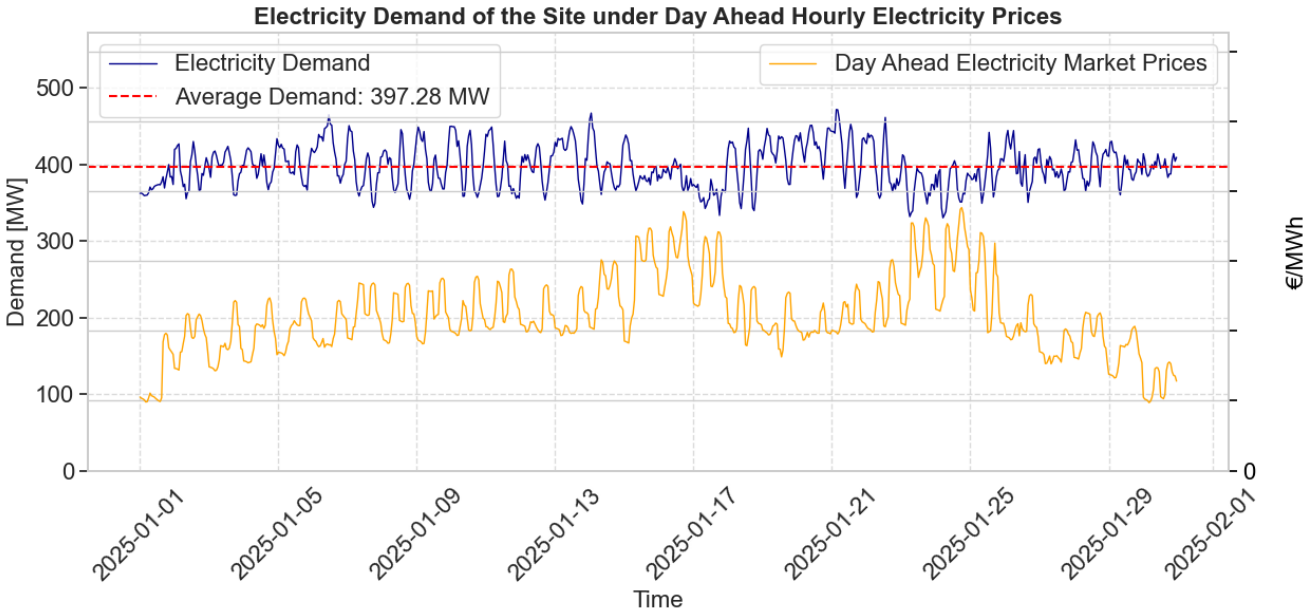

Figure 68: The electricity demand of the site plotted together with the electricity prices for a month

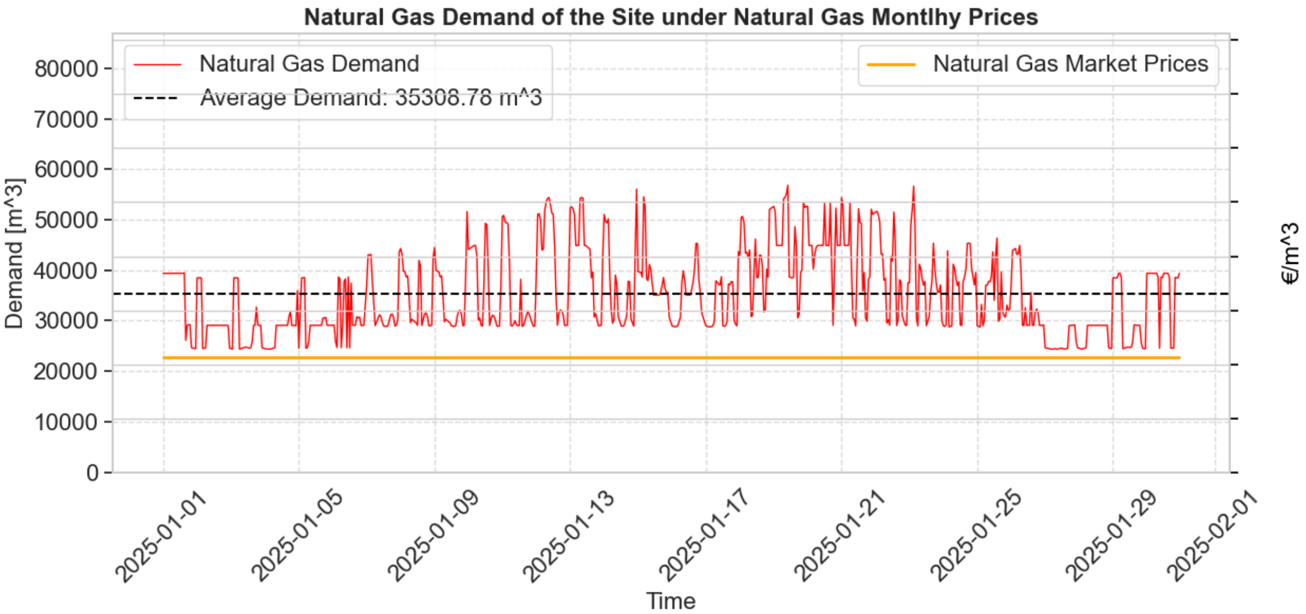

Figure 69: The natural gas consumption of the site against the constant natural gas price for the month.

Parameters	Values
Steel Cost	[redacted] eur/ton
Electricity Consumption Avg	397.28 MW
Natural Gas Consumption	35308.78 m^3
CO2 Emissions	1122099.22 tons
Electricity Consumption Total	0.2789 TWh
Total WAGs Generation	0.2493 TWh
Max Electricity Demand	465 MW

Table 6: Main Results of this test case

Active Constraints

At this point, let us delve deeper into the bottlenecks of the current configuration or, mathematically speaking, the active constraints of the optimization problem. While we provide some insights here and present an approach to identify key active constraints within the model, it is important to note that the active constraints can vary depending on different price scenarios, cost inputs, steel targets, or even the constraints themselves.

Furthermore, as previously mentioned, the site's real-world operations differ in several respects from our modeling approach, as explained in the methodology chapter. Consequently, the bottlenecks identified in this model may not fully align with those observed in reality.

It is also important to acknowledge that performing a comprehensive sensitivity analysis for every constraint in the optimization problem is beyond the scope of this work. This would involve examining the impact on the objective function for every possible change in a constraint across all specific processes—a task that requires significant computational and analytical resources.

Therefore, the approach and conclusions presented here should be regarded as an initial exploration rather than an exhaustive sensitivity analysis of all constraints and parameters in the system.

As demonstrated in the previous section, some plants frequently operate at their upper allowed limits, indicating potential bottlenecks or active constraints. However, as explained, the processes are interconnected, making it challenging to identify unique bottlenecks since each process is influenced by the surrounding system. The same principle applies to storage limitations.

From the previous figures, we observe that certain materials, like coke, can be stored without strict limitations, with the only constraint being the cyclic constraint in PyPSA terminology. This means that the initial storage level must match the storage level at the final instant of the simulation. On the other hand, materials like hot iron cannot be stored indefinitely due to physical restrictions, such as the capacity of torpedo ladles used for transporting hot iron.

To better understand these limitations, let us first remove the storage constraints and analyze the resulting differences in the cost of produced steel and the storage quantities that the optimizer selects as optimal.

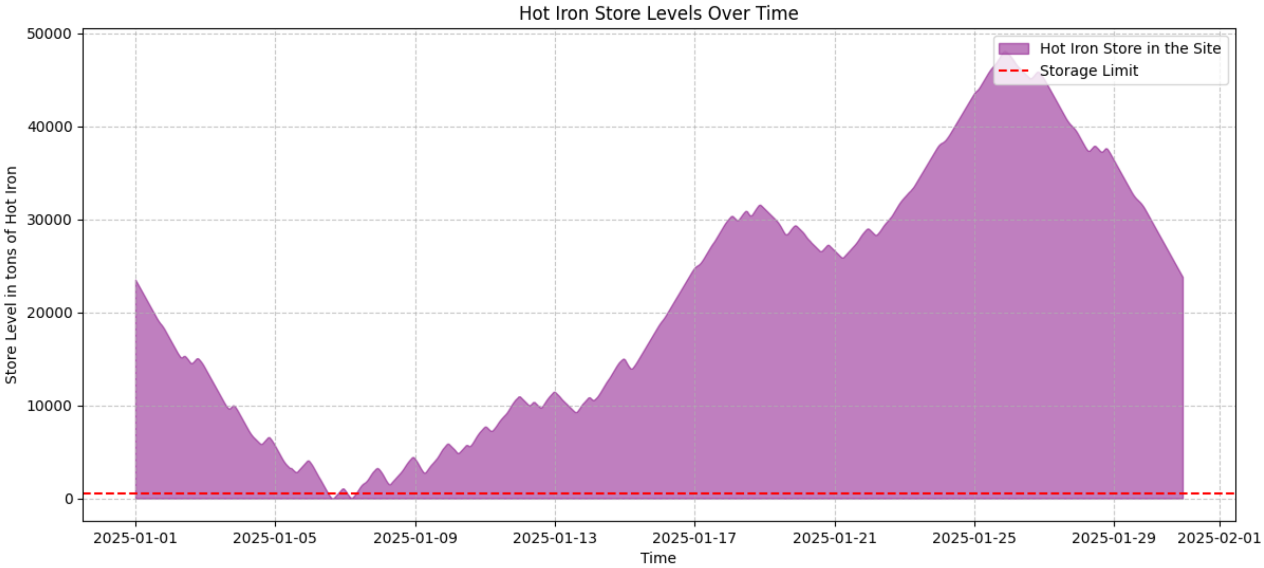

Figure 70: Hot Iron optimal storage pattern when the storage capacity is unlimited

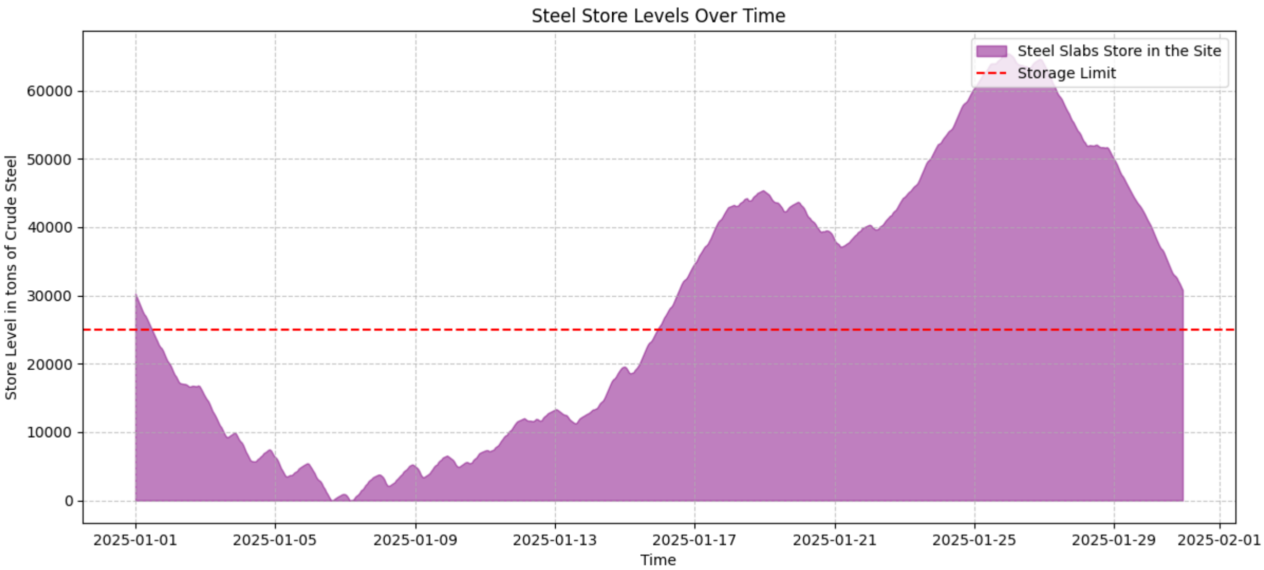

Figure 71: Crude Steel optimal storage pattern when the storage capacity is unlimited

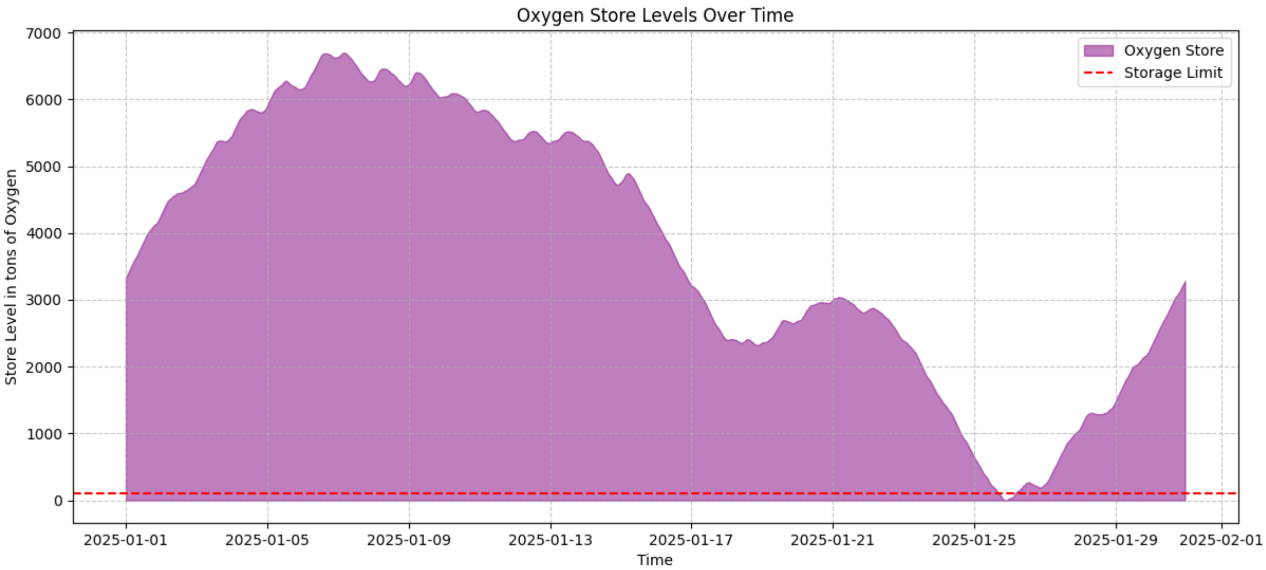

Figure 72: Oxygen optimal storage pattern when the storage capacity is unlimited

In the Figures 70, 71 and 72 we can notice the optimal storage pattern of the optimization for these materials in case the orginal constraints were not applied. We have shown that in the original problem these storages have physical limitations but this approach help us estimate the cost savings of a possible theoretical increase of this storage capacities and also show the effect of these limitations at the value of the objective function. At the end of this section there is a table where these changes in the objective function are presented under different scenarios. With a first look we see that for example if it was possible large quantities of Hot Iron would be stored after the blast furnaces and before the BOF. This would enable the use of the full capacity of the blast furnaces and also make the BOF more flexible to operate with stored hot iron feedstock when electricity prices are low since it is also an electricity intensive process. This lowers the value of the objective function but in reality in is not possible due to the physican limitations of storing hot iron. Storing 50000 tons of hot iron is impossible however the storage limitation of 25000 tons of crude steel or slabs after the BOF is almost half compared to the unrestricted storage that the optimizer select and since this is an assumption and slabs can be easier stored if there are strong reasons for cost savings it shows that this constraint is not so important and so restricting as the hot iron one is. This can also be seen in Table 7 from the small cost saving effect of an unrestricted slab storage capacity. Refering to the oxygen storage, there is an important effect from storing more oxygen stratetically. However this is not happening at the moment and also the 7000 tons of stored oxygen is a large quantity even for a large industry like Tata Steel.

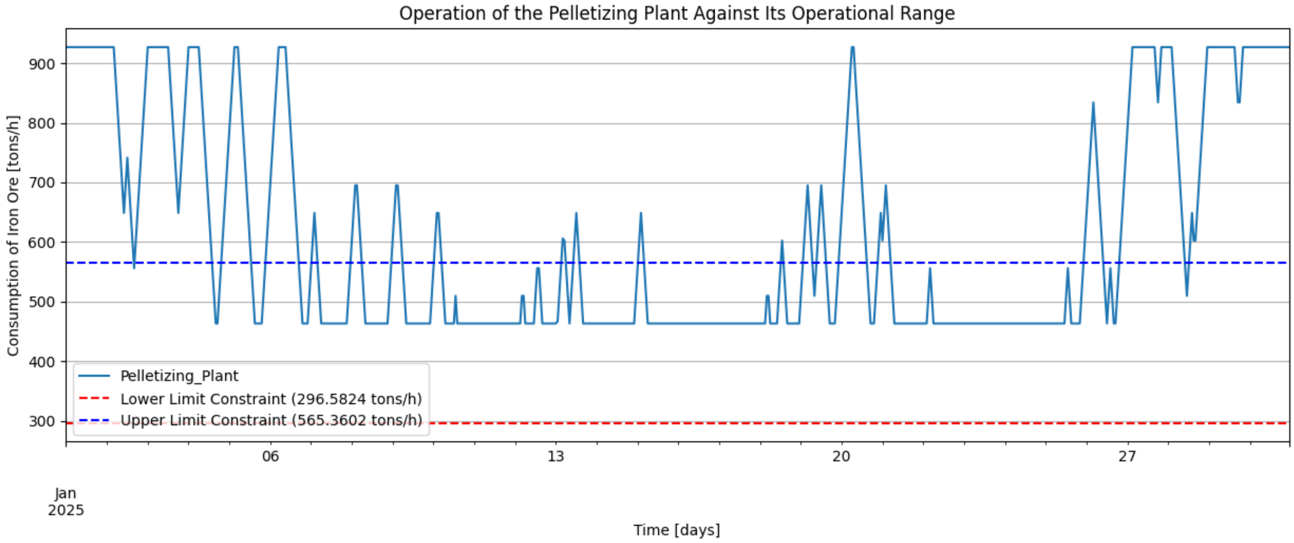

Figure 73: Pelletizing plant operation when the original range constraints are not applied

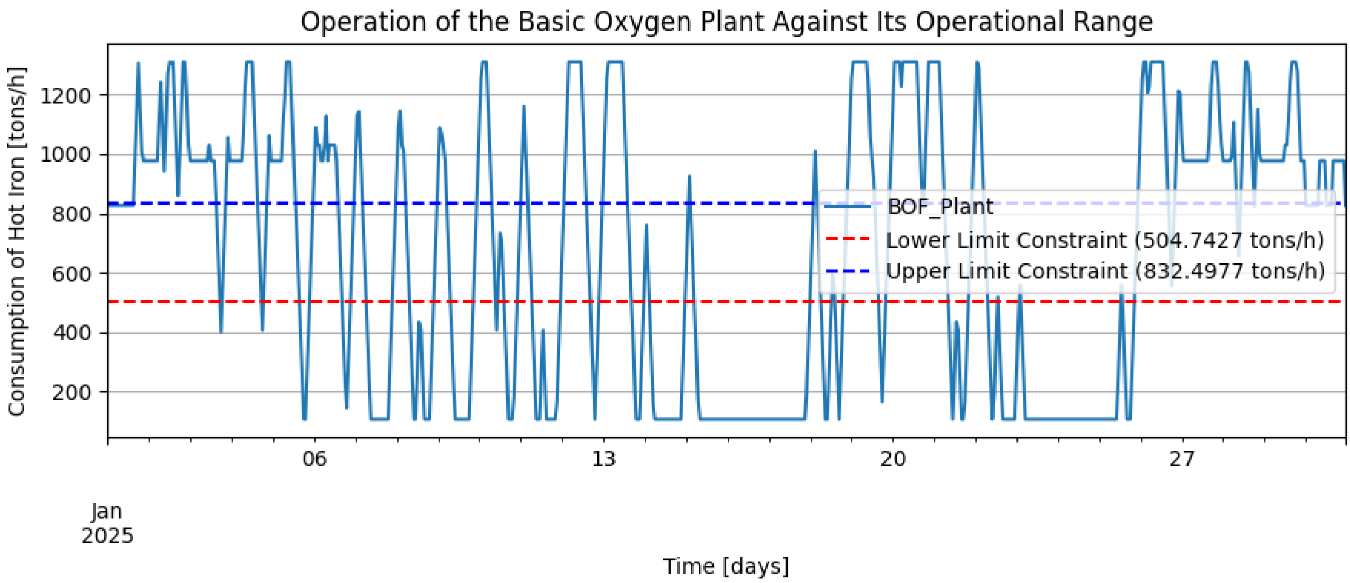

Figure 74: BOF operation when the original range constraints are not applied

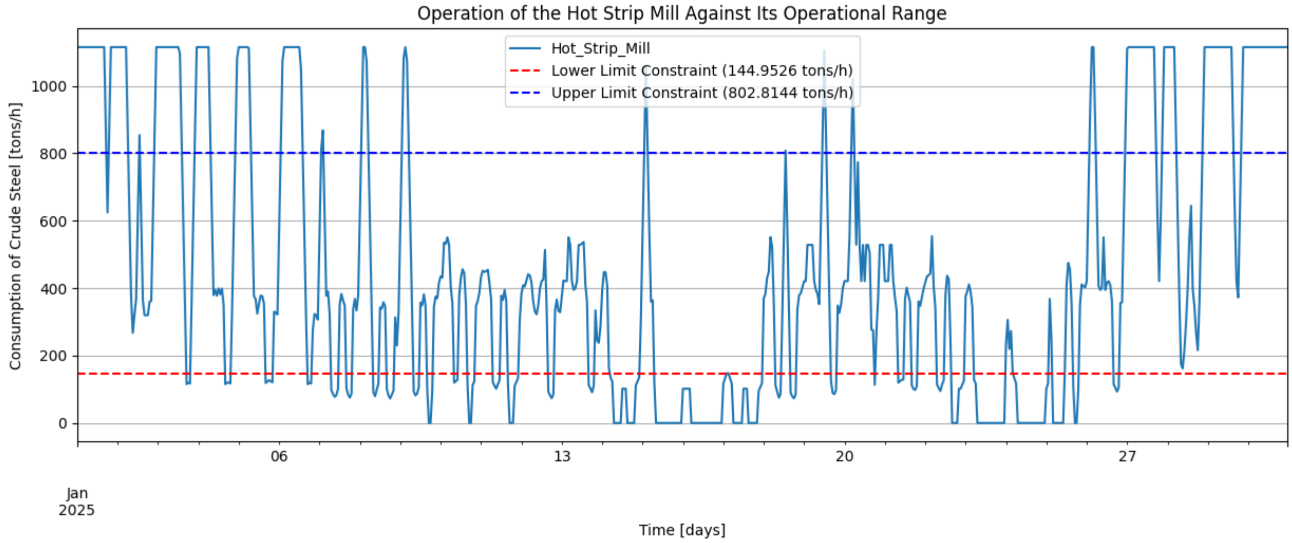

Figure 75: HSM operation when the original range constraints are not applied

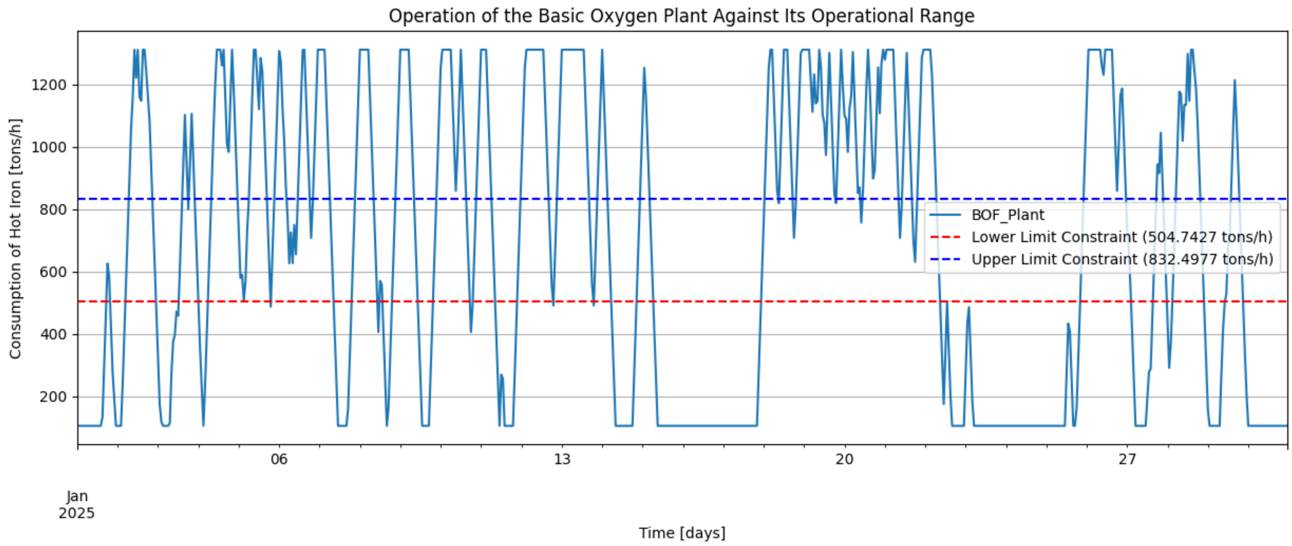

Figure 76: BOF operation when the original range constraints are not applied and also all of the storage limitations are not applied

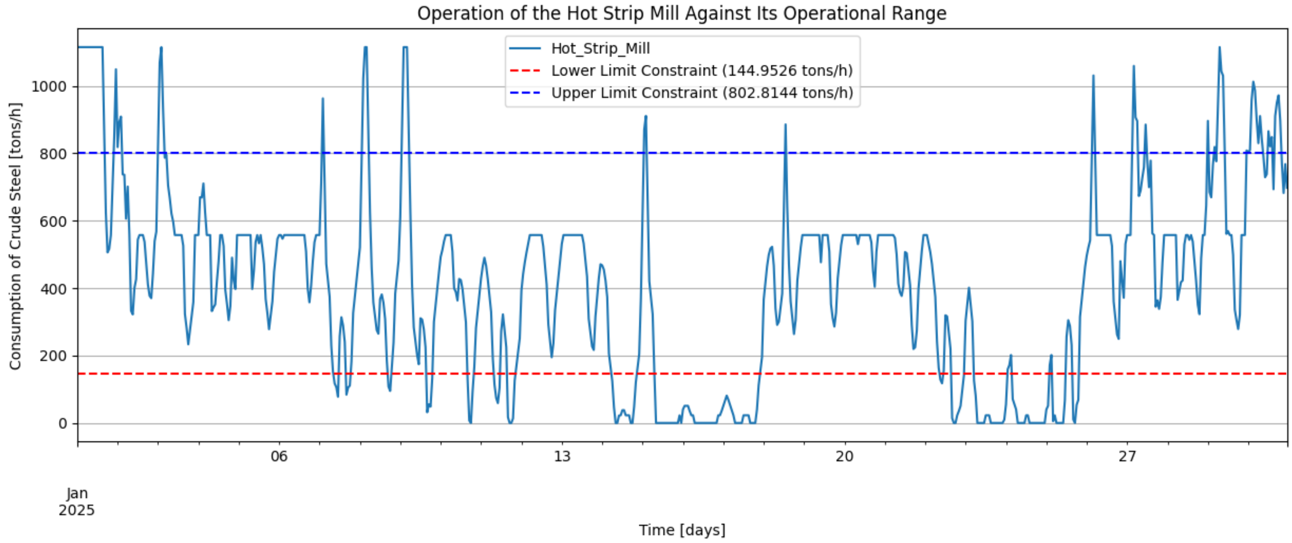

Figure 77: HSM operation when the original range constraints are not applied and also all of the storage limitations are not applied

After examining the impact of removing storage constraints for restricted materials, we proceed to analyze the effects of removing or extending the operational range limitations for all major plants. The results are presented in Figures 73 to 77, and the corresponding effects on the objective function are summarized in Table 7.

The pelletizing plant, for instance, demonstrates significant cost savings when its capacity limitation is removed, as it produces pellets more cheaply than importing them. While this is not a bottleneck in reality—since additional pellets are imported when needed—it suggests that increasing the plant's production capacity could lead to operational cost savings.

We examine the impact of removing range constraints individually for each major plant, then collectively for all plants, while keeping the storage limitations intact. Finally, we analyze the scenario where all plant constraints and storage limitations are removed simultaneously. As shown in Table 7, storage constraints play a critical role, affecting the objective function almost as much as extending the operational range of all major plants combined.

In summary, while all plants contribute to the active constraints of the problem, some have a greater potential for cost savings due to their flexibility (e.g., ramp limits that align with electricity price fluctuations) or their electricity-intensive nature. For example, the Linde plant demonstrates a significant effect, largely because it is electricity-intensive. However, strategic oxygen storage is restricted in this model to reflect the realistic constraints of the site.

The main bottlenecks are evident in the connections between the blast furnaces, hot metal storage, the BOF, crude steel storage (less significant than hot iron storage), and the final stages of the hot strip mill and direct sheet plant. These plants differ in their capacities, ramp limits, and input/output storage capabilities. Some are more electricity-sensitive and flexible, while others are not. When accounting for production security concerns and maintenance planning in a more complex real-world system, the coordination and optimization of this core part of the site are significantly more challenging than the model suggests.

Looking ahead, the introduction of DR plants capable of producing Direct Reduced Iron, which can be stored more easily and in larger quantities, along with the addition of EAFs (Electric Arc Furnaces) for greater operational flexibility, will likely alleviate some of these active constraints and bottlenecks. However, given the size and complexity of this integrated and interdependent site, these constraints will not disappear entirely.

Change	**Final Cost of Steel (eur/ton)**	**Objective Change (%)**
Base Case	[redacted]	0.00
Fully Unrestricted Plants With no Storage Limits	[redacted]	1.97
Fully Unrestricted Plants with Storage Limits	[redacted]	1.06
Linde range extension	[redacted]	0.64
DSP range extension	[redacted]	0.59
BF7 range extension	[redacted]	0.44
BF6 range extension	[redacted]	0.41
Pelletizing range extension	[redacted]	0.35
HSM range extension	[redacted]	0.25
BOF range extension	[redacted]	0.22
Base Case with all storage limits removed	[redacted]	0.17
Base Case with no HM storage limit	[redacted]	0.12
Base Case with no Oxygen storage limit	[redacted]	0.11
Base Case with no CS storage limit	[redacted]	0.03

Table 7: Sensitivithy analysis of the objective value by removing or extending different constraints

3.6.3 Verification

In this section, we perform testing to analyze the model's behavior under various scenarios. This process demonstrates that the model operates as expected in all possible scenarios and is not overly fine-tuned to specific conditions. We present three representative scenarios where the site's operation is atypical, requiring the model to minimize costs by identifying alternative solutions.

Low Electricity Prices: In this scenario, the electricity prices drop significantly, impacting the cost-effectiveness of electricity-intensive processes. The model must adapt by prioritizing operations that capitalize on lower electricity costs while ensuring production targets are met.

Non-Operation of the Large WAGs Generator: This scenario assumes that the large WAGs generator, provided by Vattenfall, is out of operation. The model must find alternative energy sources or adjust production to account for the reduced energy availability, while maintaining cost efficiency.

Low CO2 Prices: Here, the cost of CO2 emissions is reduced drastically. The model must evaluate the trade-offs between operational choices that generate higher emissions and the associated costs, potentially shifting the operational focus toward processes that were previously constrained by higher CO2 prices.

These scenarios provide valuable insights into the model's flexibility and robustness, ensuring that it can handle a wide range of operational conditions while optimizing performance and minimizing costs.

Scenario 1 - Extremely Low Electricity Prices

In this verification scenario, we are reducing electricity prices by 10% compared to the normal central scenario prices for 2025, with a monthly simulation of the current configuration. Natural gas prices remain unchanged. We expect the optimizer to adjust its behavior by taking advantage of the lower electricity prices relative to natural gas. This should result in a reduced use of natural gas where possible, while the flow of WAGs towards Vattenfall's power plants may increase, as the profit from electricity generation during this period will not be as high.

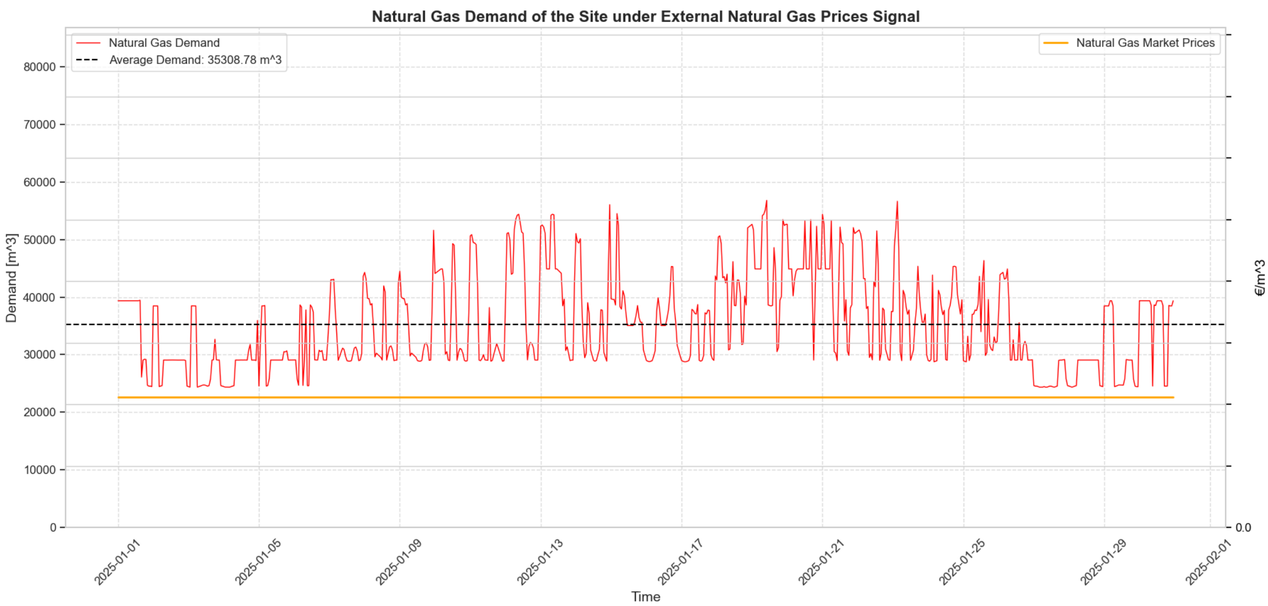

Figure 78: The natural gas consumption of the site using normal electricity prices

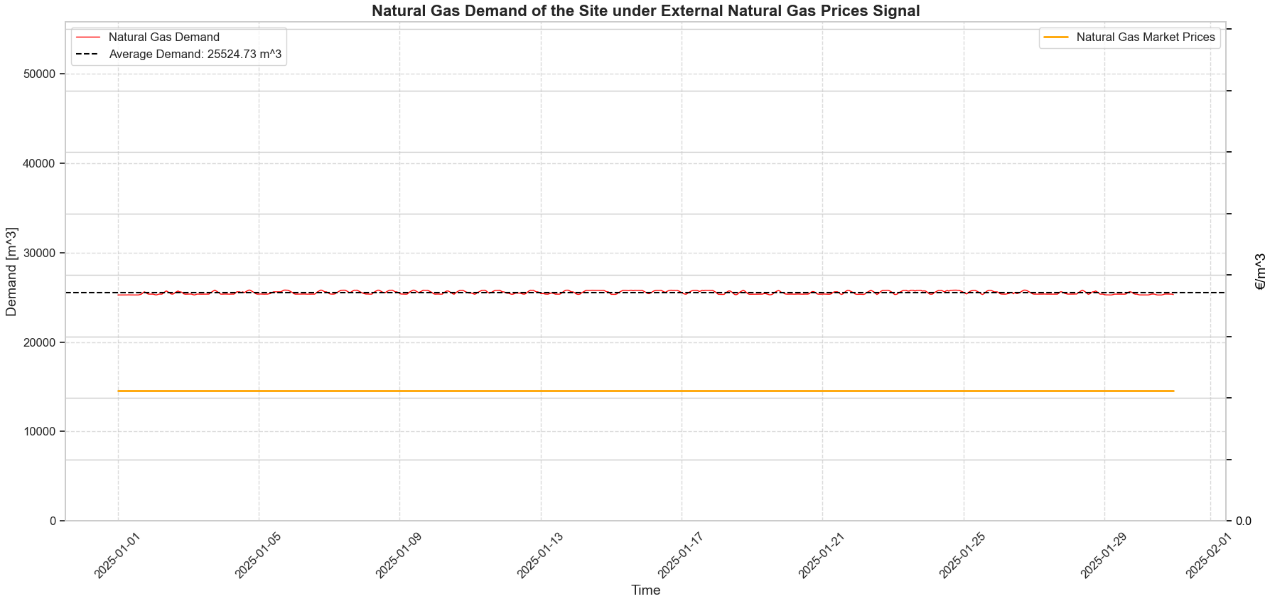

Figure 79: The natural gas consumption of the site using very low electricity prices

In Figures 78 and 79, we observe that very low electricity prices lead to a decrease in natural gas consumption. This highlights the system's interaction and the extent to which electricity can replace natural gas through the utilization of work-arising gases (WAGs). In such cases, WAGs are utilized as much as possible for heat production or other processes rather than being directed to generators for electricity production, as the profit from electricity generation is relatively low.

However, certain processes require natural gas exclusively, preventing consumption from dropping to zero, as shown in Figure 79. It is important to note that simply lowering electricity prices will not necessarily yield identical outcomes. The degree of natural gas consumption reduction and the increased internal use of WAGs, rather than diverting them to generators, depends on the price ratio between natural gas, electricity, CO2 costs, and various operational constraints. Given the system's complexity, it is challenging to generalize trends, and each scenario must be simulated by altering inputs and running the model.

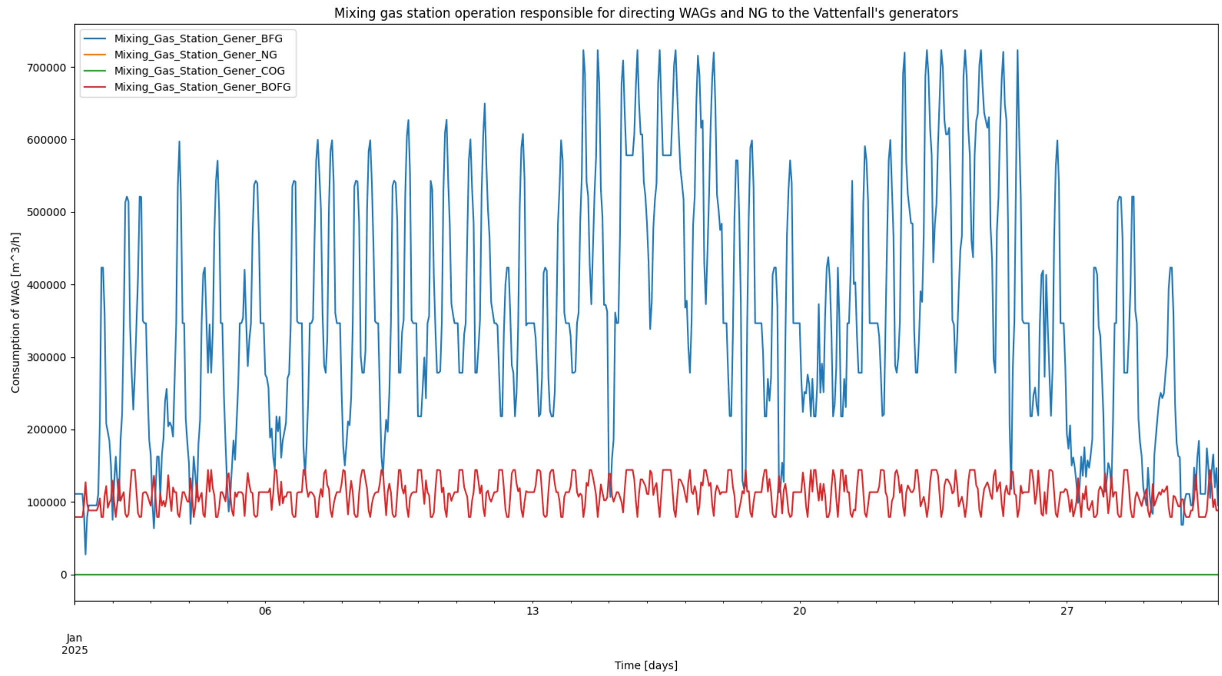

Figure 80: The normal operation of the mixing gas station mixing the gases for the Vattenfall's generators

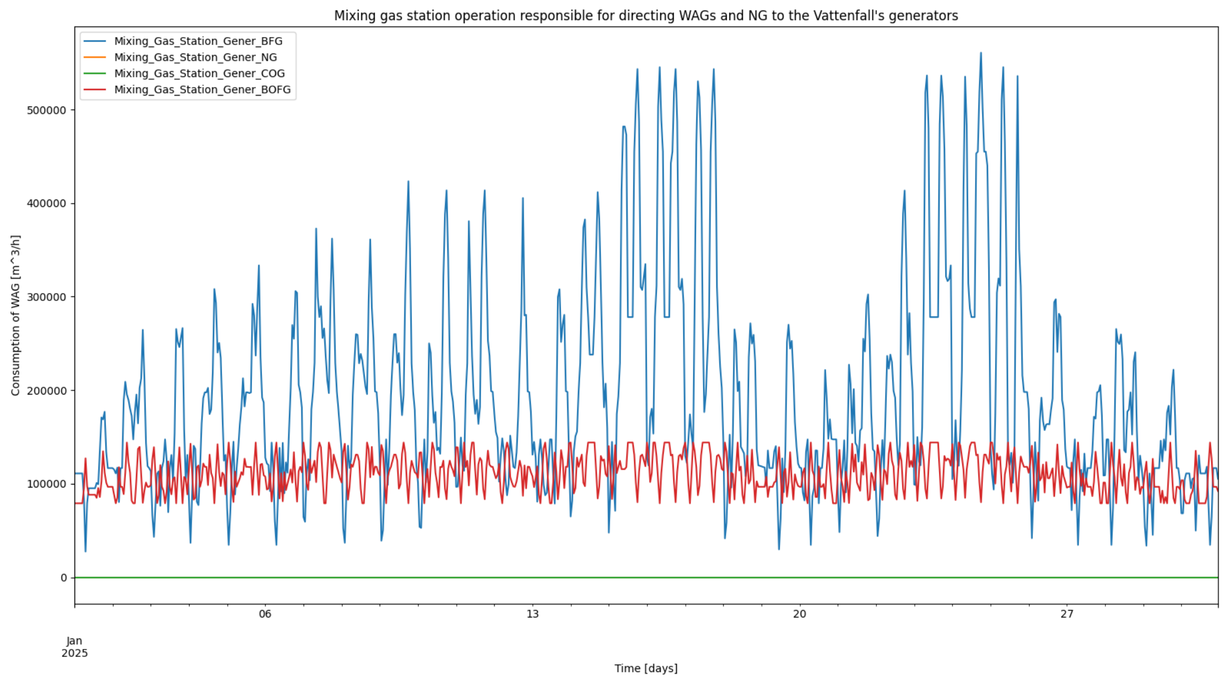

Figure 81: The operation of the mixing gas station under very low electricity prices

Examples of how this decrease in natural gas consumption occurs internally within the model are illustrated in Figures 80, 81, 82, and 83. In the first set of figures, we observe changes in the volume of gases passing through the mixing station to be sent to generators for electricity production. In the second set, adjustments in the consumption patterns of the Pelletizing Plant are shown. This plant can use COG or natural gas for one main process and BOFG or natural gas for the other main process (Malerij and Branderij*).

Under normal conditions, the optimizer tends to favor natural gas consumption, preserving as much available WAGs as possible for electricity generation. However, when electricity becomes significantly cheaper than natural gas, the optimizer prioritizes using WAGs for the operation of the Pelletizing Plant instead. Similar trends can be observed across various plants, boilers, and mixing stations on the site.

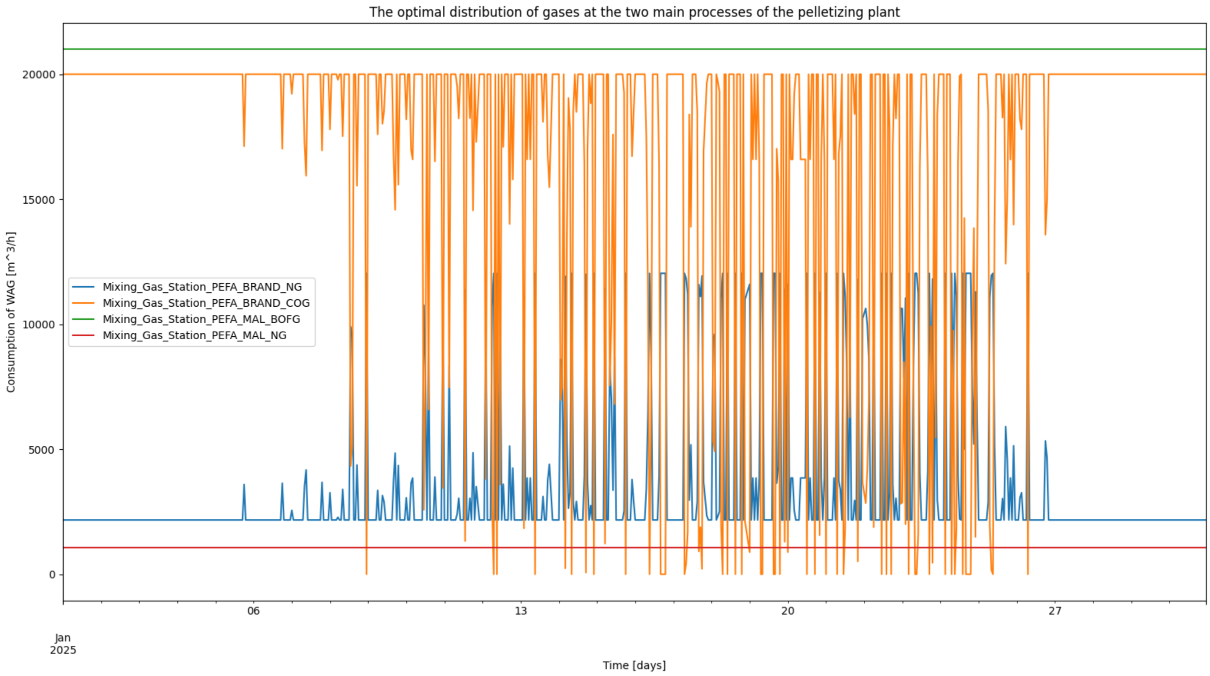

Figure 82: WAGs consumption of the Pelletizing plant under normal electricity prices

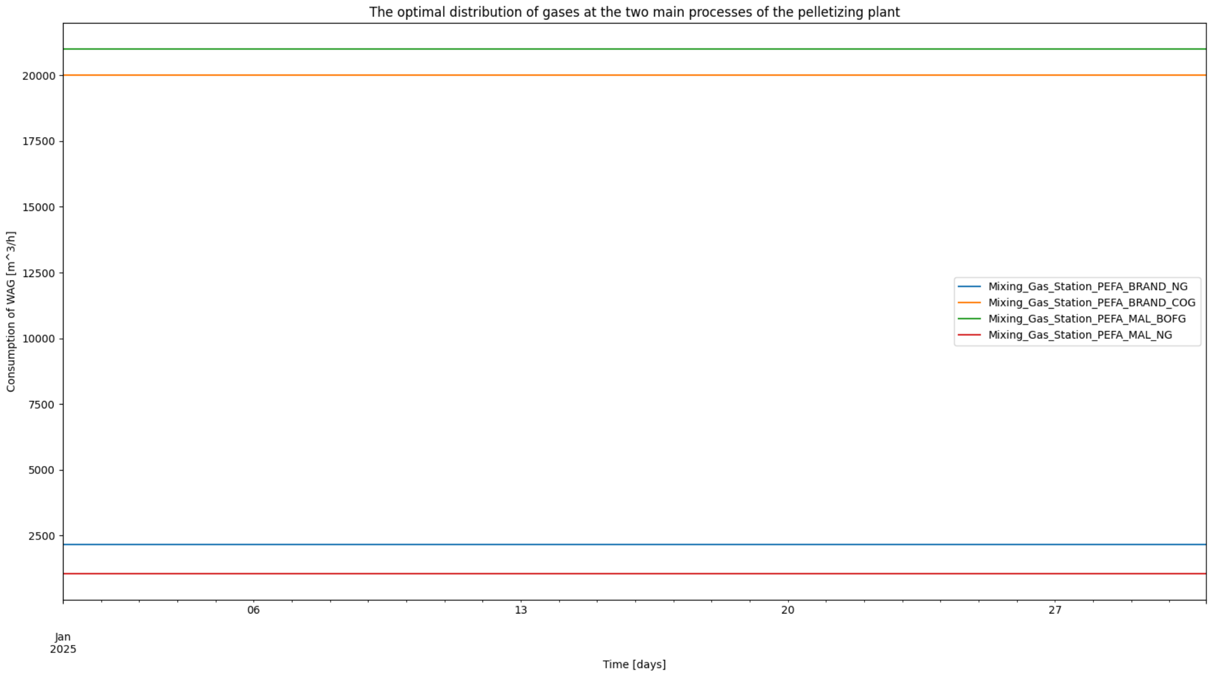

Figure 83: WAGs consumption of the Pelletizing plant under very low electricity prices

Scenario 2 - One of the Vattenfall's power plants is out of operation

In this scenario, we are restricting the available capacity for electricity generation using WAGs from the steel-making process, specifically BFG, BOFG, COG, and NG, in the appropriate ratios to match the operational range of the generators based on the Heating Value of the gas mixture. While there is a backup plant, VN24, capable of operating under such conditions, we will disregard this plant for this scenario, despite it being part of the model.

Our focus is to investigate the model's behavior under the assumption that the steel target must still be met, but the produced gases cannot be stored or fully directed to the generators. We expect the optimizer to maximize the use of WAGs for secondary processes, such as boilers or other main plants, in place of natural gas. Additionally, some excess WAGs that cannot be directed elsewhere may be flared. In this scenario, we are shutting down the larger of the two generators, VN25, which has a nominal capacity of 600,000 m^3 of WAGs and 350 MW of electricity generation.

In the following figures, we observe this behavior in action. In Figure 84, we can see the reduced natural gas consumption, as the optimizer prioritizes maximizing the use of WAGs to avoid flaring. This is due to the limited available capacity from the generators, which drives the system to optimize the use of available resources in the most efficient way possible.

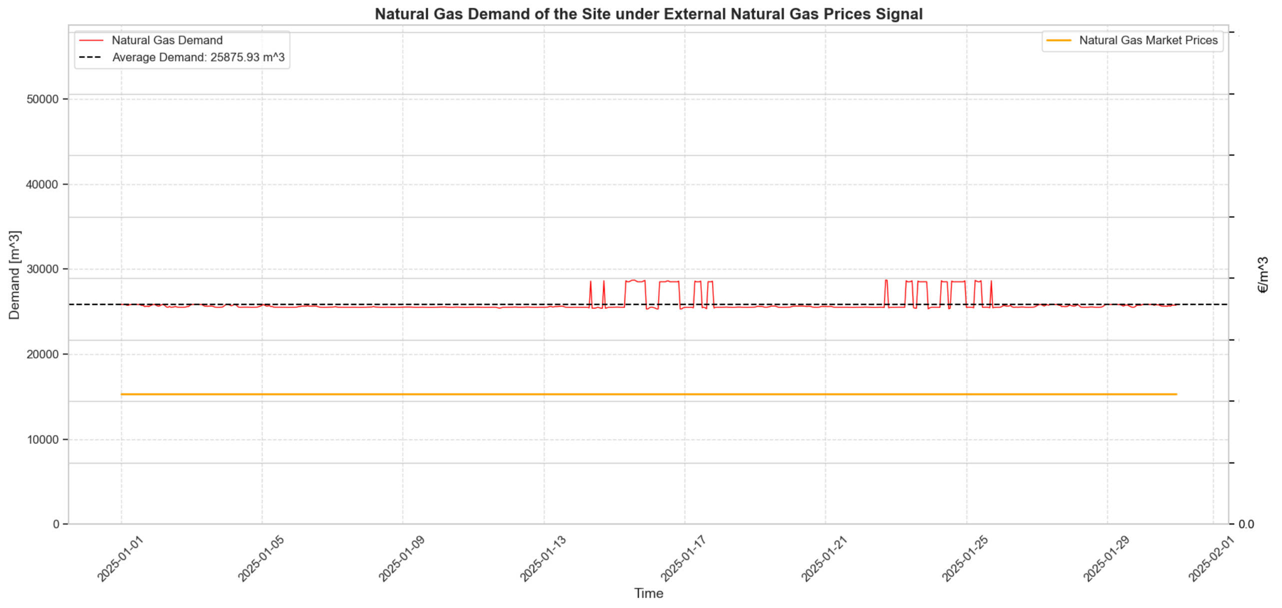

Figure 84: Natural gas consumption of the site when VN25 is not operating

In the following figures, Figure 85 and Figure 86, we compare the operation of the generators under normal conditions and with VN25 shut down. Under normal operation, flaring is expected to be zero, as the hourly time intervals in the model are too large to trigger flaring, and the real-world constraints on WAGs are stricter than those in the model, which may prevent flaring in certain cases. However, when the large VN25 generator is shut down, the optimizer resorts to flaring a significant quantity of WAGs to produce a feasible solution, as the accumulation of gases is not allowed.

Naturally, the cost of steel production will increase in this scenario, since the profits from electricity generation are reduced and the CO2 costs associated with flaring are higher.

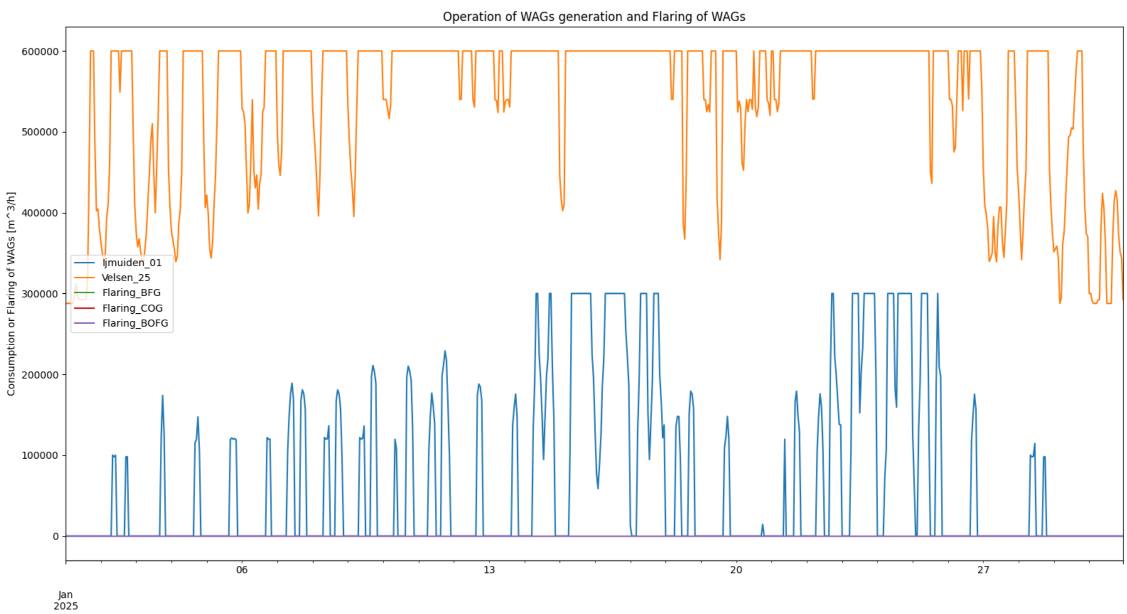

Figure 85: Vattenvall's generators and zero flaring during normal conditions

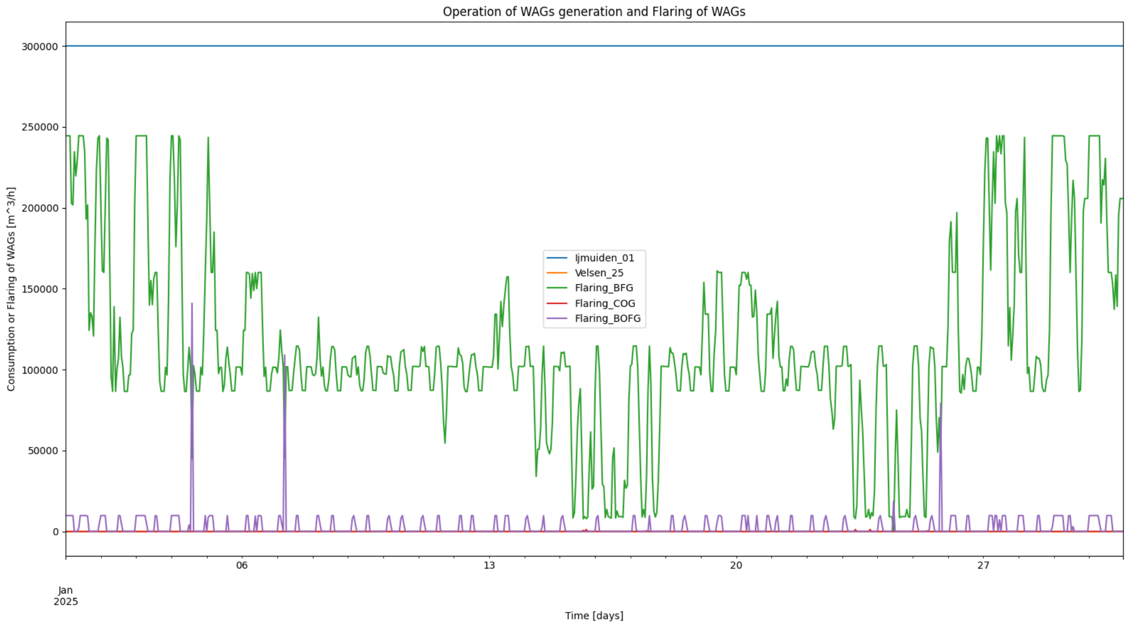

Figure 86: Vattenfall's generator IJ01 operating at the maximum and large quantities of flaring when VN25 is off

Scenario 3 - Low CO2 prices

In this scenario we are decreasing the cost of the emissions. In this case we are expecting the optimizer to adjust its consumption patterns leading to a solution which minimizes the total cost as always. Facing low emissions prices the optimizer has a different behavior compared to the previous cases. As we can see in Figure 87 the natural gas consumption increases compared to the base case, Figure 78.The optimizer is taking advantage of the low emission costs to operate the Vattenfall's generation as much as possible, since the emissions cost of the is high under normal CO2 prices. For this reason, it tries to minimize the consumption of WAGs internally replacing them with natural gas. We can see the increased operation level of the generators in Figure 88.

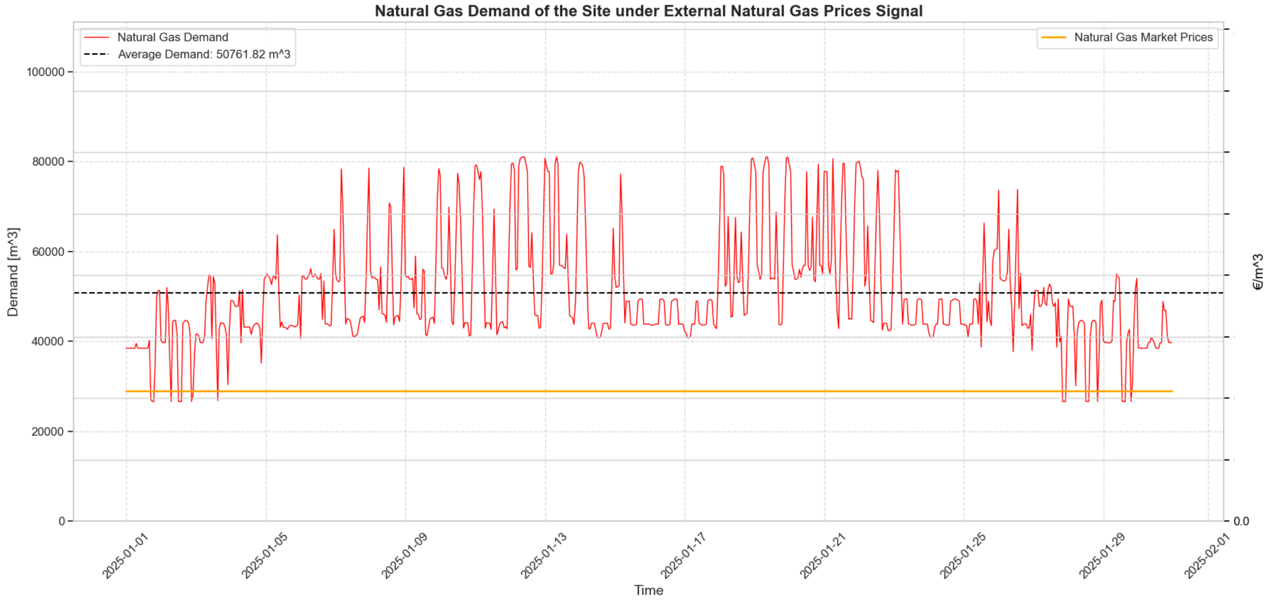

Figure 87: Natural Gas consumption of the site under low CO2 costs.

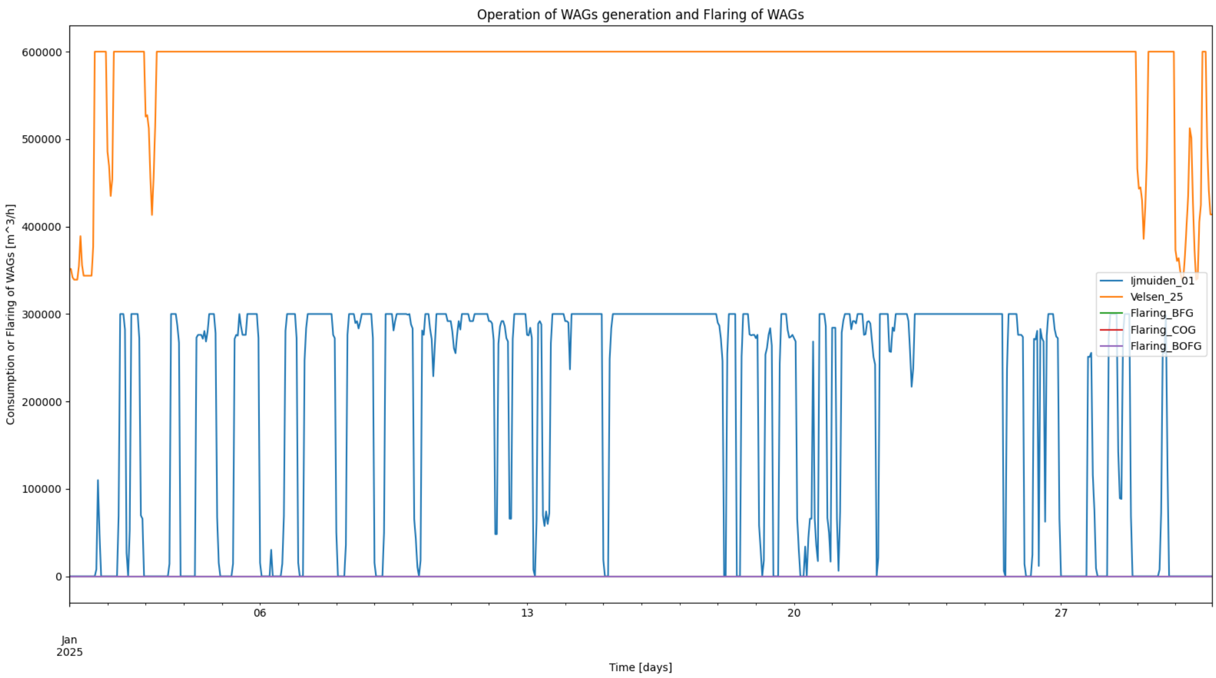

Figure 88: The operation of Vattenfall's generators under low CO2 prices.

3.6.4 Results Validation

In this section, we compare some outputs of the model with real available data. One of the most important aspects of the model is its ability to accurately model the electricity consumption of the different processes at the site and track changes during the site's transition phase. In Figure 89, we plot the hourly electricity demand of the site as output from the model and compare it with the real electricity demand, based on measured values. We notice that the average values are very close, with only a 0.1% difference. This makes sense, as the conversion factors for the processes and the limitations of the plants are based on real data, as explained previously.

The optimizer adjusts the operation of the various plants according to price signals, aiming to find the optimal operation of the site while still meeting the steel production target. We observe that the average electricity consumption of the site is determined by its specific configuration, and we can define an almost constant ratio of electricity consumed per ton of steel produced for a given configuration.

However, we also see some unusual operational points, such as complete shutdowns or low production periods, which are likely due to circumstances beyond the model's scope. While the price sensitivity of the site (particularly to electricity prices) is not the main factor driving its operation, changes in energy prices may have contributed to seasonal adjustments in its operations. Other factors, such as changes in steel demand, could also play a role.

It is important to note that the model output is based on perfect knowledge of energy prices for 2025, and the site's operation is optimized according to this forecast. In contrast, the real data from the site is from 2022.

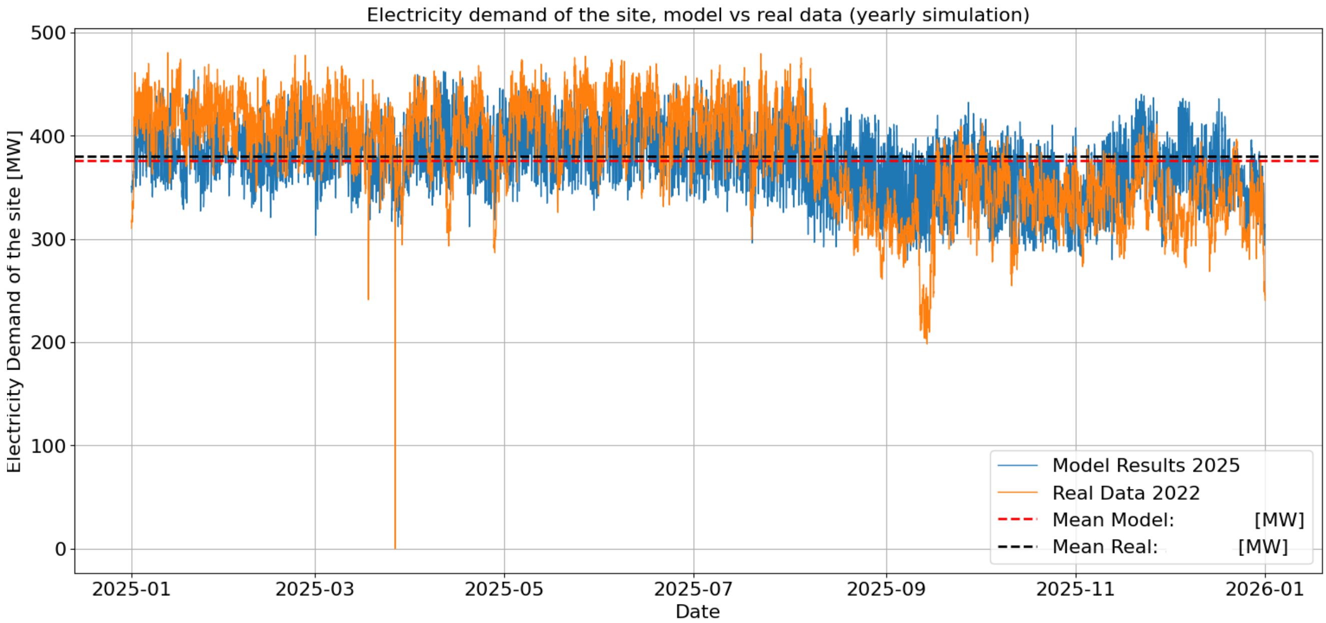

Figure 89: Comparison of the real electricity consumption of the site in 2022 versus the model results for a yearly simulation using 2025 prices

On the other hand, in Figure **??**, we observe that although the average values of the electricity demand of the site are very close, the distributions of hourly operation differ significantly. As expected, the model produces a more narrow distribution, centered around the average, with a smaller standard deviation. This is because, as explained earlier, we use a 10-90% range of the real operation of the plants for the model, which helps avoid unrealistic operational flexibility. This range allows the optimizer to operate the plants within more realistic bounds, preventing the model from exploring extreme operating conditions that would not typically occur.

In contrast, the real data shows a wider distribution with a higher standard deviation. This broader spread can be attributed to unforeseen circumstances, outages, and the maintenance schedules of different plants, which are not accounted for in the model. The real-world data also reflects periods where the site may produce more steel than usual, such as during high steel prices, or when taking advantage of unexpected low energy prices. The symmetrical operation around the average observed in the model represents the optimal, stable operating conditions, while the slightly right-skewed distribution of the real operation demonstrates the impact of external factors, including maintenance or strategic production adjustments.

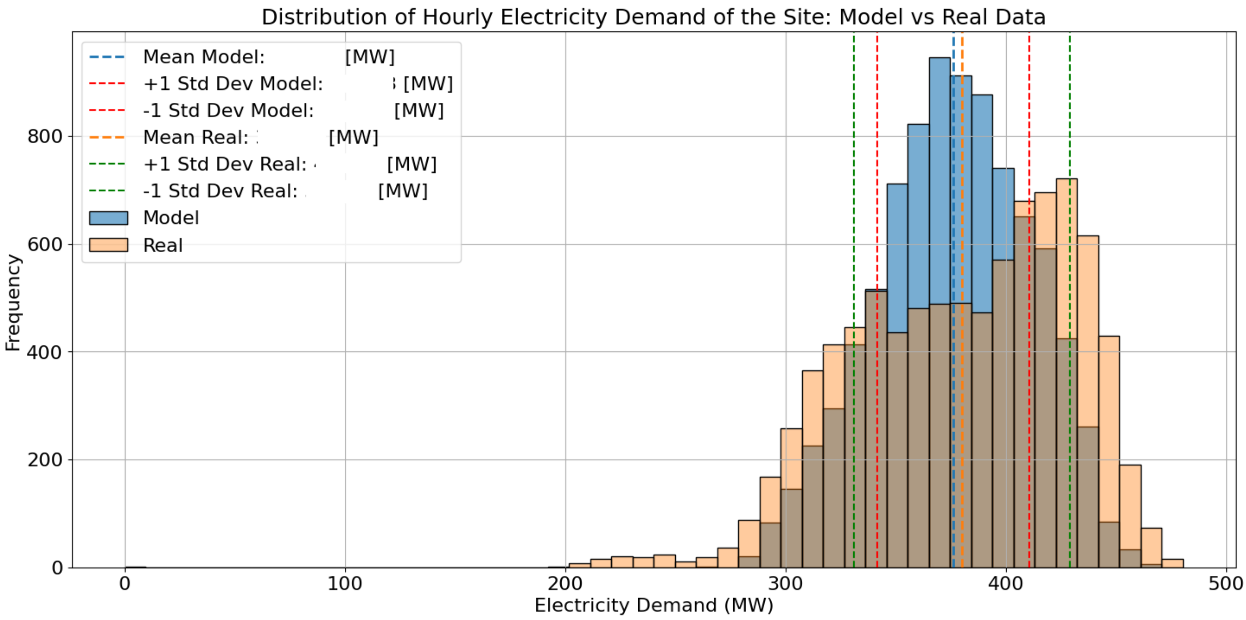

Figure 90: The real distribution of the hourly electricity consumption of the site (Orange) versus the model output for the hourly consumption of the site (Blue).

In Figure 91, we compare the model's outputs with real data from the site for the year 2022. Since the primary focus of this work is to model the electricity consumption of the site as accurately as possible, the model also tracks the other main material and energy flows across the entire site. However, the accuracy of these other flows cannot match the precision of the electricity demand profile.

To elaborate, the model calculates CO2 emissions based on the operation of each plant and the conversion factors between material consumption or production and CO2 emissions. Additionally, as outlined in the methodology section, some constant average values of emissions relevant to each configuration are incorporated to ensure that the total emissions of each configuration are close to real-world values. However, the model cannot account for special occurrences, such as increased flaring or other unforeseen circumstances that may have taken place during 2022.

Despite these limitations, the difference between the real emissions and the model's estimates is considered acceptable for the purpose of creating transition configurations. In fact, the model's emissions align closely with the CO2 reduction targets, demonstrating its ability to represent the overall trends and objectives of the site's emissions management.

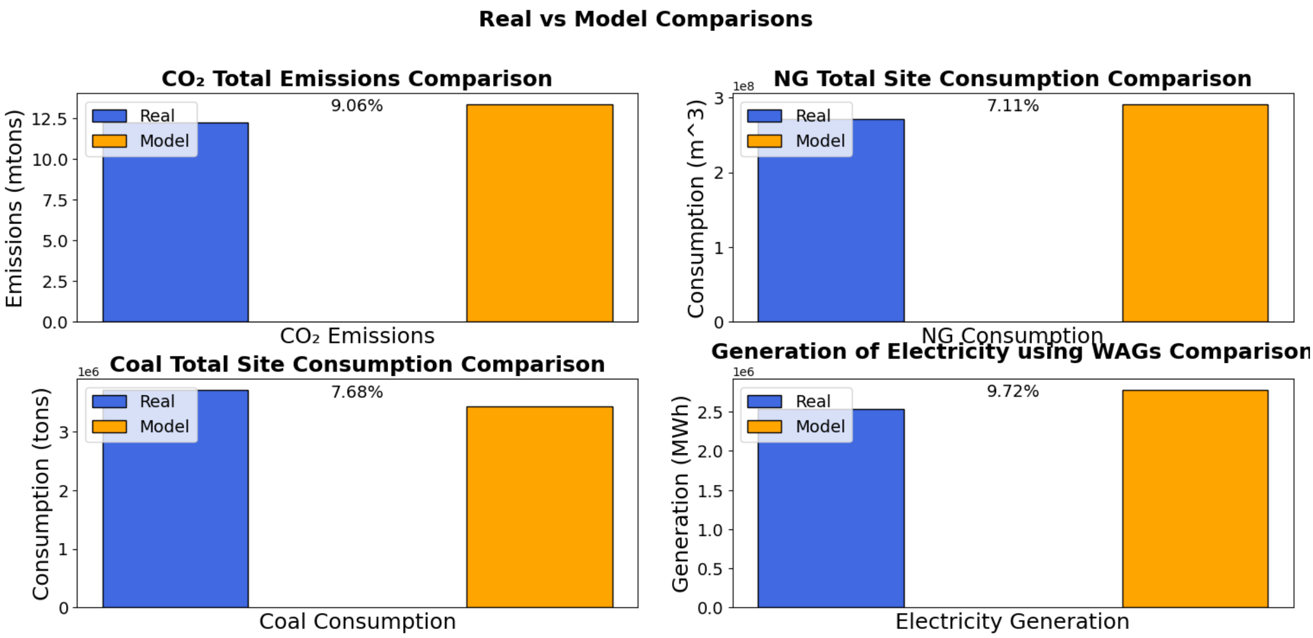

Figure 91: Comparison between model outputs and real data of the site.

Natural gas and WAGs generation from the external Vattenfall generators are also within an acceptable range when compared to real data. The differences can be attributed to the internal optimization of the model regarding these flows, which is simpler than the real-world distribution process. In reality, natural gas is used in boilers and other plants when WAGs are either unavailable or of insufficient quality to meet the requirements of specific processes. This control process happens in real-time at very frequent intervals, and the distribution of gases is complex, influenced by factors such as production security and gas quality (which depends not only on the operation of the plants producing them but also on the initial coal quality). These factors are difficult to include in the model.

In the model, we aim to simplify the general concept of prioritizing WAGs usage over natural gas (through cost minimization) while respecting basic constraints of the plants, generators, and boilers that determine which gases or mixtures can be used, based on their heating values. However, some amount of natural gas is always required since certain processes rely on it. The consumption of WAGs for electricity generation follows a similar logic, balancing between usage in boilers or main plants and directing them to generators for power generation, and subsequently generating profits from electricity sales. The optimization logic in the model approaches the real-world behavior by considering the constraints of power plants, efficiency limits, and ramp-up restrictions in a cost minimization problem. However, it cannot fully capture smaller phenomena or more nuanced factors that could affect or alter the optimization process.

The difference in coal consumption arises from slight variations in the conversion factors used in the model, which apply to the initial coal entering the coking plants and blast furnaces, and the conversion of steel from the BOF process to rolled steel in the Hot Strip Mill and DSP plants. Despite these small differences, the model performs well in capturing the main energy and material flows of the site. It provides a detailed representation of the quantities and energy flows into and out of each of the main plants. The model approximates real-world values for emissions, natural gas, and electricity consumption by incorporating constant or time-series loads for processes that are not modeled analytically. Furthermore, it resolves the complex issue of flow distribution (primarily WAGs) by suggesting a simplified approach that leads to reasonable results, as demonstrated in the verification section.

3.7 Price Scenarios - Cost Inputs

In this section, we discuss the costs used as inputs to the model. More detailed information on these costs, including some confidential details due to restrictions from Tata Steel, can be found in the Appendix of this report (confidential version). Tata Steel has provided key cost inputs based on its internal analyses and external market data sources.

The price projections used in this work are based on representative years for each transition phase and configuration of the site. Specifically, the year 2025 is used for the current configuration, 2030 for Phase 1, 2037 for Phase 2, and 2045 for Phase 3, in line with Tata Steel's decarbonization goals outlined in earlier sections. The provided cost data reflect expected market trends and assumptions regarding future energy prices.

In Table **??** in the Appendix, we present a breakdown of which cost inputs vary on an hourly, monthly, or yearly basis, where multiple scenarios are available, and which inputs are sourced from providers other than Tata Steel. While different scenarios exist, we primarily use the central case provided by Tata Steel for all main results.

As a general overview, we have already explained how we handle cost inputs in our model, primarily using PyPSA components for generators or other practices to assign the marginal cost of each input energy or material to the model. The main costs included in the model are electricity, natural gas, coal, iron ore, imported pellets, scrap, CO2, hydrogen, network tariffs, and profits from electricity generation using WAGs from the site.

Tata Steel provides electricity, natural gas, coal, and CO2 prices for the reference years relevant to the analysis. The remaining cost inputs are sourced from literature or real market data. It is important to note that the profit stream from electricity generation at the site is linked to the electricity day-ahead market prices provided by Tata Steel.

Additional details, values, and plots of the different prices are included in the Appendix for the committee of this thesis. However, due to confidentiality agreements, this data cannot be shared publicly.

It is also important to note that the prices provided by Tata Steel are structured into four different scenarios:

- **Central Scenario**: The most probable scenario, representing expected market conditions.
- **Net Zero Scenario**: Similar to the central scenario but aligned with the Dutch government's target to decarbonize the power sector.
- **High Price Scenario**: Represents an upper limit for commodity prices, considering market volatility and potential price surges.
- **Low Price Scenario**: Represents a lower limit for commodity prices, accounting for favorable economic conditions or market downturns.

4 Results and Discussion

In this section, the model outputs for various price scenarios and configurations are presented, followed by a discussion and comparison of the impact of Tata Steel's transition plans. Initially, basic results for each of the four configurations (Current, Phase 1, Phase 2, and Phase 3) are outlined. Subsequently, a sensitivity analysis is performed for each configuration.

For the sensitivity analysis, the four price scenarios that are used are utilized to investigate the impact of price changes under each configuration. Following this, a comparative analysis of the basic outputs across the configurations is conducted. An in-depth examination of network costs is also included.

Additionally, a section is dedicated to exploring the site's flexibility after the installation of the Electric Arc Furnace (EAF) compared to the current configuration. The effect of EAF size is analyzed for various electricity and network cost scenarios. Finally, the viability of utilizing electrolysis for hydrogen production at the site, as an alternative to external procurement, is assessed for different hydrogen price levels and three electricity price scenarios.

4.1 Main results and sensitivity analysis of the 4 configurations

Current

Using the price scenarios introduced in the previous section, the following figures present the main results of the model, starting with the current configuration. In Figure 92, the site's electricity demand is plotted against hourly electricity prices after running the model for the central price scenario in the year 2025. The average demand, including approximately 30 MW of self-generation from the site, is around [redacted] MW with peaks reaching close to 500 MW.

The optimizer attempts to adjust the site's operation to align with periods of lower electricity prices. However, this adjustment is constrained by the operational limitations of the plants in the current configuration, as detailed in the validation section. While this figure does not aim to represent a direct correlation between the demand curve and electricity prices, it serves as a valuable visualization for understanding the site's average electricity demand and the extent of variation around this average.

Currently, the range of variation around the average demand is approximately 150 MW, spanning from the lowest to the highest consumption points. As the site transitions through different configurations, we will observe changes in this range.

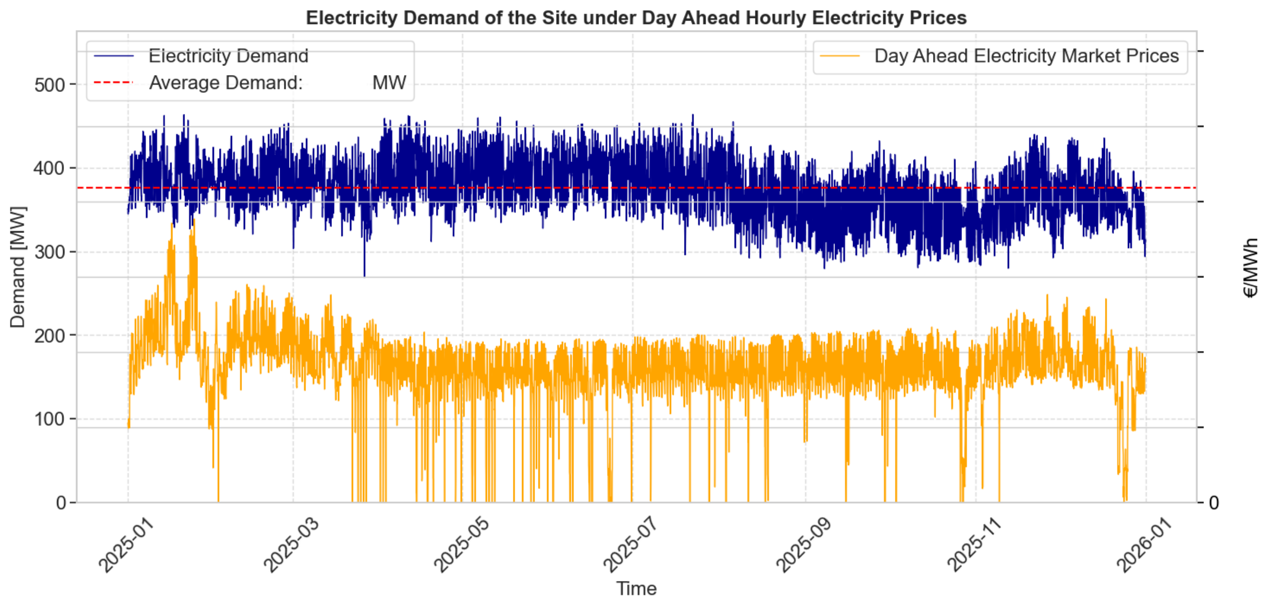

Figure 92: The electricity demand of the site for the current configuration and central prices scenario for the year 2025. The output of the model plotted against the hourly electricity prices input.

In Figure 93, the hourly natural gas consumption of the entire site is shown for the current configuration in 2025. Unlike electricity prices, which vary hourly, natural gas prices change monthly. The hourly natural gas demand is calculated as the sum of consumption from various plants, boilers, and generators operating at each specific timestep.

As expected, the optimizer tends to increase natural gas usage during periods of lower prices. However, this does not necessarily indicate that steel production decreases during these times. The model represents a complex system with numerous energy carriers and processes, many of which can use natural gas or work-arising gases interchangeably. This flexibility allows the optimizer to adjust energy usage while maintaining the production targets.

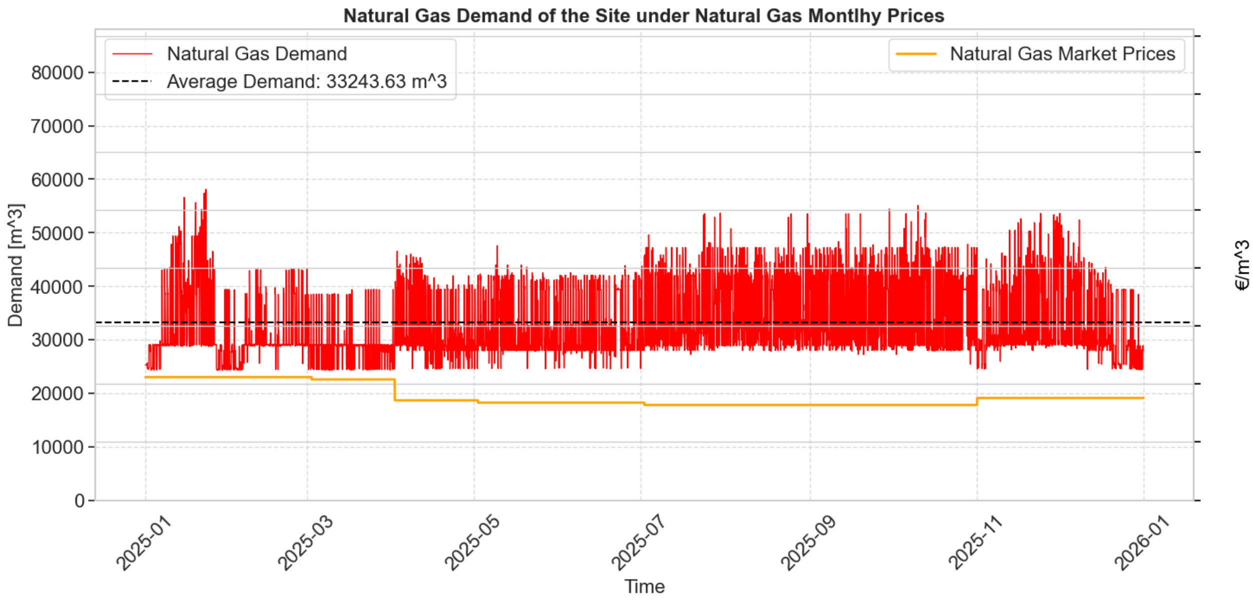

Figure 93: The natural gas demand of the site as an output of the model for the central prices scenario and the current configuration for the year 2025 plotted against the natural gas prices of the scenario having constant values per month.

The model closely follows electricity market patterns by adjusting the allocation of gases for electricity generation or diverting them to other processes (e.g., replacing natural gas consumption). However, as described earlier, reality is far more complex. The real-world operation involves significant challenges, such as ensuring that the mix of gases meets the required specifications for generator operation, achieving the appropriate heating values through precise mixing, and managing the control systems to implement such decisions effectively.

In practice, generating electricity from work-arising gases is not expected to align with electricity prices on an hourly basis, as modeled. The idealized scenario in the model assumes perfect conditions, which are difficult to achieve in reality due to various operational constraints. These constraints include real-time tracking of gas properties, mixing limitations, and the inability to operate generators in a fully price-sensitive manner.

Despite these challenges, the overarching goal remains to maximize the use of work-arising gases for electricity generation while minimizing natural gas consumption. While the deep operational details and additional constraints are not incorporated into the model, it does capture the basic logic of site operations. Importantly, the modeled yearly total electricity generation aligns well with real-world data, validating its assumptions on a broader scale.

The output of this concept by the optimizer is presented in Figure 94, which illustrates the electricity generation in MW from the work arising gases as determined by the optimizer. It is evident that the optimal generation, achieved through a precise allocation of the work arising gases and strategic generation during periods of high electricity prices, results in an average generation of 317 MW. This corresponds to approximately 85 % of the total site demand, highlighting the minimal exposure of the current configuration to variations in the electricity market.

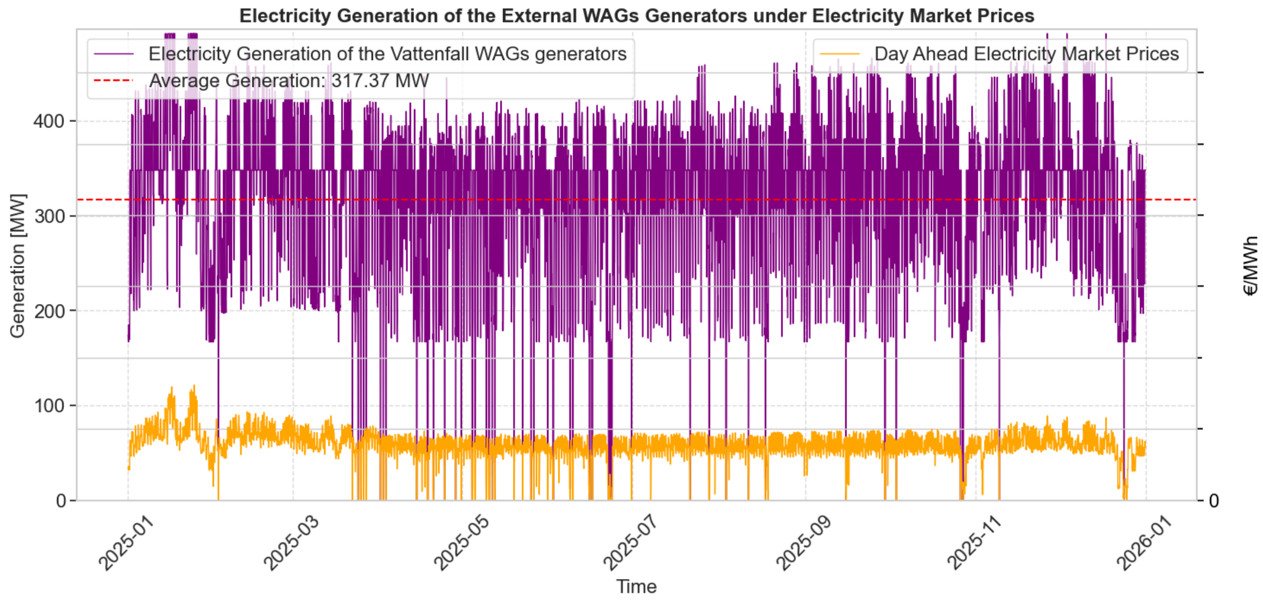

Figure 94: The electricity generation of the Vattenfall's generators where the Work Arising Gases of the site are directed to, indicating the decreased exposure of the site to the electricity market.

Figure 95 illustrates the cost breakdown of steel production as derived from the model's current configuration. This cost is referred to as the marginal cost, which is calculated based on the marginal cost of each plant or process consuming materials or energy. These inputs are assigned specific cost values, as described in the cost inputs section.

The total cost comprises the following components:

- Emissions costs
- Electricity costs (from the Day-Ahead market)
- Iron ore
- Coal
- Natural gas
- Imported pellets (excluding those produced by the pelletizing plant)
- Scrap

It is important to note that the total cost also factors in revenue from selling electricity generated from work-arising gases (WAGs) back to the grid. However, it does not include network costs at this stage of the analysis.

The resulting marginal cost of steel production for the site, under the central 2025 price scenario, is approximately [redacted] €/ton. This figure is reasonable and falls within the acceptable range when considering the market price of steel and comparisons with other studies that model steel production costs using similar approaches.

It is essential to acknowledge that the steel market is highly volatile and influenced by numerous factors. The marginal cost of steel, as calculated here, represents only one part of the overall cost structure. Unlike electricity market generators, who often use marginal costs as a basis for bidding or pricing, the steel industry does not rely on marginal cost in the same manner.

In practice, the final steel cost includes additional components such as capital investments, labor costs, and other fixed expenses. Therefore, this work focuses solely on marginal cost, as defined within the parameters of this analysis.

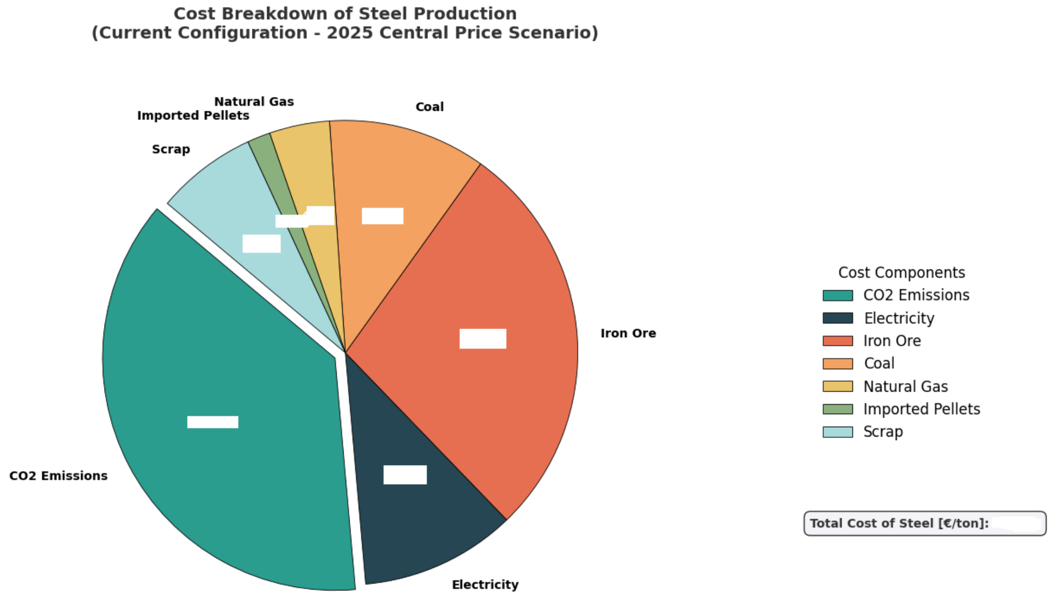

Figure 95: The cost breakdown of the current configuration and the marginal cost of steel production

Figure 96 highlights the energy breakdown for the site under the current configuration. Coal stands out as the primary energy carrier, reflecting its dominant role in the steel production process, particularly under the BF/BOF route. As coal progresses downstream in the production process, it is partially converted into work-arising gases (WAGs), which are further utilized in various stages of steel production.

Electricity and natural gas are the other significant energy carriers in this configuration, albeit to a lesser extent compared to coal. Together, these energy carriers demonstrate the diverse but coal-heavy energy profile of the site.

It is noteworthy to mention the energy intensity of the steel industry, with a total energy consumption of approximately 100 PJ. For context, this is four times the annual energy consumption of a town with a population of 500,000 people, which typically consumes around 25 PJ of energy annually.

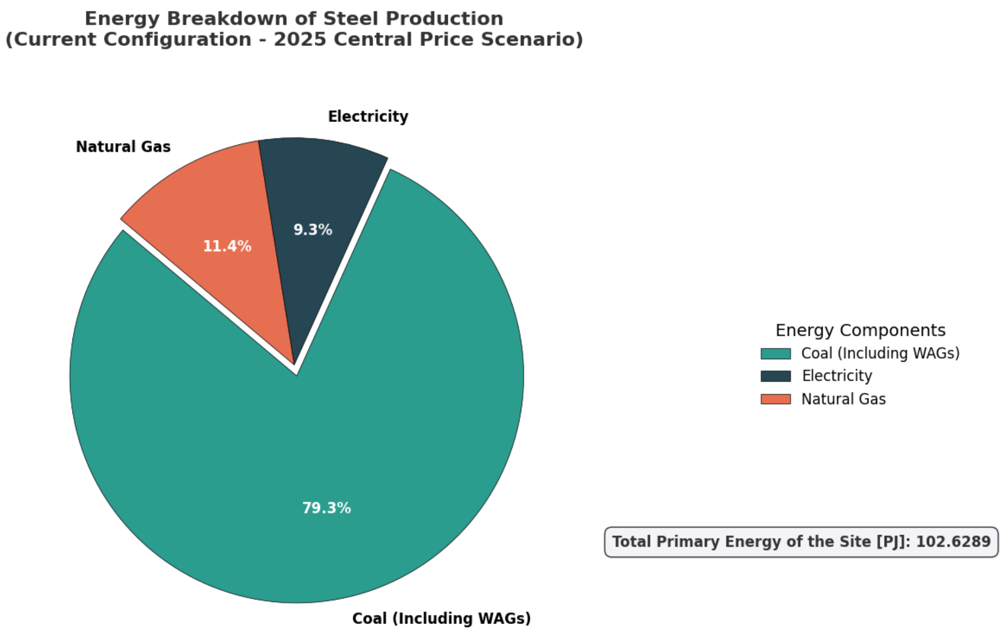

Figure 96: The energy breakdown of the current configuration and the total energy consumption of the site

Parameters	Values
Steel Cost	[redacted] eur/ton
Electricity Consumption Avg	[redacted] MW
Natural Gas Consumption Avg	33243.63 m^3
CO2 Emissions	13365216.16 tons
Electricity Consumption Total	3.17 TWh
Total WAGs Generation	2.74 TWh
Peak Electricity Load	[redacted] MW

Table 8: Main outputs of the central scenario of the yearly simulation for the current configuration

In Table 8, the key outputs from the yearly simulation results for the current configuration are summarized.

Sensitivity

After obtaining the main results for the current configuration, a sensitivity analysis was performed using the other available scenarios: High, Low, and Net Zero. We investigated changes in the cost of steel, natural gas consumption, electricity consumption, and emissions. The analysis revealed that the only parameter to change significantly was the cost of steel, while the other factors were more configuration-driven and less influenced by external costs of energy or materials. For example, to produce a specific amount of steel under a given configuration, the site must emit a certain amount of CO2, which cannot be affected by changes in the cost of energy or materials. However, the cost of steel, as expected, changes significantly across the different scenarios. The variation across scenarios is shown in Figure 97. Specifically, the cost of steel in the High Price scenario is 20 % higher, while in the Low Price scenario, it is 13.5 % lower.

The exact effect of each cost component on the final price of steel for each scenario is displayed in Figure 98. In all scenarios, the cost of emissions remains the most significant contributor to the final cost. The participation of electricity in the final cost varies depending on the scenario but remains relatively low. The participation of iron ore costs changes due to the variation in the total cost, not the price of the iron ore, which was kept constant.

Overall, the scenarios primarily affect energy and emissions costs, with materials costs remaining stable.

The figures for the sensitivity analysis on other parameters, such as emissions and natural gas consumption, show minimal differences across the scenarios and can be found in the Appendix.

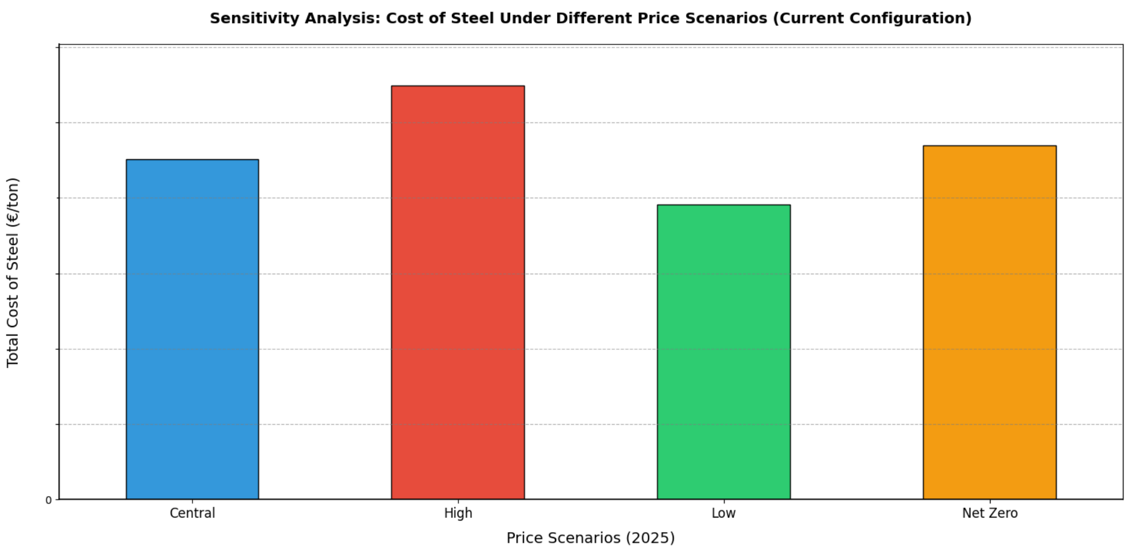

Figure 97: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the current configuration.

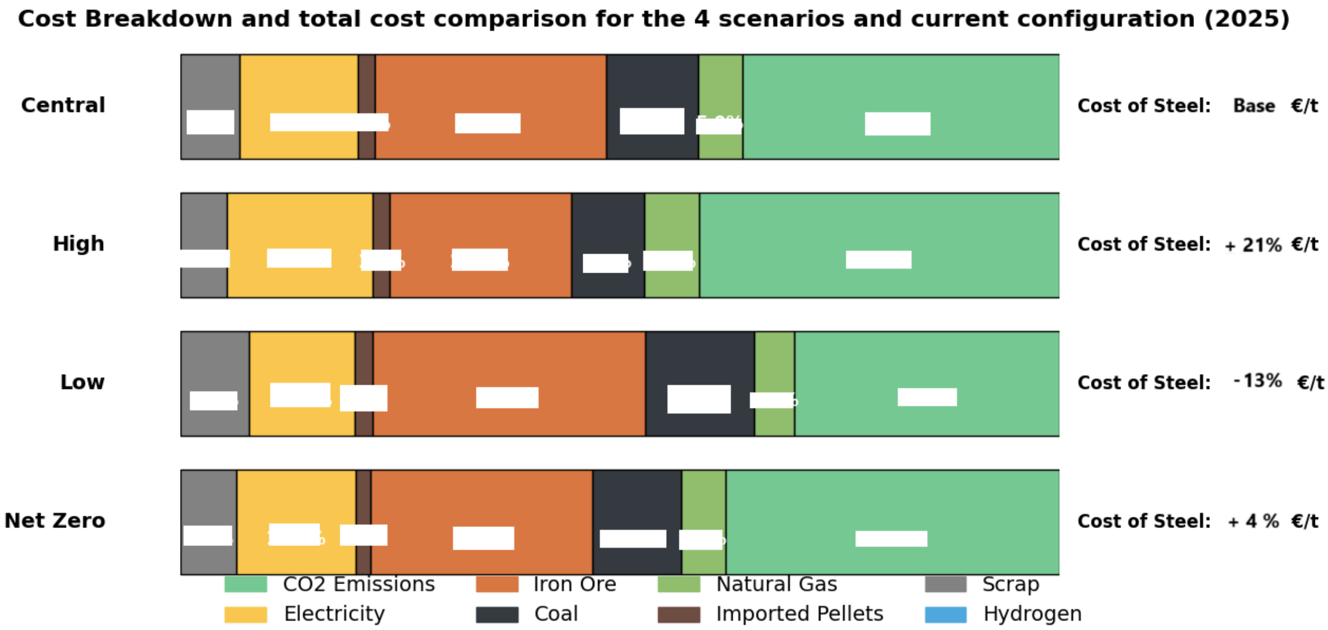

Figure 98: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the current configuration and including cost breakdowns

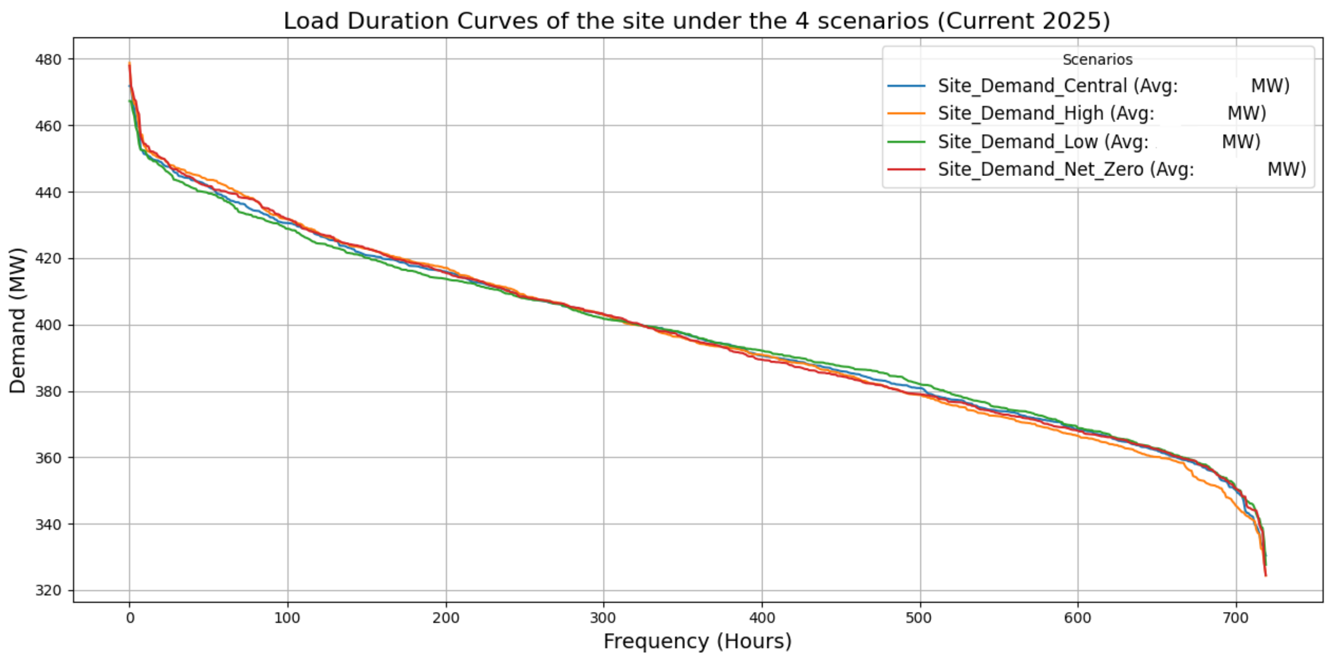

Figure 99: The load duration curves of the whole site and the 4 scenarios for the current configuration

In Figure 99, the load duration curves for a monthly simulation of the total site load under the four scenarios are depicted. It is evident that the variations in these curves across different price scenarios are minimal, indicating that the site's flexibility or demand does not significantly adjust to changing prices, particularly electricity prices. Greater variation between scenarios is anticipated in future configurations, though this also depends on the characteristics of the input electricity prices for each reference year. The input prices though do not differ so much between scenarios for each year to justify the big differences we see in the shape of the load duration curves of the site. These changes are mostly affected by the change in the configurations of the site during its transition.

For instance, if the electricity input time series varies only in absolute values rather than in structure, the optimizer generates similar load patterns, even if the absolute values differ. While the duration curves of the input prices cannot be included here due to confidentiality constraints, they are available exclusively for the committee of this work in the appendix.

The key observation is the limited flexibility of the site, as indicated by the duration curve's relatively long mid-section with a gentle slope, reflecting a narrow operational range around the average load. The curve exhibits a minor and abrupt drop towards the end, which suggests some potential for load reduction during periods of extremely high prices. However, this occurs infrequently and the magnitude of the reduction is not substantial.

Phase 1

The reference year for Transition Phase 1 is 2030, a period aligned with the planned decommissioning of Blast Furnace 7 and Coking Plant 1 at the IJmuiden site. In their place, a Direct Reduction Plant (DRP) and an Electric Arc Furnace (EAF) are introduced to handle the remaining steel production not covered by the continued operation of Blast Furnace 6 and the Basic Oxygen Plant.

The DRP utilizes natural gas to produce direct reduced iron (DRI), which is then processed in the EAF. The EAF is a significant electricity consumer, with a maximum capacity of 200 MW, while the DRP is a highly natural gas-intensive process, consuming approximately 100,000 m3 of natural gas per hour.

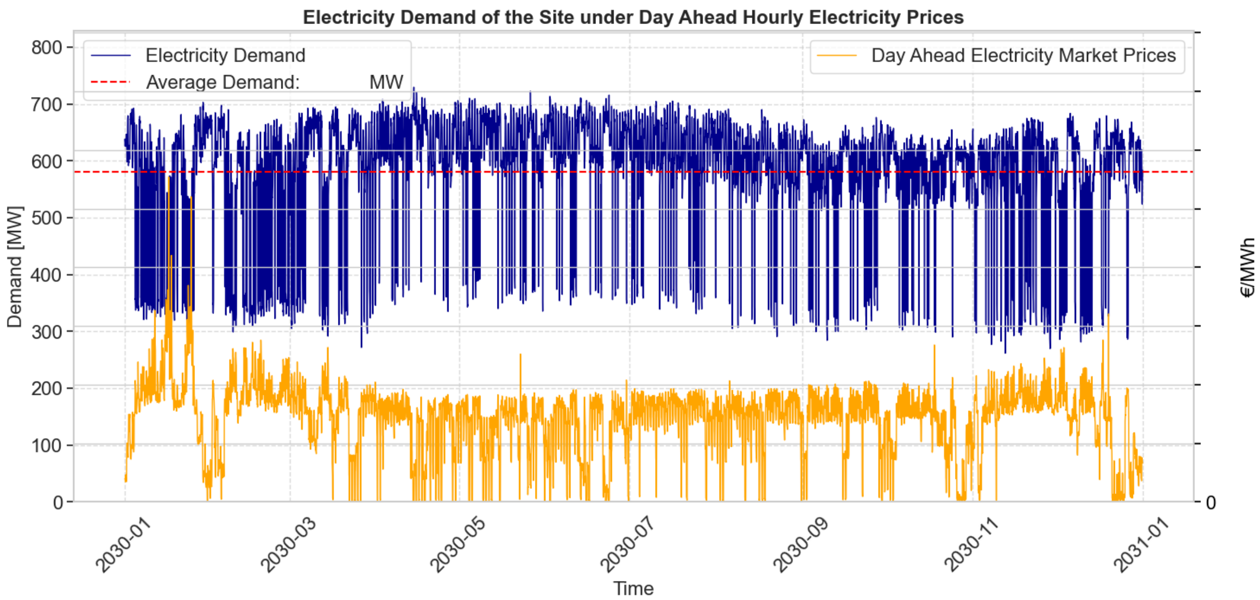

Figure 100: The electricity demand of the site for the Phase 1 configuration and central prices scenario for the year 2030. The output of the model plotted against the hourly electricity prices input.

As a result, there is a noticeable increase in both electricity and natural gas consumption at the site, as illustrated in Figures 100 and 101. While the natural gas consumption pattern does not exhibit significant flexibility in this configuration, electricity consumption—primarily driven by the operation of the EAF—has become more sensitive to price fluctuations compared to the current configuration. This aspect will be explored further in a separate section.

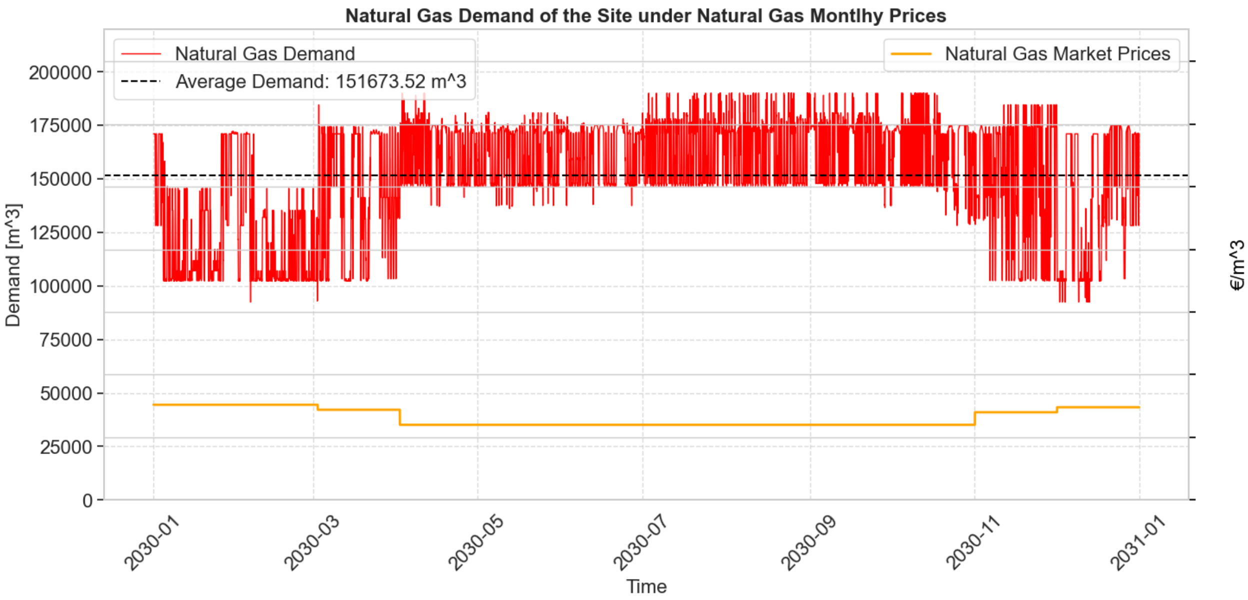

Figure 101: The natural gas demand of the site as an output of the model for the central prices scenario and the Phase 1 configuration for the year 2030 plotted against the natural gas prices of the scenario having constant values per month.

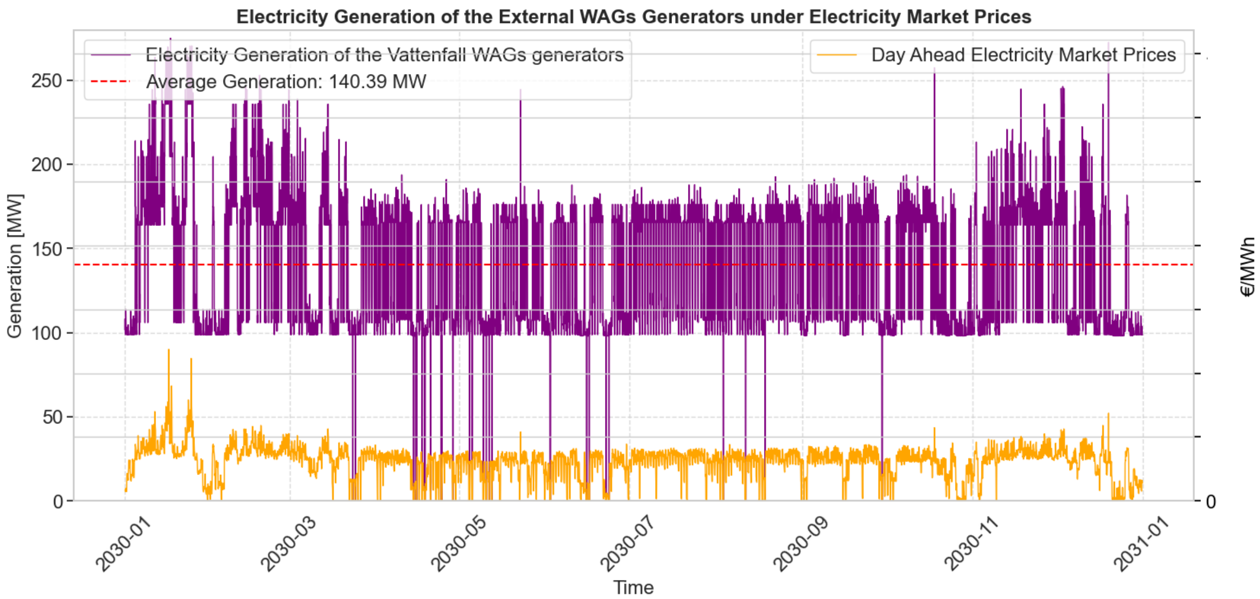

Figure 102: The electricity generation of the Vattenfall's generators where the Work Arising Gases of the site are directed to, decreased at the Phase 1 configuration.

The generation of electricity from the WAGs at the site is reduced significantly, as anticipated, due to the limited availability of Blast Furnace Gas from BF7 and Coke Oven Gas from the decommissioned Coking Plant 1. Under this configuration, the average electricity generation from WAGs is reduced by more than half, which increases the site's exposure to the electricity market environment, as shown in Figure 102.

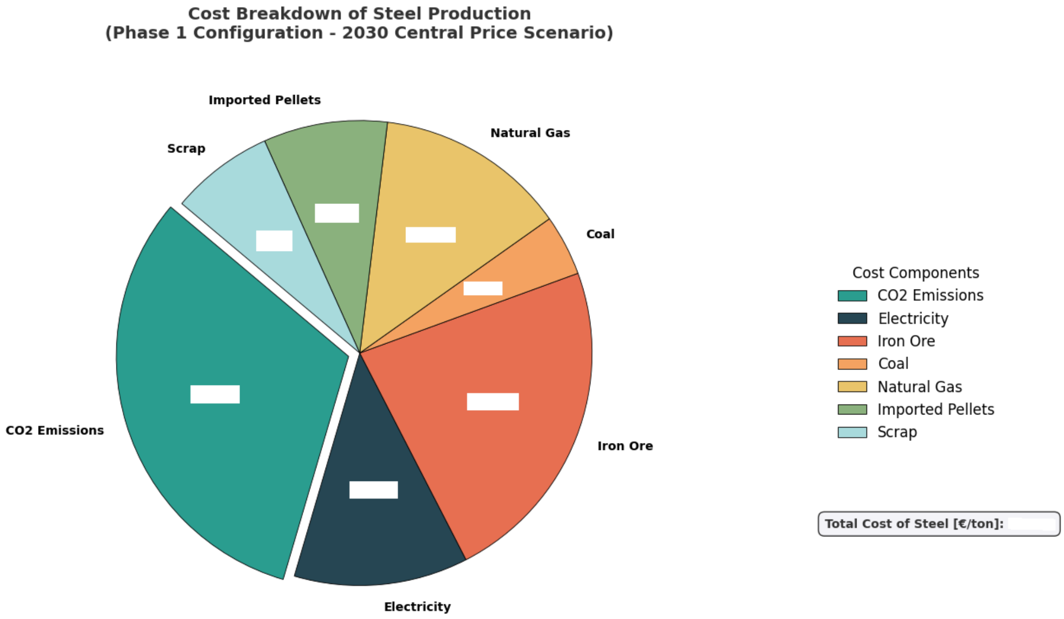

Figure 103: The cost breakdown of the Phase 1 configuration and the marginal cost of steel production

In Figure 103, the increased cost of steel in the Phase 1 configuration is evident. The electricity share in the cost has slightly increased, while the emissions cost has decreased. Regarding the energy balance, coal consumption has declined due to the decommissioning of the Coking Plant, with natural gas and electricity compensating for this reduction. It is worth noting that the reduction in CO_2 emissions (in tons) is not directly proportional to the reduction in emissions cost, primarily due to the anticipated higher carbon price in 2030.

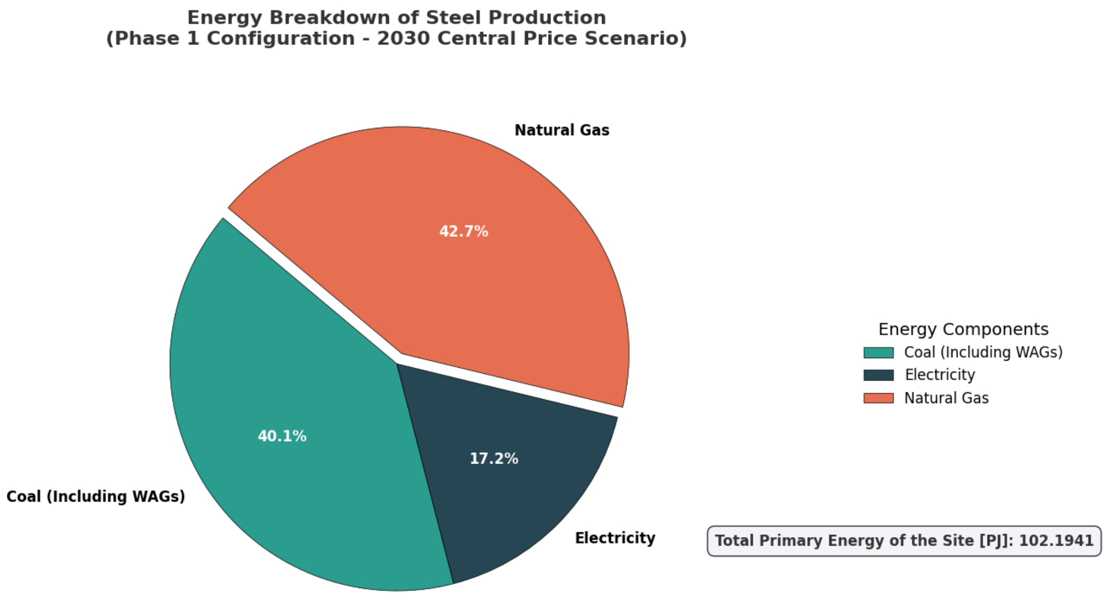

Figure 104: The energy breakdown of the Phase 1 configuration and the total energy consumption of the site

Energy-wise, natural gas and coal are nearly equal as the primary energy carriers in this configuration, as illustrated in Figure 104. Natural gas emerges as an intermediate energy carrier, facilitating the sector's transition from coal to hydrogen, as indicated by the results.

Parameters	**Values**
Steel Cost	[redacted] eur/ton
Electricity Consumption Avg	[redacted] MW
Natural Gas Consumption Avg	151673.52 m^3
CO2 Emissions	9107793.17tons
Electricity Consumption Total	4.89 TWh
Total WAGs Generation	1.23 TWh
Peak Electricity Load	[redacted] MW

Table 9: Main outputs of the central scenario of the yearly simulation for the Phase 1 configuration

In Table 9, the key outputs from the yearly simulation results for the Phase 1 configuration are summarized.

Sensitivity

Under a sensitivity analysis using the 2030 price scenarios, the cost variation shows a difference of approximately 25 % between the central and high scenarios, and around 20 % between the central and low scenarios. Interestingly, the central and Net Zero scenarios result in nearly identical steel costs. Figure 106 illustrates the cost breakdown for each scenario, providing a clearer understanding of the final steel price variations. Natural gas emerges as a more significant contributor to the final cost across all scenarios, reflecting its growing role in the cost structure.

Figure 105: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the Phase 1 configuration.

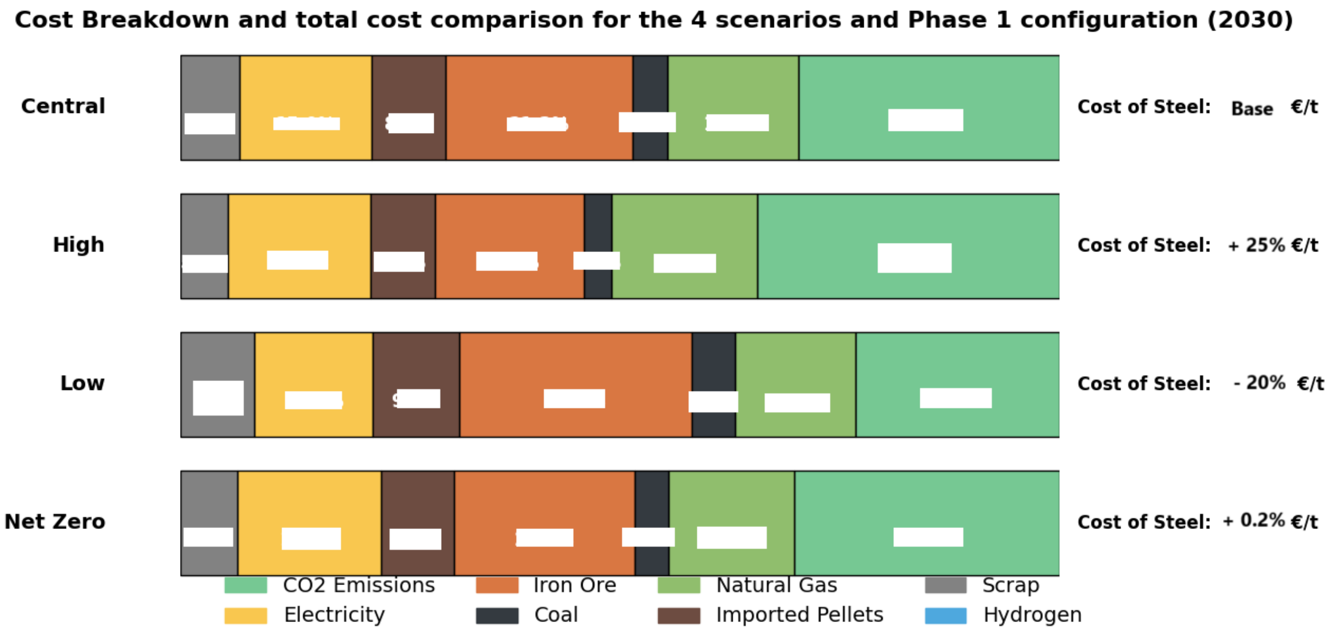

Figure 106: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for Phase 1 configuration and including cost break downs

In Figure 107, the impact of the EAF installation along with the DRI process on the site's electricity consumption is evident. The first noticeable change is the increase in both the peak and average load.

Additionally, a distinct drop in the load curves for approximately 100 hours during the monthly simulation is observed—a feature absent in the load curves of the current configuration. This drop, corresponding to a reduction in EAF operation or complete shutdown during periods of high electricity prices, highlights the EAF's responsiveness to price signals. The magnitude of this drop is around 200 MW, matching the EAF's electrical capacity.

Interestingly, the differences between scenarios are not significant, suggesting that the price variations between scenarios mainly affect absolute values rather than structural changes in the load curve.

As described in the model behavior section, while a single plant cannot inherently make the site more flexible due to interconnected processes, the DRP-EAF line offers additional storage capacity for DRI compared to hot iron, the BOF's input. This extended storage capability enables the EAF to operate more flexibly, as its primary input remains available for longer periods. Furthermore, the EAF's inherent flexibility—characterized by its ability to quickly shut down, restart, and adjust operation levels—enhances the site's overall adaptability to electricity price variations.

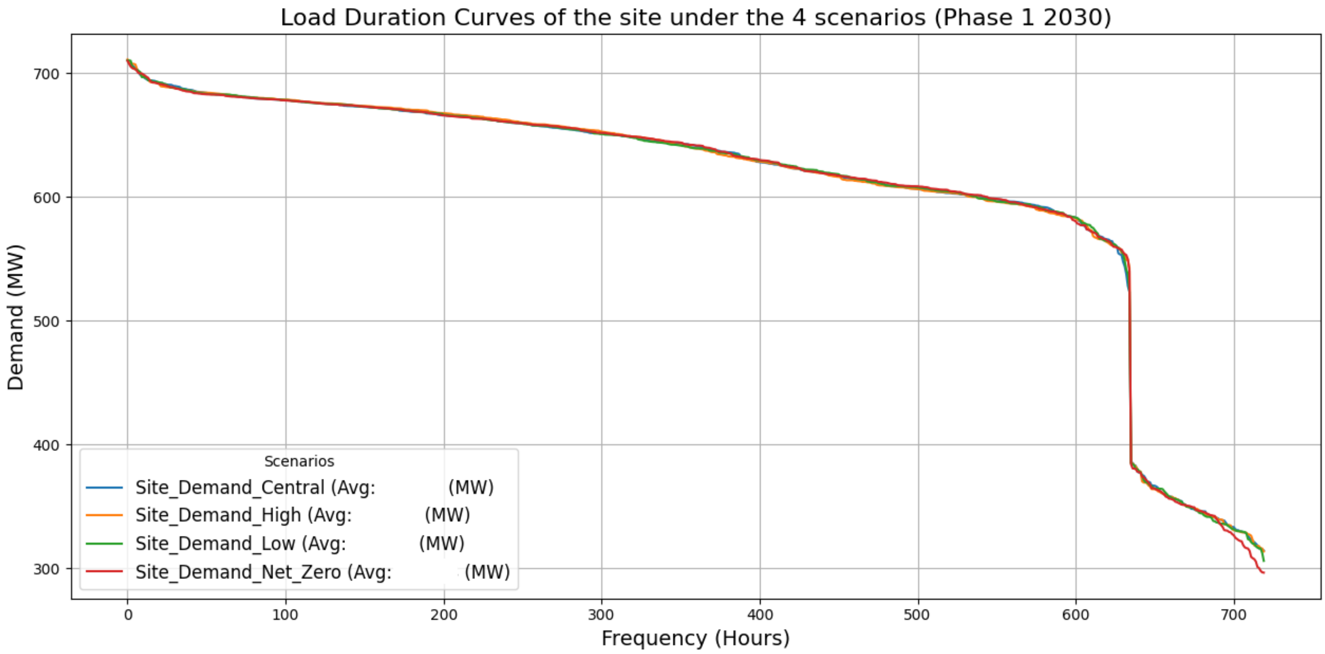

Figure 107: The load duration curves of the whole site and the 4 scenarios for the Phase 1 configuration

Phase 2

For Phase 2, the addition of the SAF (Submerged Arc Furnace) to melt the direct reduced iron for the Basic Oxygen Furnace significantly increases the site's electricity demand, adding an additional 400 MW of consumption. It is important to note that the SAF is modeled as a continuous process rather than a batch process like the EAF (Electric Arc Furnace). Consequently, the flexibility potential of the SAF is not as high as that of the EAF.

The EAF, both in the model and in reality, can remain off for extended periods when electricity prices are high. This shutdown capability can occur more frequently throughout the year if the EAF is oversized relative to the minimum size required to meet the site's steel production targets.

Natural gas consumption also increases in Phase 2 due to the addition of a second DRP (Direct Reduction Plant) operating on a mix of natural gas and hydrogen. The decommissioning of Blast Furnace 6 and Coking Plant 2 significantly reduces the availability of work-arising gases (WAGs) on-site. Under this configuration, only the BOFG (Basic Oxygen Furnace Gas) from the steel plant and a new gas stream from the SAF (SAFG) are available. However, these gases are insufficient in quantity and composition to meet the requirements of Vattenfall's generators. As a result, electricity generation from WAGs is no longer expected in this phase.

Instead, the remaining WAGs (BOFG and SAFG) are repurposed for internal processes such as the Pelletizing Plant and the Hot Strip Mill. While some boilers remain operational and can run on natural gas or the limited WAGs, electric boilers are also introduced to supplement energy needs.

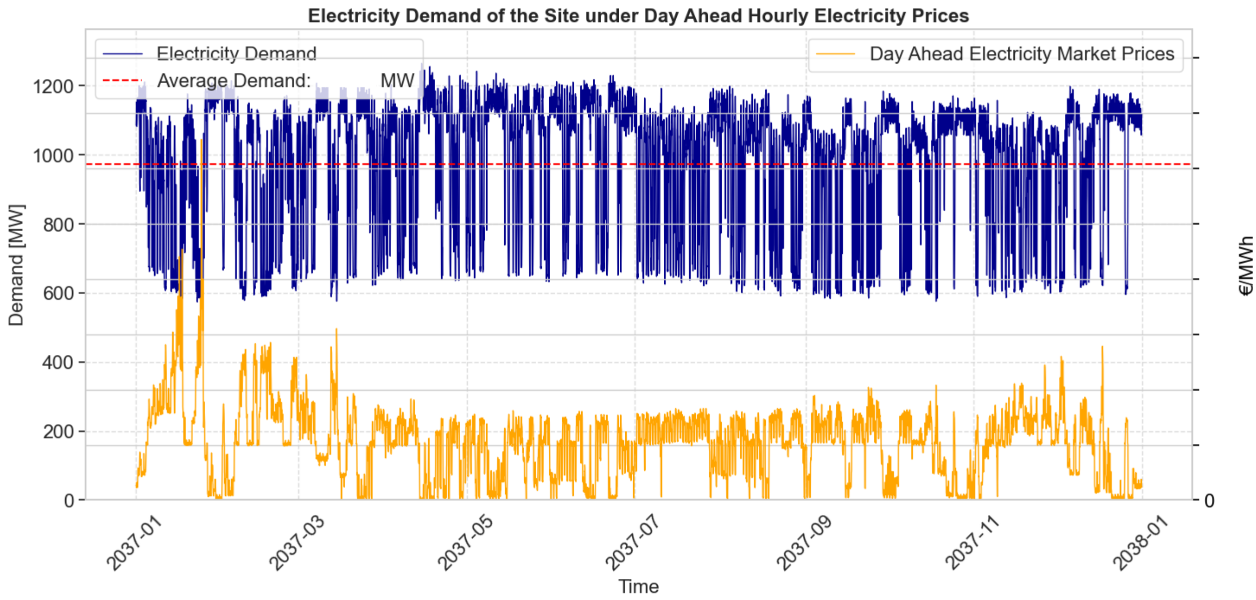

Figure 108: The electricity demand of the site for the Phase 2 configuration and central prices scenario for the year 2037. The output of the model plotted against the hourly electricity prices input.

The electricity consumption has increased by approximately 68 % from Phase 1 to Phase 2, while natural gas consumption has risen by 30 %. The updated values and their respective ranges can be observed in Figures 108 and 109.

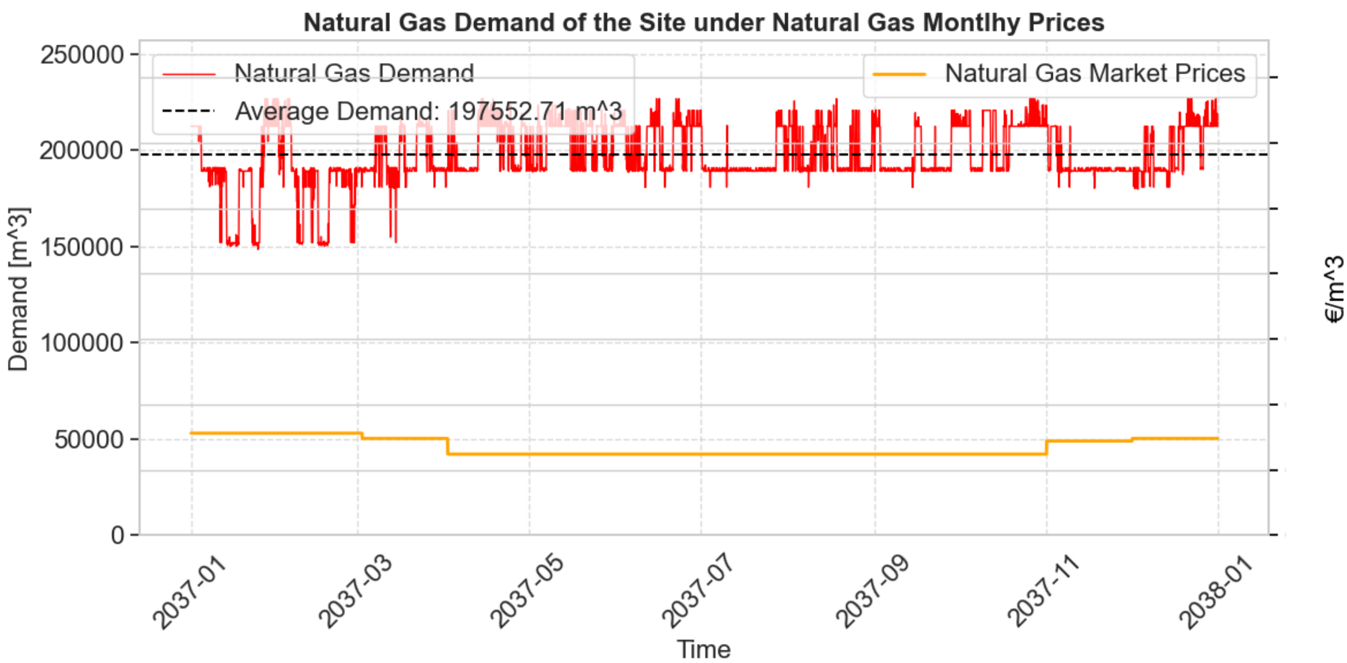

Figure 109: The natural gas demand of the site as an output of the model for the central prices scenario and the Phase 2 configuration for the year 2037 plotted against the natural gas prices of the scenario having constant values per month.

As shown in Figure 110, the cost breakdown indicates a further reduction in emissions costs, accompanied by an increase in electricity and natural gas expenses. The demand for imported pellets rises significantly due to the high consumption requirements of the DRP plants. Additionally, hydrogen begins to appear as a cost component, reflecting its utilization in one of the two DRP units.

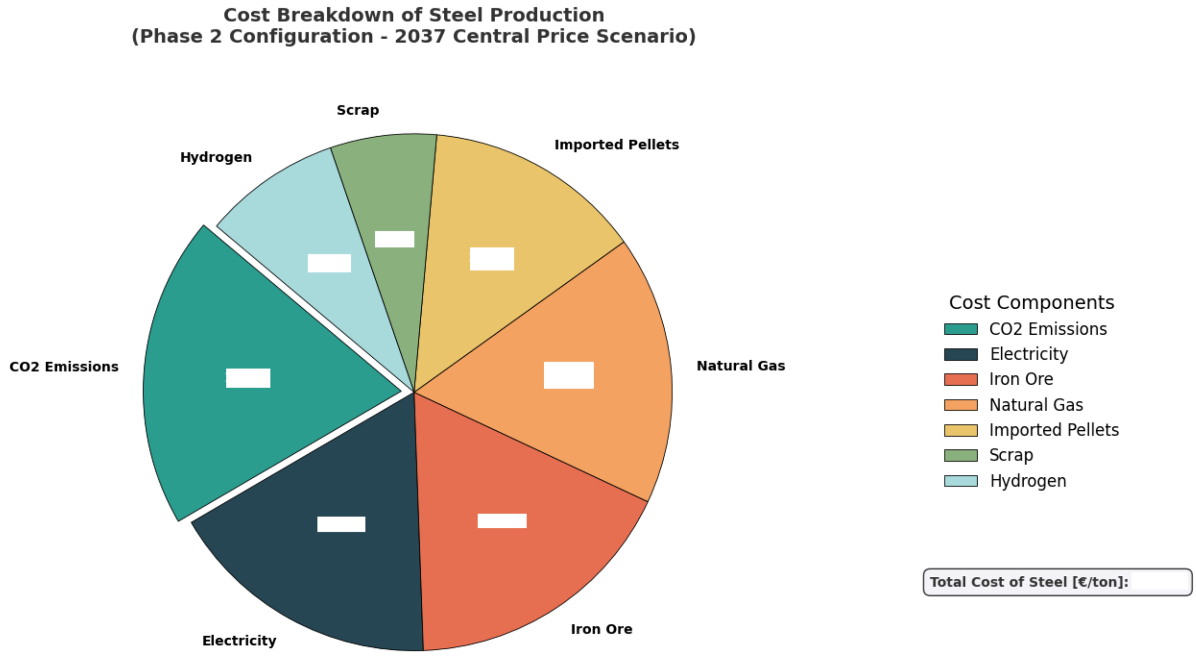

Figure 110: The cost breakdown of the Phase 2 configuration and the marginal cost of steel production

Regarding the energy mix, this is the first configuration in which coal is no longer consumed. Natural gas becomes the largest energy carrier, although it does not reach the proportion of coal in the current configuration. Electricity accounts for over 30 % of the energy mix, nearly double its share when evaluated in terms of cost.

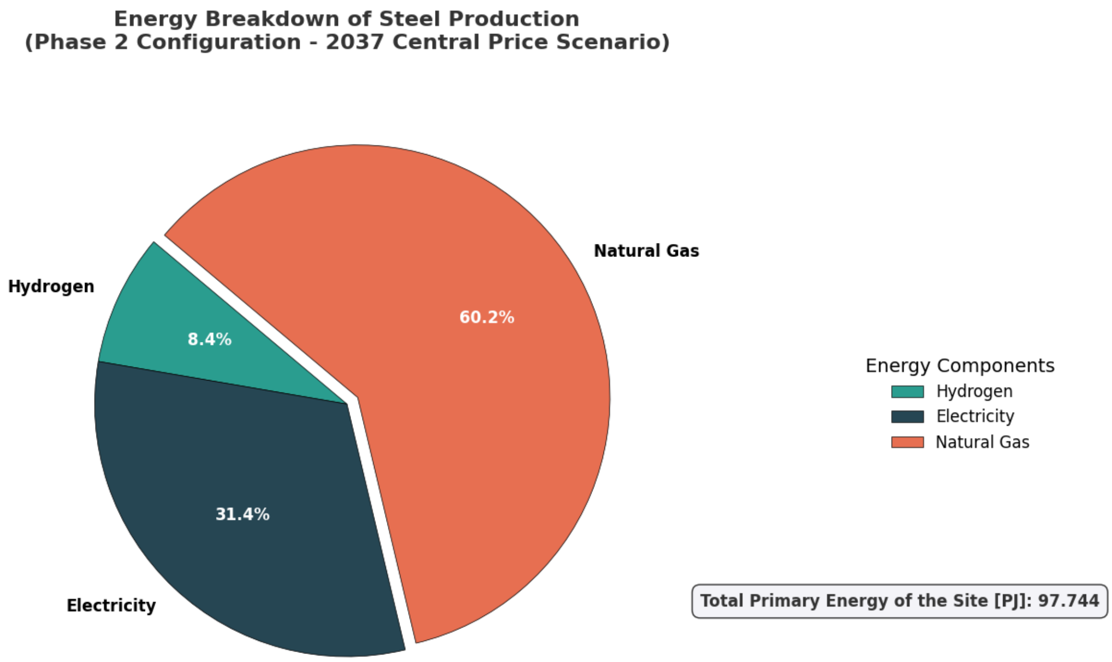

Figure 111: The energy breakdown of the Phase 2 configuration and the total energy consumption of the site

Parameters	Values
Steel Cost	[redacted] eur/ton
Electricity Consumption Avg	[redacted] MW
Natural Gas Consumption Avg	197552.71 m^3
CO2 Emissions	5475770.03 tons
Electricity Consumption Total	8.46 TWh
Total WAGs Generation	0 TWh
Peak Electricity Load	[redacted] MW

Table 10: Main outputs of the central scenario of the yearly simulation for the Phase 2 configuration

In Table 10, the key outputs from the yearly simulation results for the current configuration are summarized.

Sensitivity

For the sensitivity analysis of the cost in Phase 2, the difference between the central and high scenarios is approximately 24%, while the difference between the low and central scenarios is around 22%. The exact values can be observed in Figure 112. The increased proportion of electricity costs in the total cost of steel is evident across all four price scenarios. Additionally, the lower contribution of reduced emissions costs is noticeable, despite the expected significantly higher CO2 prices in 2037. The cost breakdown for all scenarios is illustrated in Figure 113.

Figure 112: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the Phase 2 configuration.

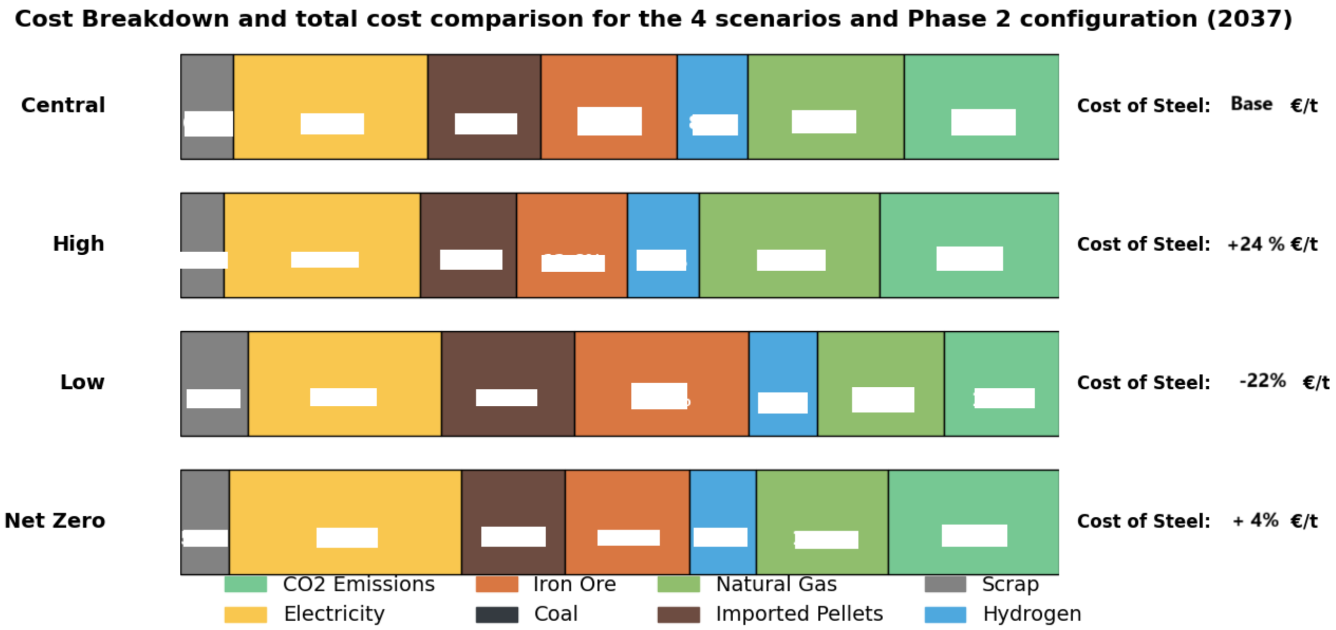

Figure 113: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the Phase 2 configuration and including cost break downs

In the load curves and in Figure 114 we can see them dropping for almost half of the hours of the montly simulation. This variation can also be noticed in the wider range of the demand plot of the site in Figure 108. The load duration curves have two distinguished dropping points with ranges matching to the EAF and SAF electrical capacities. The one with the higher slope is the EAF which can completely shut down and the smoother one is the SAF which can lower its production levels.

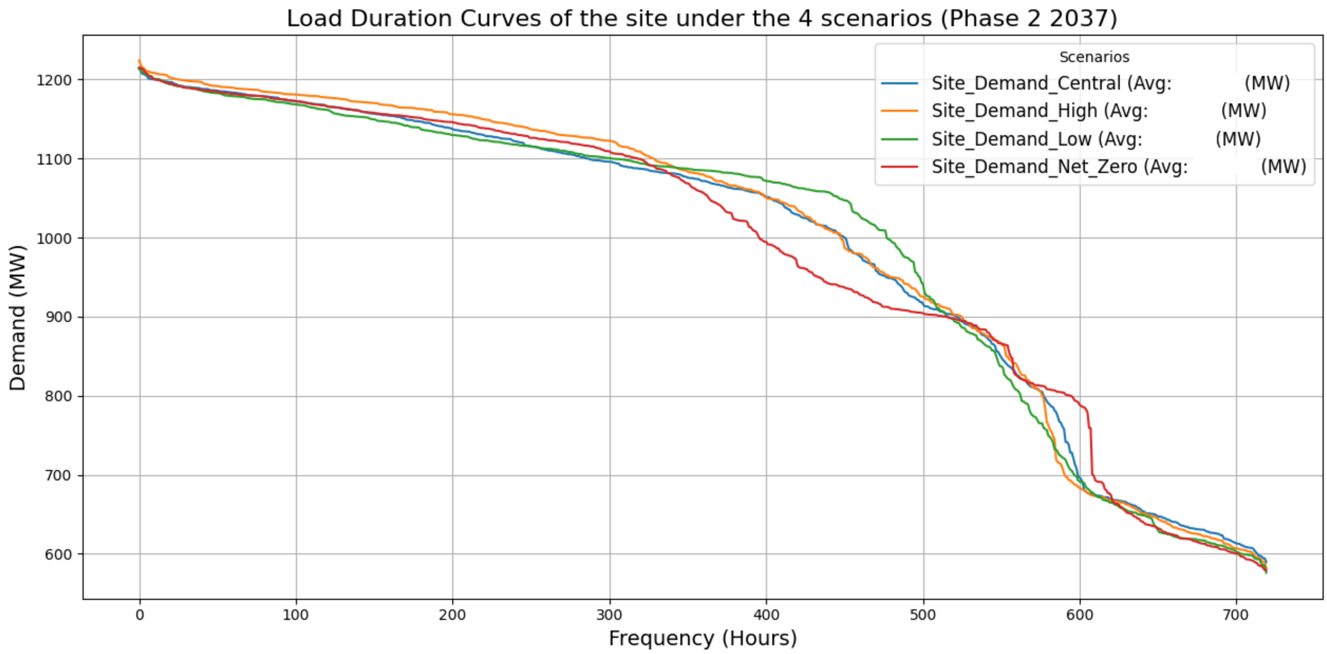

Figure 114: The load duration curves of the whole site and the 4 scenarios for the Phase 2 configuration

Phase 3

In Phase 3, the major changes pertain to the operation of the DRP plants, which now primarily consume hydrogen instead of natural gas. The site's electricity demand remains nearly unchanged, assuming hydrogen is not produced via electrolysis onsite in this baseline scenario. The demand for natural gas decreases significantly due to the transition of the DRP plants, as shown in Figure 116. The steam demand, which has been substantially reduced compared to the current configuration, is met entirely by electric boilers.

As in Phase 2, the small quantities of WAGs produced by the BOF and SAF are utilized internally and are insufficient for viable electricity generation. Consequently, the site becomes fully exposed to fluctuations in the electricity market. While there is potential to leverage the substantial hydrogen quantities strategically—by installing electrolyzers and utilizing them during periods of low electricity prices—this approach is not included in the core Phase 3 configuration. It is assumed that both hydrogen and electricity are sourced directly from the market.

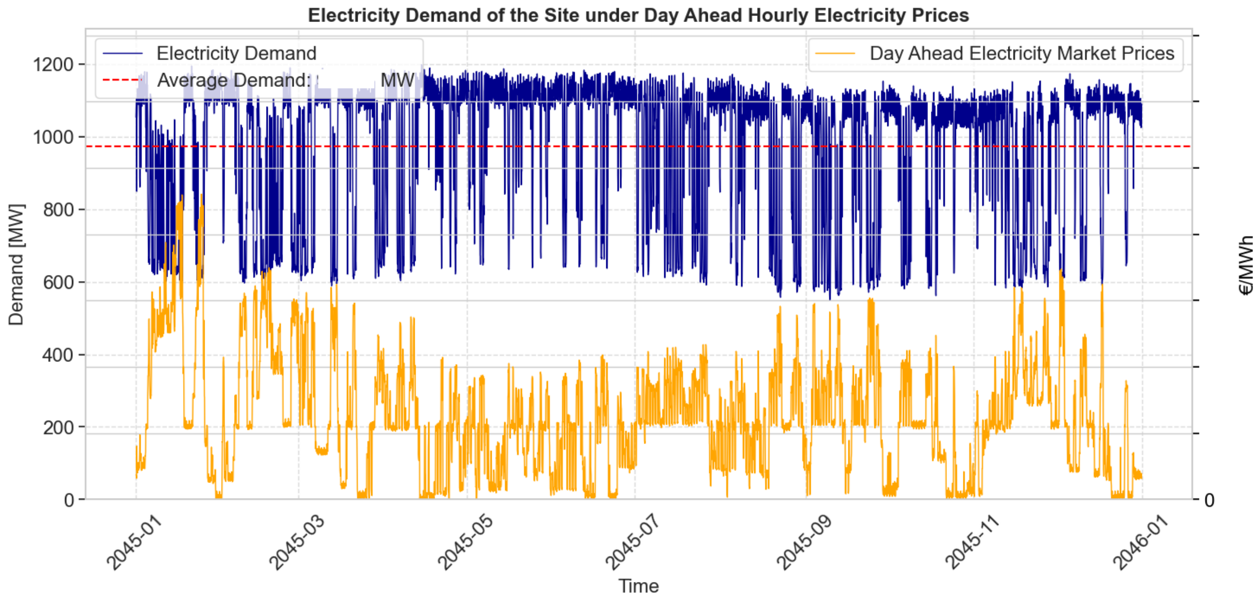

Figure 115: The electricity demand of the site for the Phase 3 configuration and central prices scenario for the year 2045. The output of the model plotted against the hourly electricity prices input.

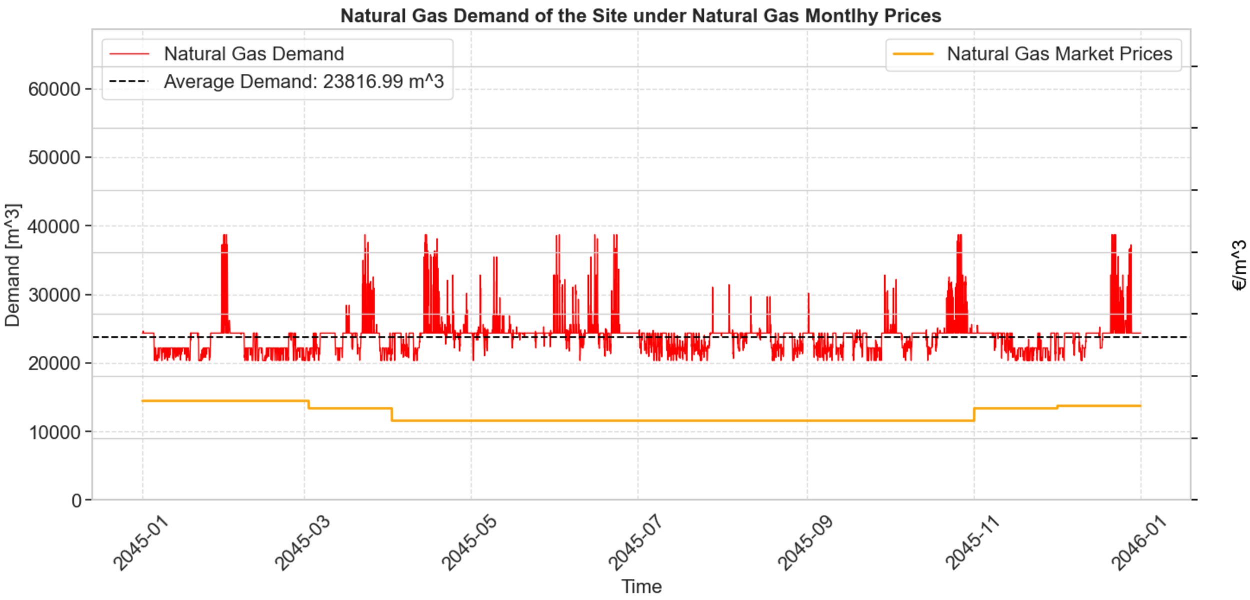

Figure 116: The natural gas demand of the site as an output of the model for the central prices scenario and the Phase 3 configuration for the year 2045 plotted against the natural gas prices of the scenario having constant values per month.

In the central scenario, the cost of steel increases to [redacted] €/ton, with hydrogen becoming the primary cost driver, contributing approximately 47% to the total cost. Although the quantity of electricity consumed remains unchanged, its cost contribution diminishes as hydrogen's share rises. Natural gas now accounts for the smallest portion of costs, reflecting the minimal consumption by the DRP plants.

From an energy perspective, hydrogen emerges as the dominant energy carrier, contributing around 60 PJ of energy.

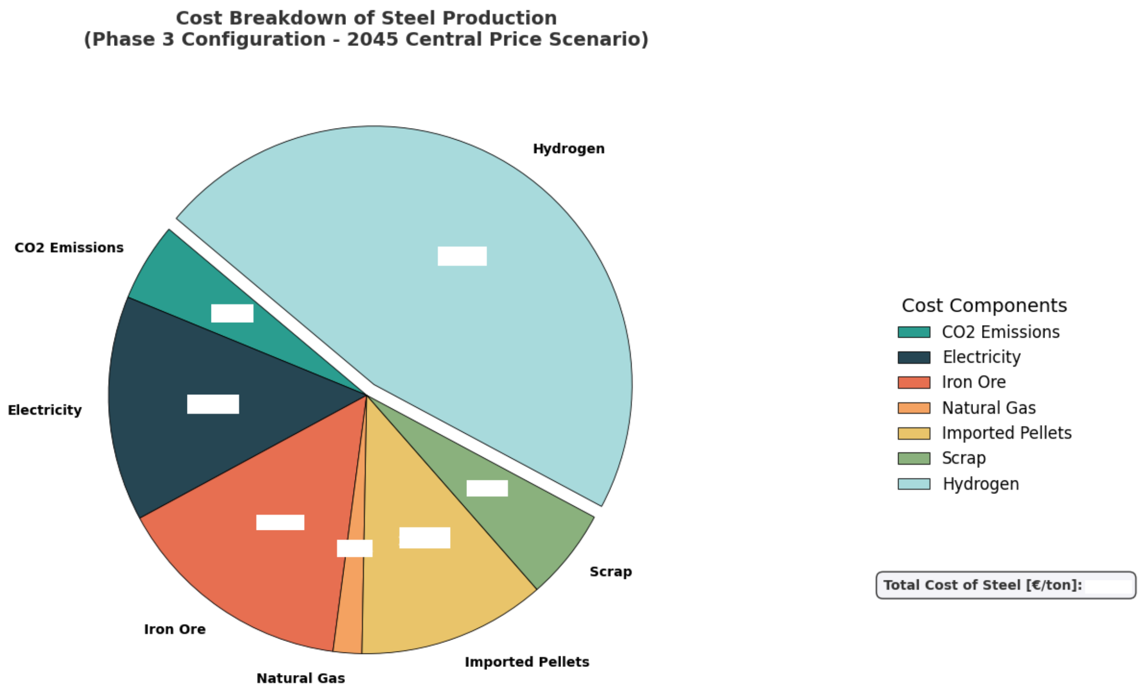

Figure 117: The cost breakdown of the Phase 3 configuration and the marginal cost of steel production

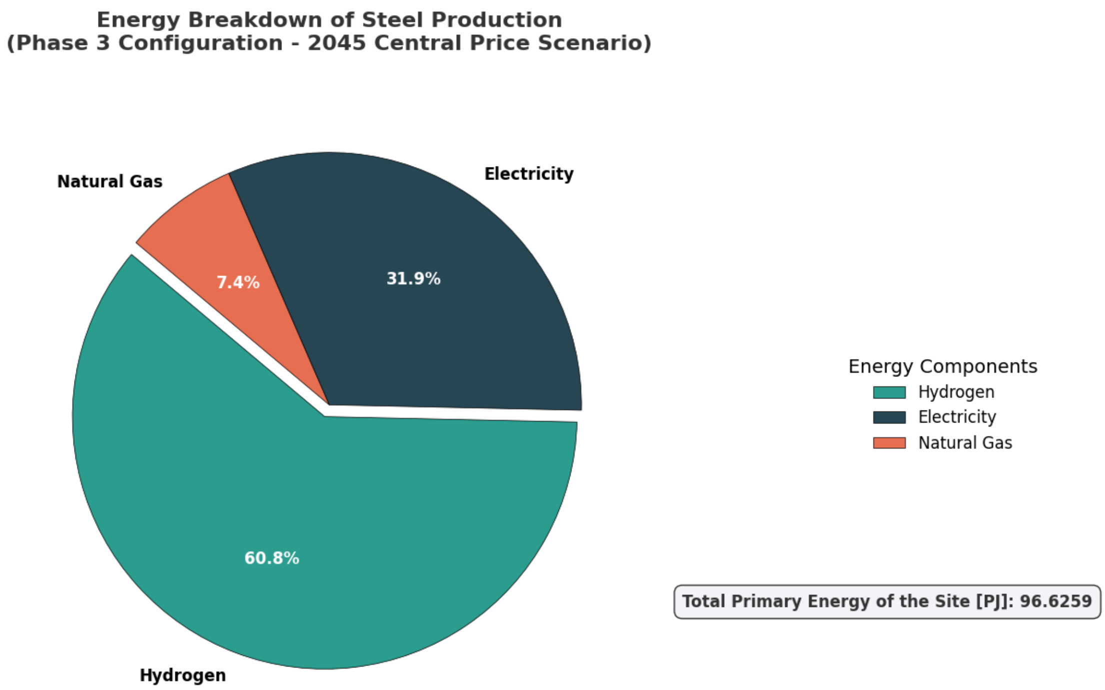

Figure 118: The energy breakdown of the Phase 2 configuration and the total energy consumption of the site

Parameters	**Values**
Steel Cost	[redacted] eur/ton
Electricity Consumption Avg	[redacted] MW
Natural Gas Consumption Avg	23816.99 m^3
CO2 Emissions	1464160.40 tons
Electricity Consumption Total	8.53 TWh
Total WAGs Generation	0 TWh
Peak Electricity Load	[redacted] MW

Table 11: Main outputs of the central scenario of the yearly simulation for the Phase 3 configuration

In Table 11, the key outputs from the yearly simulation results for the Phase 3 configuration are summarized.

Sensitivity

In the sensitivity analysis of steel production costs for Phase 3, the cost differences between the central and high scenarios, as well as between the central and low scenarios, are approximately 18 %. The steel costs for each scenario are shown in Figure 119. Figure 120 reveals no significant differences in the contribution of various cost components to the final steel cost. The increased contributions of electricity and hydrogen are evident, while emissions costs are significantly reduced.

The load duration curves in Figure 121 closely resemble those of Phase 2 for similar reasons. The SAF and EAF remain the primary drivers of electricity consumption due to their high demand.

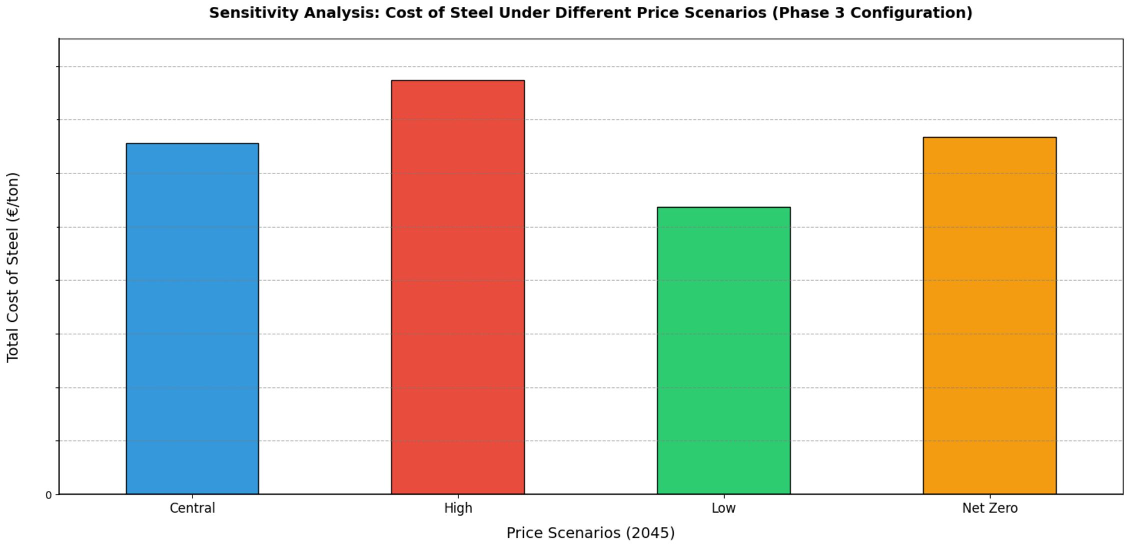

Figure 119: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the Phase 3 configuration.

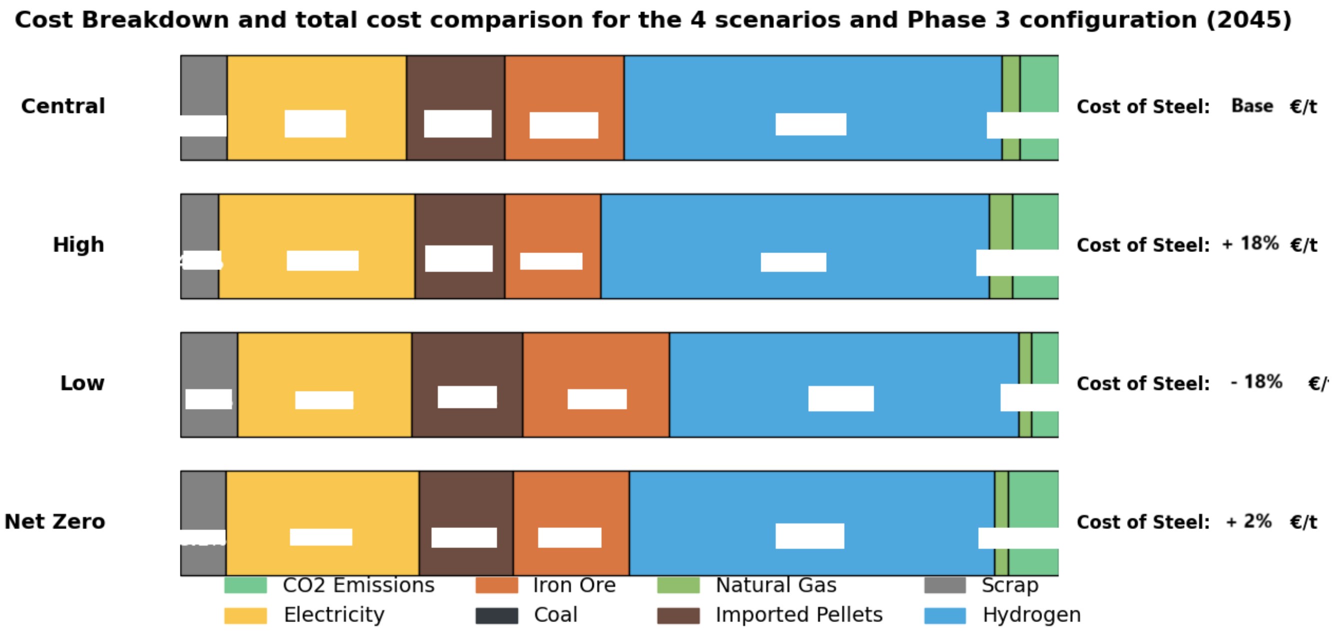

Figure 120: Sensitivity analysis of the marginal cost of steel production under 4 different price scenarios for the Phase 3 configuration and including cost break downs

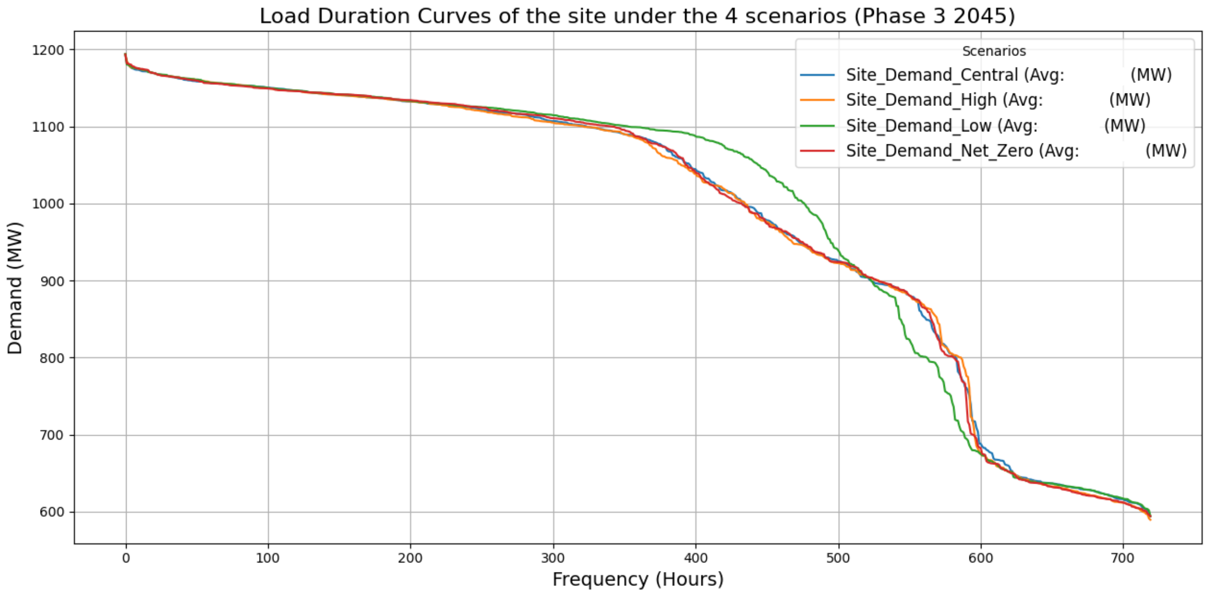

Figure 121: The load duration curves of the whole site and the 4 scenarios for the Phase 3 configuration

4.2 Transition Configurations Comparison - Central Scenario

This section compares the four configurations in terms of steel cost, cost breakdown, and energy breakdown. In Figure 122, we observe the anticipated increase in steel production costs based on yearly simulations for the reference year of each configuration. The cost increase is expected and is not attributable to inflation, as all prices are expressed in real 2022 values. Instead, the increase is primarily due to the higher anticipated costs of electricity, natural gas, and, in the final configuration, hydrogen. These energy carriers are projected to be more expensive than coal, which is currently the dominant energy source, even when considering the reduced emissions costs associated with the future configurations.

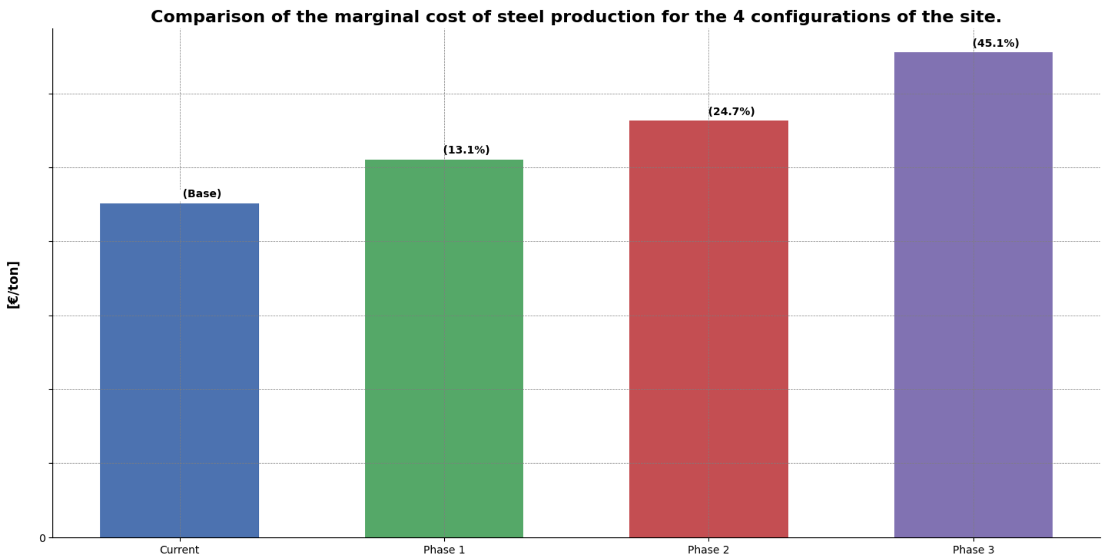

Figure 122: Comparison of the total marginal cost of steel production for the 4 configurations

Figures 123 and 124 illustrate the expected changes in cost and energy breakdowns throughout the site's transition. The emissions and coal costs from the current configuration are gradually replaced by natural gas and electricity costs in the earlier phases, and later predominantly by hydrogen and electricity. The iron component of the steel, represented by a combination of iron ore and imported pellets, remains relatively stable as a sum across all configurations. Similarly, scrap use remains unchanged, reflecting the assumption of a consistent scrap-to-steel ratio in future configurations. It is worth noting that this ratio may be adjusted in response to the company's policies regarding the quality of steel to be produced.

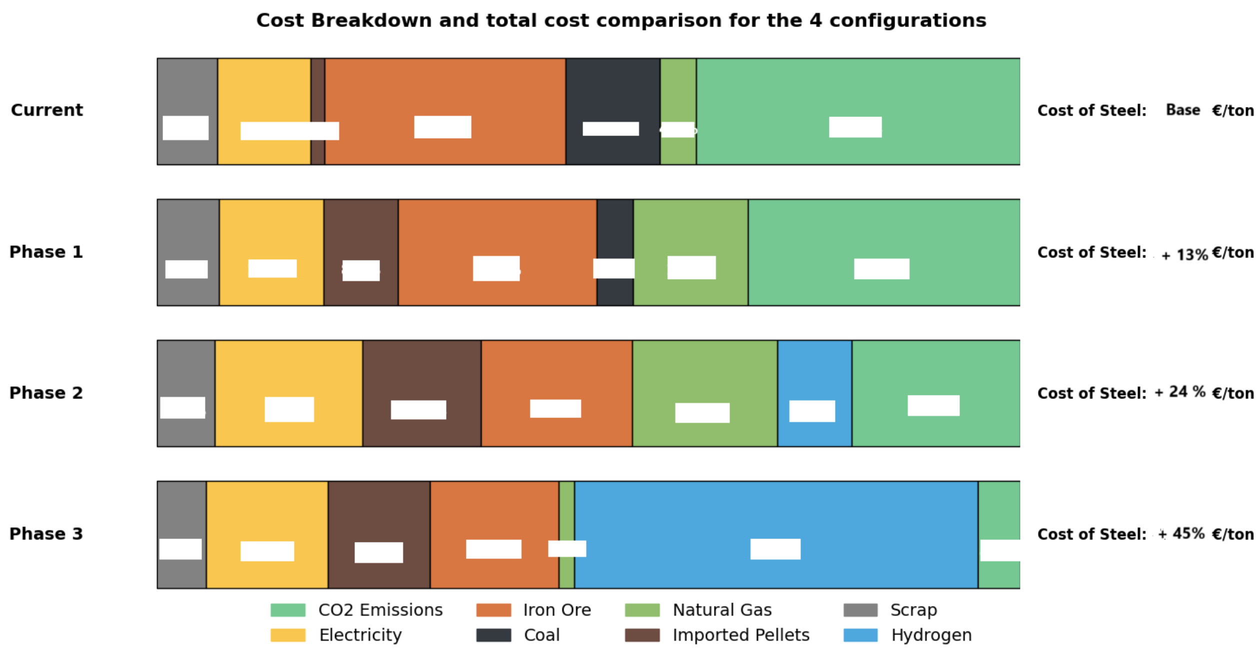

Figure 123: Cost breakdown comparison between the 4 configurations for the site

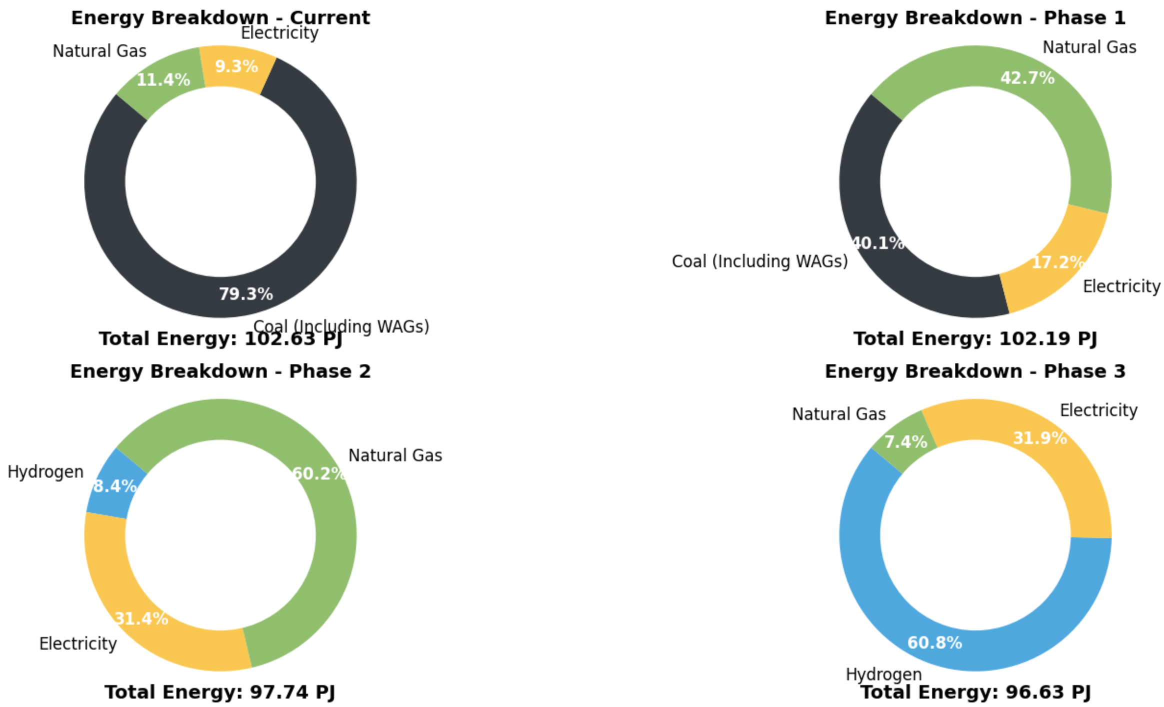

Figure 124: Energy breakdown comparison for the 4 configurations.

In Figure 125, the load curves of the site are compared across the four modeled configurations, from the current setup to Phase 3. The current configuration's load curve is noticeably flatter and features lower absolute values, reflecting the site's relatively low electricity consumption. As we transition through the phases, the curves show progressively higher and more flexible loads. This flexibility allows the site to reduce electricity consumption during periods of high prices to manage costs. A significant shift is observed in Phase 1 with the introduction of the EAF, which emerges as the sole flexible component, causing a distinct drop in the load curve. In Phases 2 and 3, the addition of the SAF leads to smoother declines in the load curves, indicating a more distributed and gradual flexibility across the site's operations.

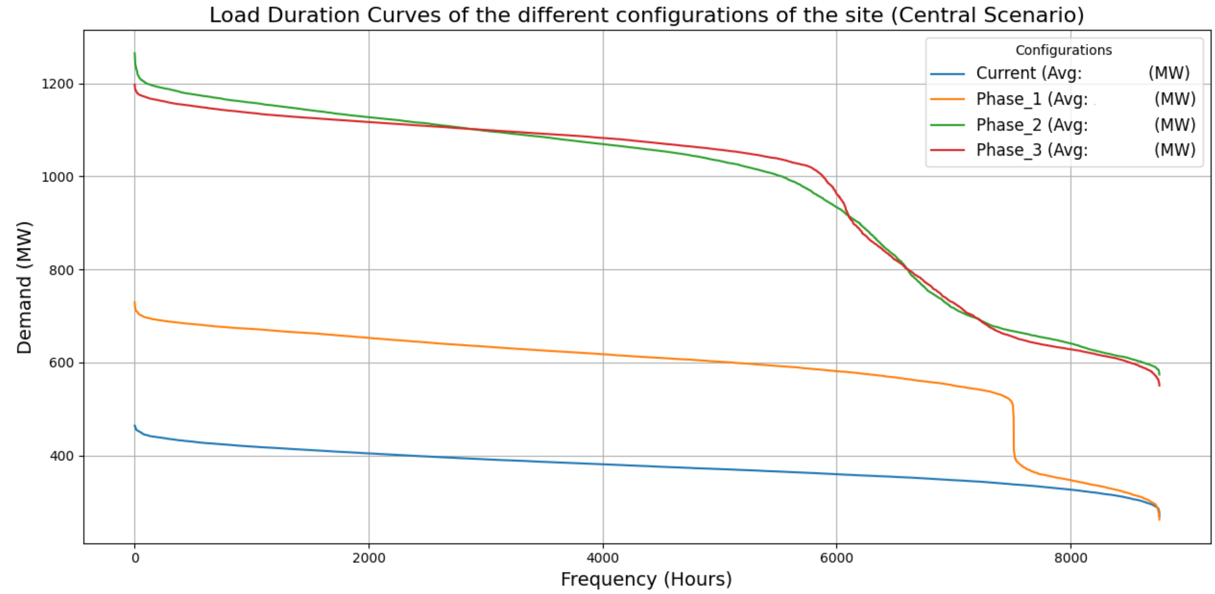

Figure 125: The load curves of the site during the transition phases

4.3 Network Cost Effect

In this section, we discuss the network cost, which pertains to the maximum electricity consumption of the site on both a monthly and annual basis. The scheme under examination applies a specific factor to the maximum monthly values and a larger factor to the maximum (peak) annual demand. Combined, these costs constitute the network cost in our model, which closely resembles the real network cost scheme applied to Tata Steel.

A more detailed explanation of the network tariff scheme and how it was incorporated into the objective function of the problem can be found in Figure 3.4. In practice, there are fixed costs associated with grid usage; however, we are only considering marginal costs in this work. Marginal costs, as defined here, are those influenced by the quantity of electricity consumed or produced and are therefore not fixed. Fixed costs are not relevant to the optimization being performed in this study.

The following figures illustrate how this additional cost is expected to influence the total cost of steel production and the extent to which it affects each configuration. The specific factors used for the monthly and yearly peaks cannot be disclosed due to confidential agreements between Tata Steel and the grid distributors and operators. However, readers can estimate these charges based on the policies of the DSOs (Distribution System Operators) and TSOs (Transmission System Operators) in the Netherlands for large consumers.

In this work, we have assumed that the current factors remain constant and stable, even for future configurations, without considering any potential increases over time. This approach was intended to enable a comparison of different configurations and the impact of tariffs without the confounding influence of fluctuating prices. By doing so, we focus solely on the effect of a consistent tariff on the configurations.

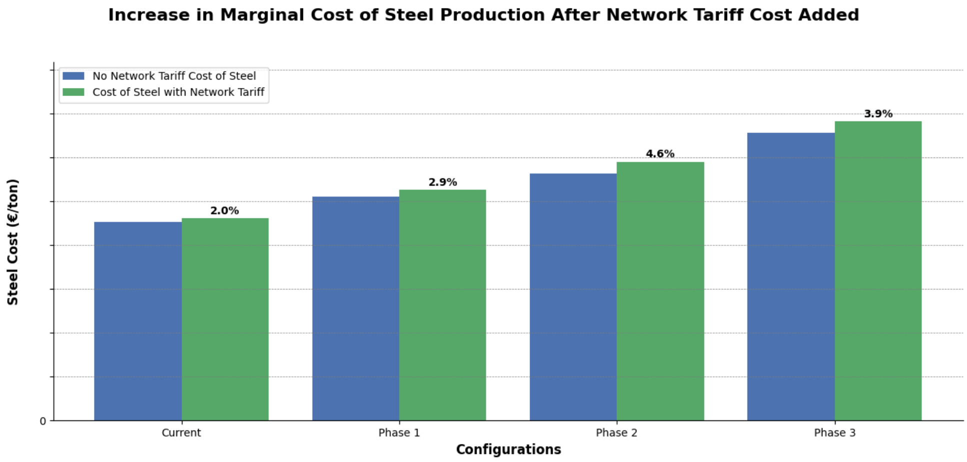

Figure 126: The effect of the network cost at the marginal cost of steel production for the 4 configurations.

In Figure 126, we can clearly observe that the impact of the network cost is higher in the last two configurations. This is because electricity consumption increases significantly under these configurations, leading to higher maximum values charged under the scheme.

Between transition phases 2 and 3, we observe only a small difference in network costs. Since there are no major changes in the site's electricity consumption behavior between these two configurations—with both the EAF (Electric Arc Furnace) and SAF (Submerged Arc Furnace) operational—the difference can be attributed to the larger share of electricity as part of the total cost in Phase 2. This is due to the use of expensive and large quantities of hydrogen in Phase 3, which reduces electricity's relative contribution to the total cost.

The detailed cost breakdown, including the network cost as described, is presented in Figures ?? through 127.

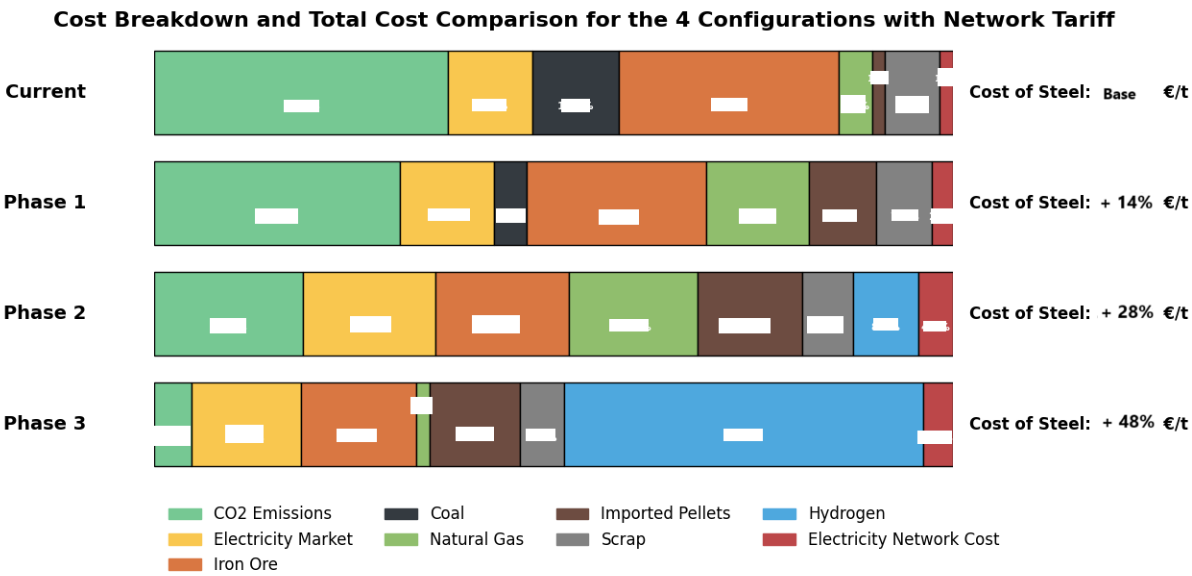

Figure 127: The cost breakdown of the Phase 3 configuration and the marginal cost of steel production with the addition of network cost.

To gain deeper insights into the impact of network cost on the electricity consumption pattern of the site, as modeled in our study, we present a comparison of network cost applications for a monthly simulation. This comparison provides a clearer understanding of the effects.

In Figure 129, the optimizer adjusts the site's operations to avoid peaks in electricity demand. This represents the optimal way to operate under the network cost scheme we have described. Conversely, Figure 128 illustrates the standard output without network tariffs applied.

In practice, the optimizer, with perfect knowledge of prices over the simulation horizon, calculates the maximum demand necessary to meet the production target within this horizon. It then ensures that no demand peak exceeds this calculated limit. However, without perfect knowledge of future prices and in the face of unforeseen circumstances—such as plant malfunctions or sudden breakdowns—it becomes much more challenging to maintain such controlled load profiles across the entire site.

Under a simulation with a rolling horizon—or in real-world conditions—it would be interesting to observe how the site operates after an extreme peak event. From that point onward, until the end of the month, the site would still be able to operate at relatively high levels, though not exceeding the extreme peak, thereby avoiding additional charges at a higher tariff factor.

Although our approach differs slightly from real-world scenarios, it effectively highlights how network tariff schemes like this restrict large industries from leveraging their flexibility. Even with limited flexibility, these industries are discouraged from operating with fluctuating peaks and low loads, as they must keep their peak demand as low as possible to minimize charges. This approach runs counter to policymakers' objectives, which aim to enhance industrial flexibility as the energy transition progresses, necessitating greater adaptability on the demand side.

This issue is further exacerbated by the discontinuation of a discount on network costs for large industries in the Netherlands, which took effect in 2024. Capacity-based network tariff schemes are generally disadvantageous for large industries, as they impose significant financial burdens. Moreover, according to the (E-Bridge, 2024) report comparing network costs for large industries across Central European countries, the Netherlands has by far the highest network costs. This places Dutch industries at a competitive disadvantage compared to their counterparts in neighboring countries.

Beyond industrial competitiveness, these rising costs are expected to increase further due to the substantial grid investments required to support the country's growing energy demands. According to the same report, these high network tariffs not only impact large industries but also make the Netherlands less attractive for investments in electrolysers. Electrolyser projects, which depend on large electricity capacities and flexible operation, are particularly sensitive to network tariffs, as their profitability relies on strategic electricity consumption.

An example using the EAF will be presented in a subsequent section.

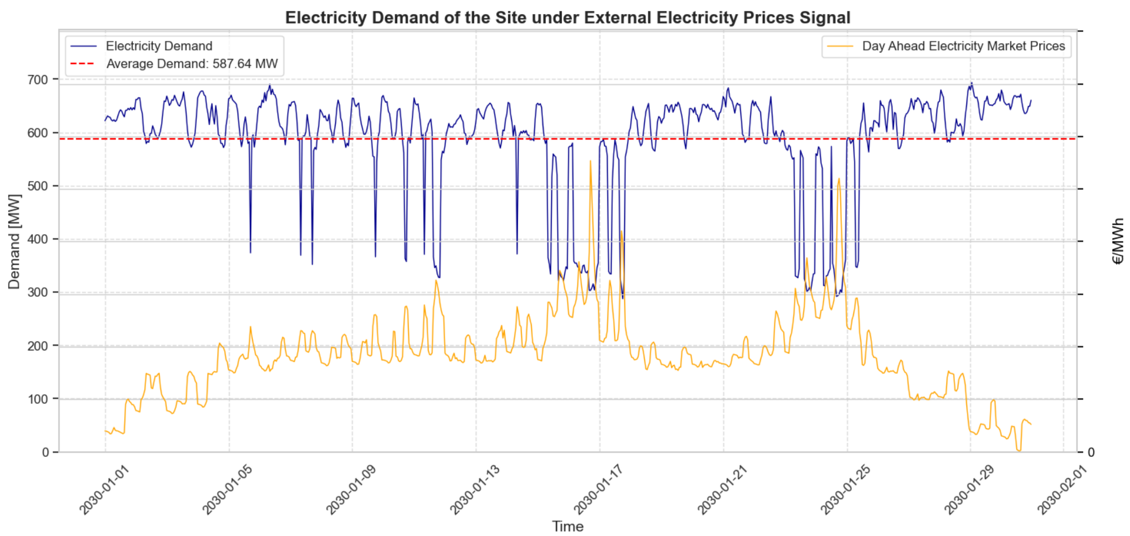

Figure 128: A monthly simulation without network cost for Phase 1 configuration

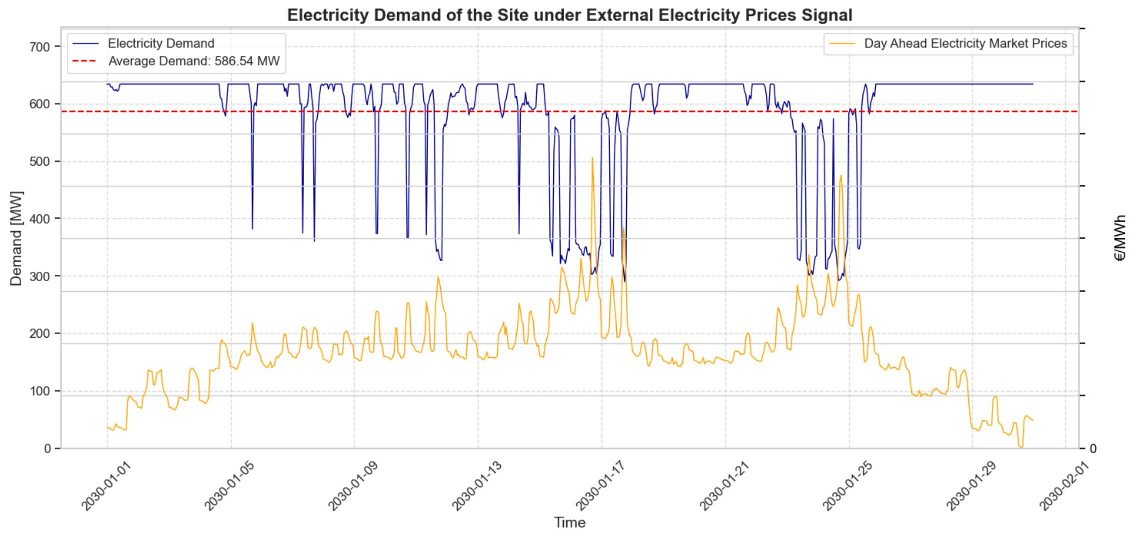

Figure 129: The same simulation with the effect of the network cost

4.4 Flexibility and Price Responsiveness Comparison: Current vs. Phase 1 Configurations

In this section, we discuss the flexibility of the site, or more specifically, its ability to respond to changes in external electricity prices. In the demand response sector, flexibility can also be defined as the product of the load and the duration (in hours) during which an application can shift its load within a given period.

Although there are methods to calculate this metric from our model, here we focus primarily on the site's response in terms of increasing or decreasing production levels of processes rather than shifting loads entirely. Within the type of model used in this study—where a specific steel production target must be achieved by the end of the simulation period—load shedding is not a viable option. This is because a fixed amount of electricity is required to produce the predefined quantity of steel.

The key question, therefore, is not whether load can be shed but rather how much of it can be shifted and how quickly the processes can adapt to electricity price signals. This exploration provides insights into the site's operational responsiveness and its potential to optimize costs under varying electricity price conditions.

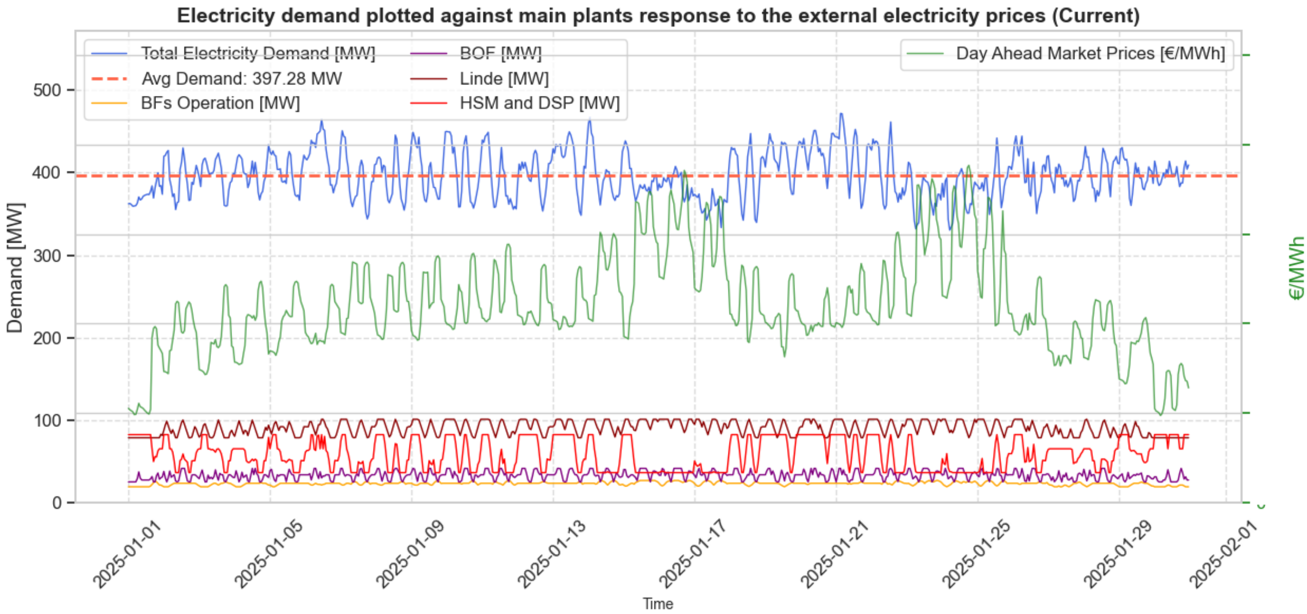

Figure 130: The effect of the main plants of the current configuration at the electricity consumption of the site plotted together with the electricity prices

In Figures 130 and 131, we observe the operation of the main plants for the Current and Phase 1 configurations, respectively, displayed in the lower section of each plot. In the middle section, the electricity price signal is represented in green as a cost input to the simulation. The blue line illustrates the site's hourly electricity demand curve.

As previously discussed, both the average electricity load and the variability around this average are significantly larger in Phase 1. These plots highlight the substantial electricity consumption of the Electric Arc Furnace (EAF) compared to other plants, as well as the additional flexibility it provides. Notably, the demand curve of the site closely follows the operational trends of its plants, which is expected since it represents the aggregate demand of all operational units (not limited to those shown in the plots).

In Phase 1, the EAF is not only a significant electricity consumer but also a key source of flexibility. Its ability to be turned on and off enables the site to remove up to 200 MW of load when required. Incorporating the EAF into the configuration enhances the site's overall flexibility and improves its responsiveness to electricity price signals.

As explained in the methodology section, a single process alone cannot dramatically influence the entire site's operation due to constraints imposed by the interconnected system. However, in this case, the EAF's operation is complemented by the Direct Reduced Iron (DRI) produced by the Direct Reduction Plant (DRP). Since the DRI is not hot, it can be stored for longer periods, allowing the EAF to operate with greater flexibility.

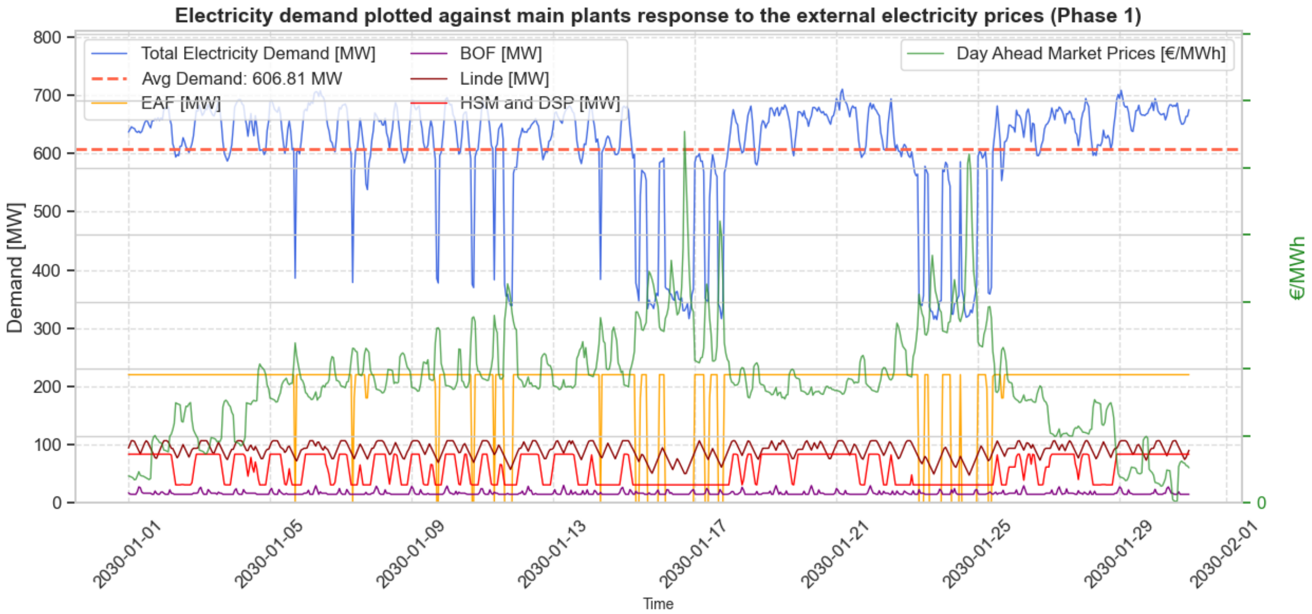

Figure 131: The effect of the main plants of the Phase 1 configuration at the electricity consumption of the site plotted together with the electricity prices

In Figures 132 and 133, we observe similar outcomes. In the current configuration, the Linde plant is the largest electricity consumer. However, its flexibility is significantly constrained due to the storage limitations of oxygen, as previously explained. These limitations compel the Linde plant to operate primarily to meet the oxygen demands of the blast furnaces (BFs) and the Basic Oxygen Furnace (BOF). Consequently, its operation pattern closely mirrors that of the BFs and BOF, as it functions as an auxiliary process tied to their production.

As expected, the operation of the BFs and BOF is remarkably stable and consistent, with limited flexibility. The only notable flexibility in this configuration stems from the HSM (Hot Strip Mill) and DSP (Direct Sheet Plant) plants at the final stages of the steel-making process. These plants exhibit some flexibility because their inputs—slabs—can be stored in measurable quantities, allowing minor adjustments to their operation.

In Phase 1, the EAF introduces substantial flexibility, capable of remaining off for nearly 100 hours during the monthly simulation. This level of operational flexibility significantly enhances the site's ability to respond to electricity price fluctuations. Meanwhile, the flexibility of the DSP and HSM plants remains unchanged, further augmenting the overall price responsiveness of this configuration.

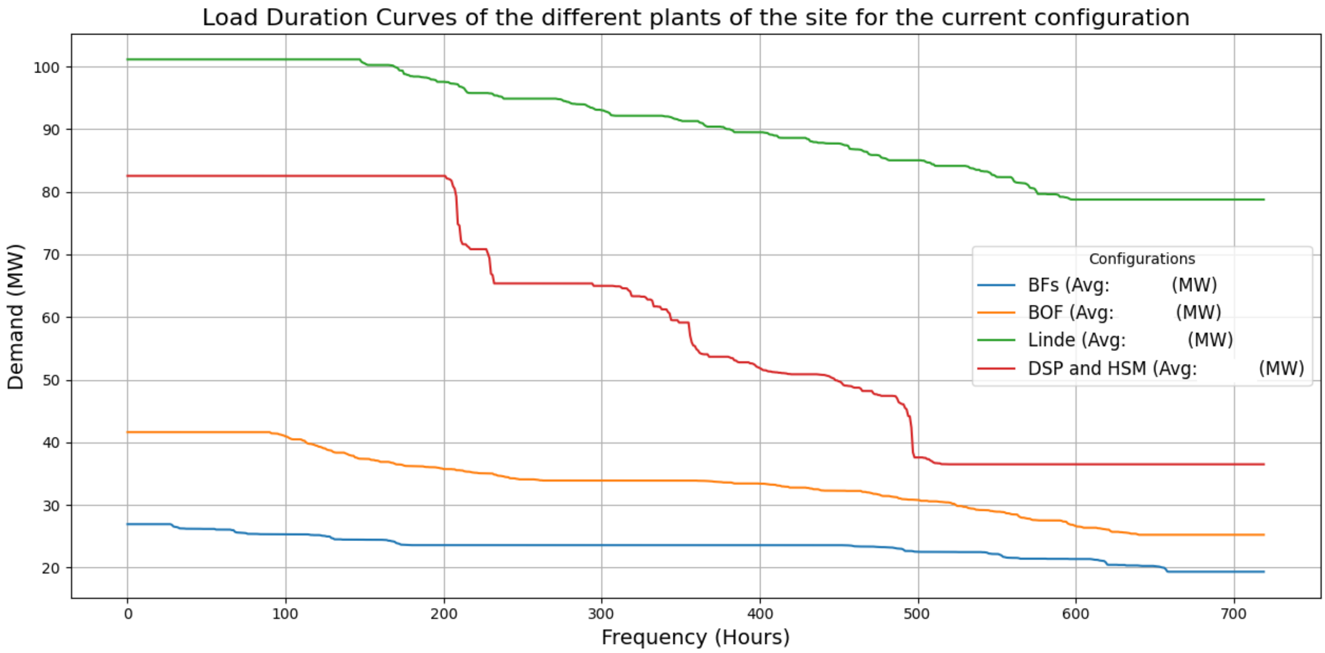

Figure 132: Load Duration curves of the main plants of the current configuration

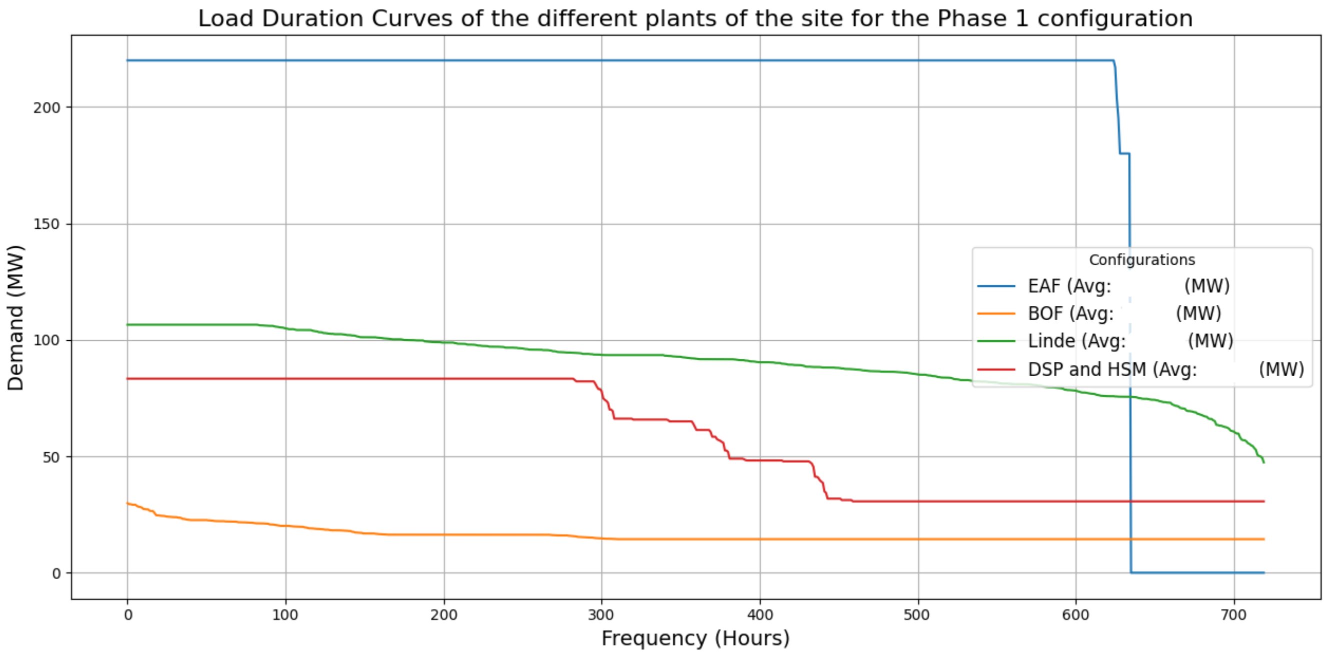

Figure 133: Load Duration curves of the main plants of the Phase 1 configuration

4.5 EAF Sizing against Day Ahead and Network Cost increase

In this section, we investigate the impact of the EAF's size on steel production costs and assess how a potential oversizing of the EAF could affect Tata Steel's operational expenses. Scenarios were analyzed for EAF sizes ranging from 400 to 550 tons of DRI per hour, with simulations conducted under central price scenarios both with and without network tariff costs. All simulations were carried out for Phase 1.

As shown in Figure 134, network cost tariffs significantly limit the cost-saving potential of oversizing the EAF. We observed cost savings of up to approximately 0.5% when the EAF capacity was increased from 400 to 550 tons of DRI per hour. However, with network tariffs applied, the cost savings were reduced to just 0.15%. This highlights the adverse impact of network tariffs on utilizing larger EAF capacities for demand response.

Nevertheless, further investigation is needed to determine whether the cost savings achieved through oversizing the EAF would offset the additional investment costs required for the larger capacity. It is also evident that after a certain point—sooner when network tariffs are applied—the benefits of oversizing diminish. This is due to system constraints around the EAF, such as storage capacities and bottlenecks in other plants, which limit the effective utilization of the larger EAF capacity.

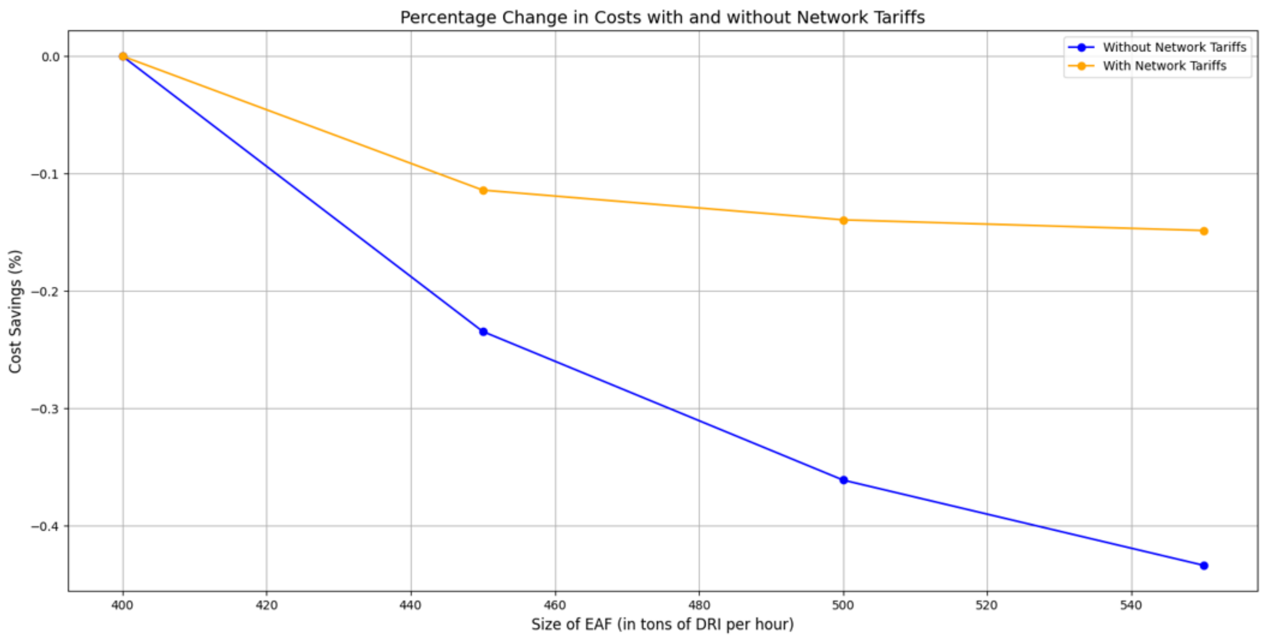

Figure 134: The cost benefit from oversizing the EAF at the Phase 1 configuration with and without network tariff cost.

In Figure 135, we present the load duration curves for different EAF sizes. As expected, larger EAFs offer greater flexibility, as they can produce more steel during periods of low electricity prices. This results in more hours of reduced or no operation during periods of high electricity prices, provided the surrounding system and steel production target allow such adjustments.

In Figure 136, we compare the duration curves of EAFs with capacities of 400 and 500 tons of DRI per hour under scenarios with and without network tariffs. For the 400-ton EAF, the curves are identical, indicating that network tariffs do not impact its operation. However, for the 500-ton EAF, the curve with the network tariff applied shows reduced flexibility compared to the non-tariff scenario, with fewer hours of reduced operation.

This observation supports our claim that the current network tariff scheme negatively affects flexibility, particularly by restricting the cost benefits and operational flexibility associated with oversizing the EAF.

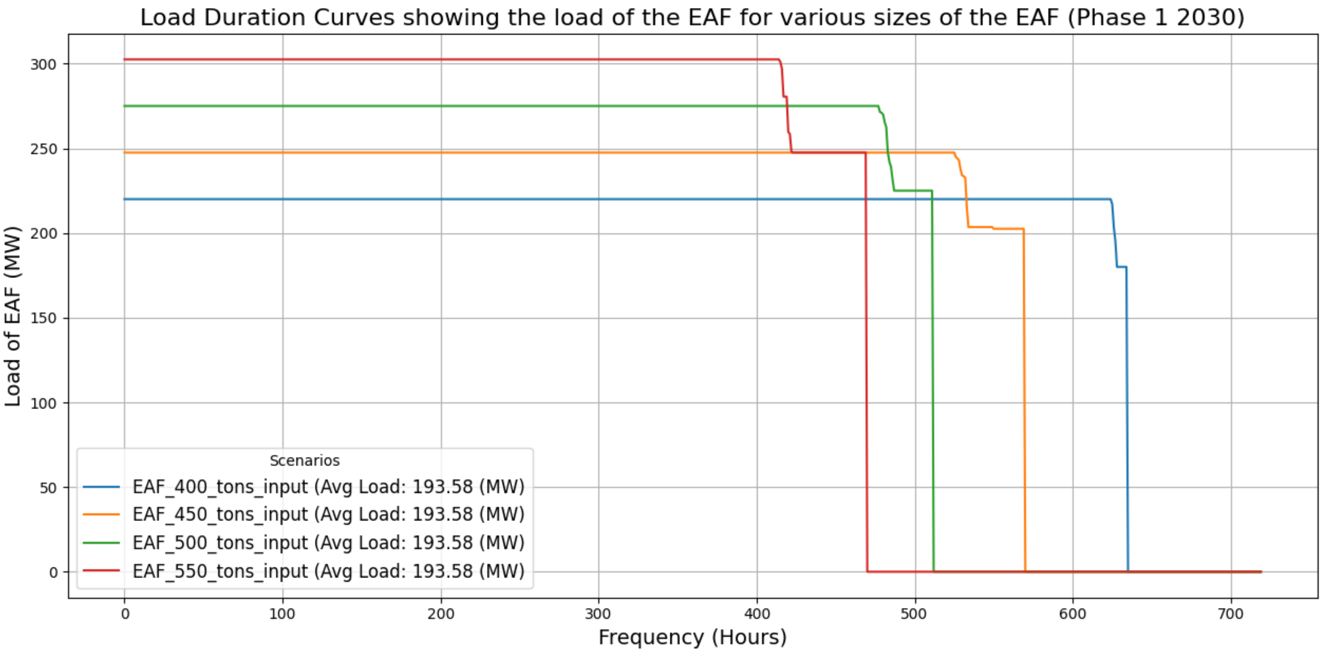

Figure 135: The load duration curves of different sizes of EAF in Phase 1

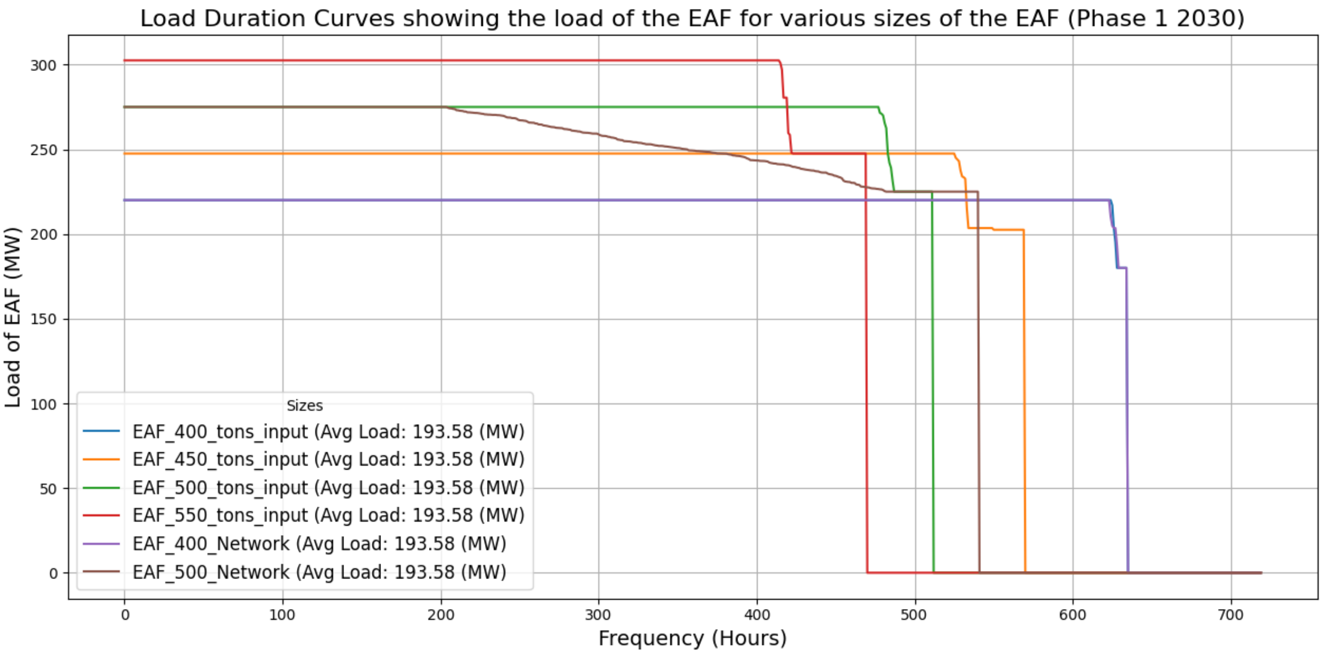

Figure 136: The load duration curves of different sizes of EAF in Phase 1 with the addition of the load curves for 400 and 500 tons of EAF at simulations including network tariffs costs.

4.6 Sensitivity Analysis of the hydrogen price at which electrolysis become viable

In this final section of the results, we present a test case for the use of electrolysis during Phase 3 of the site's transition. Given the uncertainty surrounding hydrogen prices, which are not provided by Tata Stee;, we performed a sensitivity analysis by varying the hydrogen price within a range anticipated by the literature, considering three different electricity price scenarios for 2045 (Central, Low, and High). Additionally, we incorporated a 1 GW electrolyzer capacity into our configuration and allowed the optimizer to determine whether the site's hydrogen supply should come from on-site electrolysis using a portion of the available electrolyzer capacity or from the hydrogen market, with the price set according to the hydrogen cost scenario. The results are shown in Figure 137. The assumption of 1 GW electrolyzer capacity is considered feasible based on the expected future availability of the site's connection infrastructure. To translate this into hydrogen production, a 1 GW electrolyzer is capable of generating approximately 20 tons of hydrogen per hour.

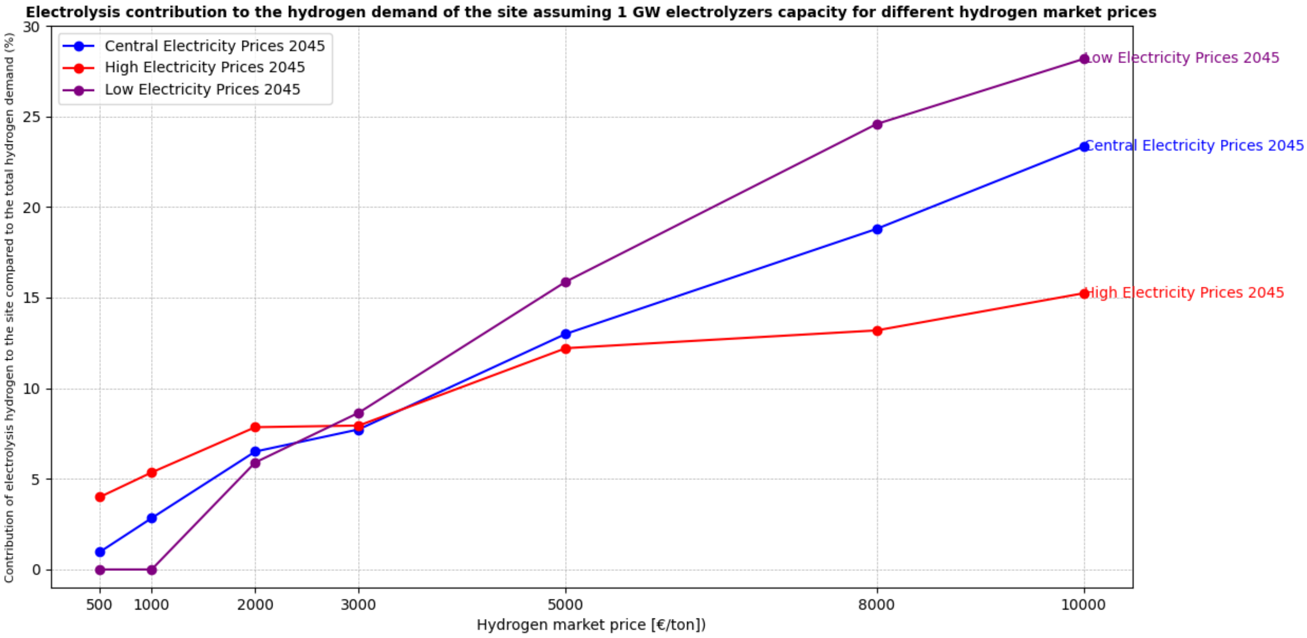

Figure 137: The contribution of electrolysis hydrogen as a percentage of the total hydrogen demand of the site under different hydrogen market prices for 2GW installed capacity of electrolyzers.

In all three electricity price scenarios, when hydrogen prices exceed 3000 €/ton, the site utilizes the electrolyzer capacity, ranging from 7% (approximately 80 MW) across all scenarios to nearly 30% (around 300 MW) when electricity prices align with the low scenario. In contrast, under the high price electricity scenario, electrolysis utilization reaches a maximum of 30% only at very high hydrogen prices of 10,000 €/ton. Figure 137 illustrates the various possible scenarios for this configuration, providing insight into the hydrogen price thresholds at which electrolysis becomes a viable option for Tata Steel, depending on the expected electricity prices and considering only operational costs.

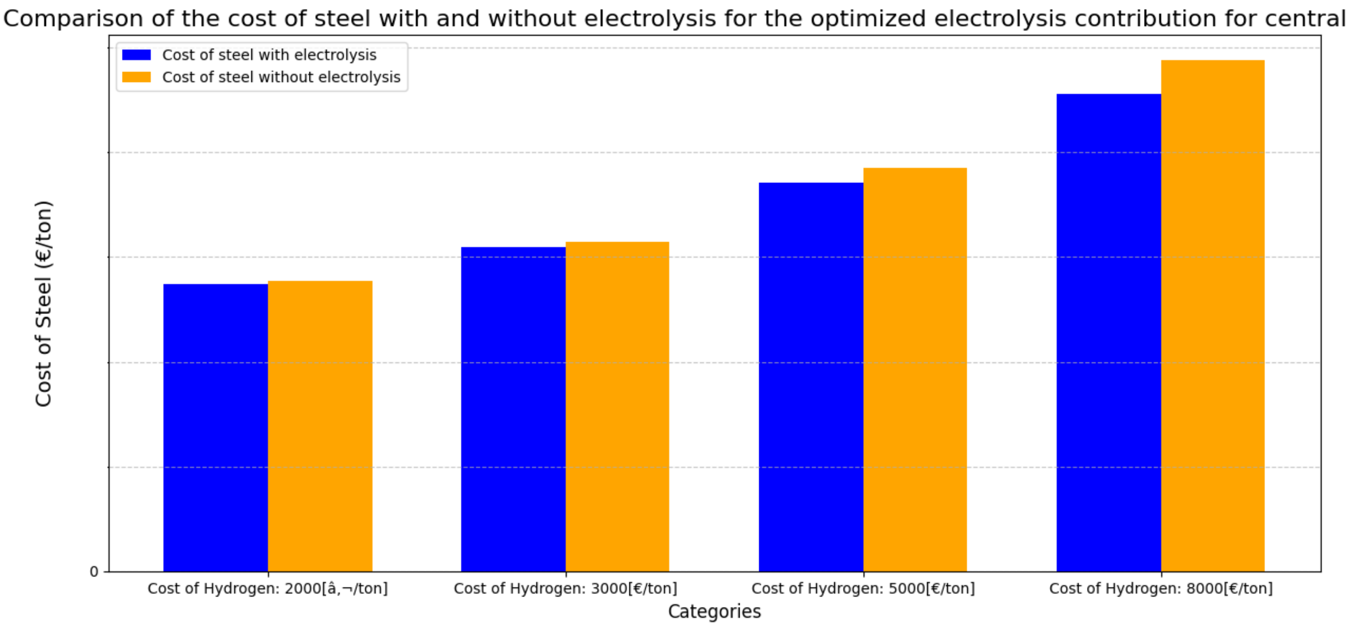

Figure 138: Comparison of the total cost of steel production for different hydrogen prices and central electricity prices with and without electrolyzing capacity (1GW)

Finally, Figure 138 presents the cost savings from installing the 1 GW electrolyzer capacity at different hydrogen price points. As expected, the highest cost savings occur at elevated hydrogen prices. However, even at hydrogen prices of 3 and 5 €/kg, the cost savings are approximately 10 and 25 €/ton of steel, respectively, under the central electricity price scenario. These savings significantly surpass those resulting from oversizing the Electric Arc Furnace (EAF). That said, the capital expenditures (CAPEX) associated with electrolyzers, along with other limitations such as the available connection capacity and network costs, must also be taken into account. Further cost savings are anticipated if strategic hydrogen storage can be implemented as part of the system.

Key Points

The key findings of the results section are summarized as follows:

- **CO_2 emissions as a cost driver:**
  - CO_2 emissions are the largest cost driver in the current steel production configuration, accelerating the transition toward more sustainable alternatives.
  - Although new configurations may not immediately reduce steel production costs, they are essential for lowering emissions.
  - The transition from coal to natural gas, and eventually to hydrogen, is a crucial step toward achieving green steel production. Natural gas serves as an intermediate energy carrier, a common approach in the energy sector.
- **Impact of price scenarios:**
  - The effect of price scenarios is more pronounced in the marginal cost of steel production compared to CO_2, natural gas, and electricity consumption.
  - While configuration primarily determines these costs, external price fluctuations still have a slight impact on overall cost.
  - In some cases, future configurations may result in lower costs than current high-cost configurations. However, under the same price scenarios, steel production costs are expected to rise in the future.
- **Electricity dependence in future configurations:**
  - Future configurations will rely more on electricity, though it will not become the dominant cost component.

  - New plants, particularly the Electric Arc Furnace (EAF), will have the ability to operate flexibly, benefiting from electricity price fluctuations—an advantage not available in the current setup.
  - Consequently, electricity prices will have a greater impact on the cost structure of future configurations.

- **Network costs and industrial flexibility:**
  - Network costs will become more significant in future configurations due to higher electricity consumption.
  - However, these costs will remain relatively small compared to electricity prices and other cost components.
  - Tata Steel's network cost structure allows for the avoidance of peak demand through optimization strategies. However, such schemes do not necessarily incentivize the industry to electrify and increase flexibility, as they conflict with the benefits of flexible operation.

- **Conflict between network costs and operational flexibility:**
  - The network cost structure is at odds with operational flexibility. Large electricity consumers like the EAF can operate at full capacity when electricity prices are low, but this demand pattern leads to high network costs.
  - In terms of flexibility, future configurations with the EAF will exhibit a broader range of electricity demand profiles compared to the current setup.
  - While steel production is already somewhat flexible, the new configuration's flexibility is constrained by operational limits at the Hot Strip Mill, DSP plants, and storage capacities. As a result, fluctuations in electricity demand cannot be fully realized.

- **EAF sizing and cost savings potential:**
  - Without the negative impact of network tariffs on EAF flexibility, the cost savings potential from oversizing the EAF is greater than when network tariffs are applied.
  - Under high electricity prices and no network tariffs, cost savings of up to 5 €/ton of steel are achievable, amounting to approximately 35 million euros annually for Tata Steel.
  - However, this must be weighed against the capital expenditures (CAPEX) required for oversizing the EAF to determine whether the investment is financially viable.
  - When network tariffs are applied, cost savings are significantly limited and are likely insufficient to justify the investment in oversizing such a large facility.

- **Hydrogen and electrolysis analysis:**
  - On-site hydrogen and electrolysis analysis highlights the challenges of predicting hydrogen prices while providing valuable insights into potential savings.
  - For the Phase 3 configuration, which includes a 1 GW electrolyzer satisfying up to 25% of the site's hydrogen demand, various hydrogen and electricity price scenarios were analyzed.
  - The cost savings associated with different hydrogen price levels were quantified, offering key insights for decision-making regarding hydrogen integration in steel production.

4.7 Evaluation

Model Characteristics and limitations

The model was developed in Python, utilizing PyPSA as its primary tool. A time resolution of one hour was chosen to align with the day-ahead electricity market and Tata Steel's common practices for modeling and simulation. This resolution ensures relevance for both market interactions and internal analysis. The optimization was solved using the HiGHS 1.7.0 solver, though alternatives like Gurobi or GLPK could also be employed.

Yearly simulations were conducted without employing a rolling horizon approach. This decision aligns with the model's objective of capturing the broader operational picture of the site and assessing the effects of configuration changes over at least a year. Annual simulations are particularly suitable for observing:

- Steel production targets,
- Emissions,
- Energy consumption,
- Flaring, and
- The seasonality of energy prices.

A rolling horizon approach was avoided, as it complicates the establishment of meaningful short-term targets without an overarching yearly simulation. This model thus serves as a foundation for future models focusing on short-term planning.

The model is a hybrid, designed to:

- Represent the fundamental energy and material flows at Tata Steel,
- Reflect probable electrification pathways, and
- Enable price-responsive operations.

While it does not replicate precise hourly operations, the model provides a high-level optimization framework driven by energy and material price signals.

Maintenance Planning Maintenance planning is not included in the model, meaning specific off-times for plant maintenance are not considered. While adding maintenance schedules might slightly alter operational patterns, the overall yearly results for emissions and energy consumption are unlikely to change significantly. This is due to the close linkage between steel production, material use, and energy consumption. Without maintenance planning, the operational distribution tends to be more symmetrical, with a narrower standard deviation compared to real-world conditions.

Network Costs The inclusion of network costs significantly increased computational time. These costs were modeled as a custom function manually added to the objective function after PyPSA generated the base formulation. The network cost function, which charges based on maximum monthly and yearly electricity consumption, introduced substantial complexity and computational intensity.

Solving times for yearly simulations ranged between 5 and 30 minutes without network costs, depending on the configuration. These tests were conducted using a laptop with an 11th Gen Intel Core i5-1145G7 processor and 16 GB of RAM. Configurations with complex gas flows, such as the distribution of natural gas and waste gases (WAGs) among generators, boilers, and main plants, tended to slow down the solver. However, the following strategies were employed to improve computational efficiency:

- **Avoidance of Binary Variables:** External generators were modeled with continuous operation ranges (0 to nominal capacity) and no startup costs. Ramp limits were applied without significant accuracy loss, reducing computational demands.
- **Simplification of Future Configurations:** Future configurations generally solved faster due to the absence of WAG flows and generators, despite including binary variables for electric arc furnace (EAF) operations.

Network cost modeling increased solving times to over an hour in some cases. This highlights the computational trade-offs involved in adding detailed cost structures.

The HiGHS 1.7.0 solver was selected for its balance between speed and reliability. However, alternative solvers such as Gurobi or GLPK could be explored to assess their impact on computation times and solution accuracy.

This model provides a robust framework for evaluating long-term operational strategies at Tata Steel. While it simplifies certain aspects, such as maintenance planning and precise hourly operations, it effectively captures key trends and informs decision-making on decarbonization pathways. Future iterations may incorporate rolling horizon techniques, advanced solvers, and additional features like maintenance scheduling to further enhance its utility.

5 Conclusions

Answers to the research questions

How can the current configuration of the site be optimized as a model that reflects the most important energy and material flows in a cost minimization problem, while also being adaptable for future configurations of the site?

The optimization model developed in this work is designed to accurately reflect the critical energy and material flows of Tata Steel's current site configuration while remaining adaptable to future configurations. The model ensures that the steel production target is met while minimizing costs, making it relevant throughout transition phases. By incorporating major processes and plants as decision variables and modeling their interactions, the framework effectively captures the entire process chain—from initial inputs like coal and iron ore to the final steel output. Realism is enhanced through constraints such as ramp limits, operational capacities, and material flow interdependencies.

The model's adaptability is a key strength, allowing new components and technologies to be seamlessly introduced without altering the foundational structure. This flexibility aids in identifying bottlenecks, inefficient flows, and design challenges, supporting decisions on the sizing and placement of new facilities. Additionally, the integration of time-varying cost inputs enables the model to simulate cost-optimized operational strategies that respond to fluctuations in energy and material prices. The gas network optimization, which includes interactions between natural gas and waste gases (WAGs), adds another layer of realism, while validation with operational data ensures its accuracy. Overall, the model provides a robust foundation for analyzing current operations and transition configurations.

A crucial component in achieving these model characteristics was the use of PyPSA, an open-source framework with features tailored to energy systems modeling. PyPSA's flexible components proved invaluable for this project. For instance:

- Generator components: Facilitated the assignment of marginal costs to each material or energy flow, automatically linking them to all processes consuming those resources.
- Link components: Represented processes with multiple inputs and outputs, enabling separate conversion factors between them. They also allowed for precise tuning of plant settings, such as capacity, ramp limits, and operational ranges, by controlling the main inputs and all associated flows.
- Stores: Enabled storage restrictions for intermediate products, such as hot iron (which has limited storage capacity), and helped track CO2 emissions from all processes.
- Load components: Modeled secondary system loads, including electricity, natural gas, and other resources.

To model the current configuration effectively in PyPSA, the constraints for individual plants—such as conversion factors between production and electricity demand—were derived from historical data or plant manuals. Ramp limits and operational ranges were also obtained from these sources. However, modeling a large and interconnected site required careful consideration of the scope of analysis. Time and resource constraints necessitated prioritizing systems and processes to include in the model as main plants (part of the optimizer), secondary loads (constant system loads), or processes excluded entirely.

For example, the gas network system is a complex web of flows produced and consumed by various site processes at different pressures. Though modeling it in full detail was infeasible, excluding it entirely was not an option, as these gases contain valuable energy used in multiple site processes and electricity generation. The chosen approach involved simplifying the model to track energy flows while retaining key producers, consumers, maximum capacities, and operational levels for each gas type. Similarly, secondary systems like electricity generators (e.g., Vattenfall's facilities) and boilers were incorporated at an appropriate level of detail to capture their contributions to the site's energy system.

The network-based model design allows for seamless adaptation to future configurations by replacing plants rather than building new models from scratch. This approach simplifies transitions while preserving consistency. Early decisions about the optimization strategy also played a significant role. The model was framed as a cost minimization problem, focusing on energy-intensive processes in the earlier stages of steel production. A profit maximization approach would have required detailed knowledge of the steel market and the complex revenue streams associated with later processing stages, which fell outside the scope of this work.

The steel production target was set to remain constant and close to the site's maximum capacity, reflecting the current industry philosophy of maximizing production efficiency. However, this philosophy may evolve as the industry becomes more dependent on variable energy prices, such as those for electricity and hydrogen. For instance, in future configurations, high energy prices might lead to temporary production shutdowns or reductions when steel production costs exceed market prices. While this scenario was not modeled, it highlights the potential shift in production strategies in response to economic conditions.

In summary, this model serves as a comprehensive and adaptable tool for evaluating the current and future energy configurations of Tata Steel's site, providing insights into energy efficiency and cost optimization under consistent production conditions aligned with today's industry practices.

What are the most feasible pathways toward a green steel plant, considering Tata Steel's operational constraints and the different available technologies?.

The transition pathways identified for Tata Steel are based on literature, Tata Steel's operational plans, and consultation with site experts. These pathways aim to achieve significant emissions reductions while maintaining steel production targets. The decarbonization strategy focuses on electrification, increased use of natural gas in the short term, and a gradual transition to hydrogen-based production by 2050. The pathway consists of three distinct phases following the current configuration:

- **Current Configuration:** The typical BF/BOF route is used for steel production. The site produces approximately 6.2 million tons of rolled steel annually, emitting 13.3 million tons of CO2. This results in a CO2-to-steel ratio of approximately 2.1 tons of CO2 per ton of rolled steel, as per our simulation. (Note: Since this figure is for rolled steel, the overall steel production is slightly higher, and the CO2-to-steel ratio is slightly lower.)

- **Phase 1 (2030–2037):** A natural gas-based direct reduction plant (DRP) and an electric arc furnace (EAF) are introduced, replacing one blast furnace and one coking plant. This configuration achieves a CO2 reduction of approximately 30%, emitting around 9.1 million tons of CO2 annually while maintaining the same steel production level. The CO2-to-steel ratio drops to approximately 1.5 tons of CO2 per ton of rolled steel.

- **Phase 2 (2037–2045):** A second DRP plant is installed alongside a submerged arc furnace (SAF), decommissioning the remaining blast furnace and coking plant. Emissions are reduced by 60% compared to the current configuration. In this phase:
  - The first DRP plant uses pellets and operates primarily with natural gas, supplemented by small quantities of hydrogen, to produce DRI for the EAF.
  - The second DRP plant also uses pellets but operates with a mix of natural gas and hydrogen in nearly equal quantities to produce DRI. This DRI is melted in the SAF and then processed in the BOF to produce crude steel.

  This configuration emits approximately 5.5 million tons of CO2 annually, with a CO2-to-steel ratio of around 0.9 tons of CO2 per ton of rolled steel.

- **Phase 3 (Post-2045):** Both DRP plants transition to fully hydrogen-based reduction, reducing CO2 emissions to nearly 10% of current levels. This configuration emits approximately 1.5 million tons of CO2 annually, achieving a CO2-to-steel ratio of 0.25 tons of CO2 per ton of rolled steel. It is worth noting that the site plans to be fully decarbonized by 2045, coinciding with Phase 3. However, our simulation does not include carbon capture techniques for the production of waste gases (WAGs) from the BOF and SAF or the small quantities of natural gas consumed by the DRPs.

Additional changes include transitioning boilers from WAGs to natural gas and eventually to electricity, and phasing out external WAG generators by Phase 2. This phased approach balances emissions reduction with operational feasibility, ensuring a realistic pathway for decarbonization.

While the literature suggests numerous possible pathways, the most realistic, technologically mature, and economically feasible options involve the DRP/EAF route. This approach relies on electrification and the gradual transition from natural gas to hydrogen for the DRPs. Alternative pathways, such as utilizing biomass or carbon capture in the BF/BOF route, could be applicable for the IJmuiden site. However, based on discussions and information regarding Tata Steel's original plans, the focus was placed on the more realistic transition pathway described above.

Having the current site model tested and operational before transitioning to future configuration models proved invaluable. This approach allowed for the gradual replacement of old components with new ones, ensured the appropriate sizing of new components to align with the capacities and limitations of remaining processes, and facilitated tracking the changes introduced by each component replacement.

What will be the impact of external factors, such as electricity prices, the hydrogen ecosystem, and energy policies, on the operational conditions and the marginal cost of the examined pathways toward green steel production?

The transition pathways are influenced by external factors such as electricity prices, the hydrogen ecosystem, and energy policies, primarily through their impact on operational costs. Using price scenarios (central, high, low, and net-zero) as a basis, this study highlights the interplay between external price trends and the cost of steel production:

- **Steel Production Costs**
  - Under the central scenario (the most probable), steel production costs are expected to rise compared to the current configuration, increasing from 13% in Phase 1 to 45% in Phase 3. This increase depends on the cost components of steel production. Given the projected cost contributions of electricity, natural gas, and, after Phase 2, hydrogen, steel production costs show an upward trend.
  - Sensitivity analysis reveals overlaps in cost ranges across scenarios, indicating that favorable price trends (e.g., lower-than-expected electricity prices) could result in lower steel production costs than the current configuration, though this is not the most probable scenario.
  - For the central scenario, the study estimates the following increases in marginal steel production costs:
    - Current configuration: €[redacted]/ton
    - Phase 1: €[redacted]/ton (+13.1%)
    - Phase 2: €[redacted]/ton (+24.7%)
    - Phase 3: €[redacted]/ton (+45.1%)
- **Energy Consumption and Emissions**
  - While external factors influence operational costs, they have minimal impact on annual energy consumption or emissions, which are primarily dictated by the site's design and steel production targets.
  - Each configuration exhibits specific CO_2 production levels that remain consistent regardless of variations in CO_2 prices or other energy and material costs. As a result, emissions decrease progressively from Phase 1 to Phase 3:
    - Current configuration: 13 million tons CO_2/year
    - Phase 1: 9 million tons CO_2/year
    - Phase 2: 5 million tons CO_2/year
    - Phase 3: 1.5 million tons CO_2/year (excluding potential CCUS applications for carbon neutrality)
- **Operational Conditions**
  - The steel production site comprises multiple interconnected processes, each imposing constraints on cost optimization while maintaining a specific production target.
  - In all configurations, storage capacity limitations (e.g., for hot iron or oxygen) and plant-specific operational constraints (e.g., ramp limits, range, and capacity) significantly restrict optimization.
  - Compared to the current setup, future configurations offer increased flexibility due to the electric arc furnace (EAF):

    - ∗ The EAF can ramp up or shut down faster in response to electricity prices. While this has been deemed feasible in literature, in reality, it may introduce additional costs (e.g., electrode replacements or steel quality issues).
    - ∗ Direct reduced iron (DRI) produced by the direct reduction plants (DRPs) can be stored more easily and in larger quantities than hot iron, allowing the EAF to operate with greater flexibility.
  - Despite this increased flexibility, the site remains an integrated system where external price fluctuations alone cannot dictate operations, as production targets and system constraints must still be met.
  - The transition to heavy electrification and hydrogen usage will significantly alter the site's operational characteristics, which currently rely predominantly on coal.

- **Network Costs and Operational Flexibility**
  - Network cost policies significantly impact operational flexibility and the feasibility of oversizing the EAF.
  - High network costs associated with demand peaks restrict the EAF's ability to capitalize on periods of low electricity prices.
  - Cost savings were identified by oversizing the EAF by up to 75 MW beyond its minimum required capacity, leading to savings of up to €5/ton of steel in simulations without network tariffs. However, under the current network tariff scheme, these savings are limited.
  - Beyond 75 MW of additional capacity, the benefits of oversizing diminish due to operational constraints on the EAF.

- **Hydrogen and Electrolysis**
  - Post-2045, electrolyzer capacity becomes economically viable for hydrogen prices exceeding €3/kg.
  - This shift could yield cost savings of at least €10/ton of produced steel for hydrogen prices above €3/kg.

These findings underscore the critical role of energy policies and price trends in shaping the feasibility and costs of Tata Steel's transition pathways. While external prices significantly influence operational costs, the design and constraints of the transition configurations primarily determine emissions and energy consumption.

Answer to the Main Research Question

What would be the impact of different investment decisions regarding energy transition on meeting the decarbonization goals of Tata Steel's integrated steel site in IJmuiden, Netherlands?

The research demonstrates that the energy transition of Tata Steel's integrated steel site in IJmuiden will have significant implications across three main dimensions: internal operational impacts, external environmental impacts, and broader systemic considerations. By leveraging the developed optimization model and analyzing proposed transition configurations, this work offers insights into how investment decisions affect the pathway to decarbonization, emphasizing the interplay between internal site changes, external market conditions, and the larger energy ecosystem.

- **Internal Impacts**
  - **Cost of Steel Production:** Decarbonization pathways will lead to an increase in steel production costs due to shifts in energy carriers and their projected future prices. The cost breakdown evolves with the transition from coal, characterized by stable prices and storage capacity, to more volatile energy carriers such as natural gas, electricity, and eventually hydrogen, resulting in higher production costs.
  - **Energy Mix and Site Operation:** Each transition phase introduces significant changes in the energy mix:

    * **Phase 1 and Phase 2:** Transition from coal-dominated processes to natural gas and electricity.
    * **Phase 3:** Full transition to hydrogen and electricity.

  These changes alter operational patterns, requiring increased flexibility and responsiveness to external price signals. The introduction of the EAF enhances flexibility due to its rapid ramping capabilities and the increased storage potential of DRI compared to hot iron.

  - **Flexibility and Market Exposure:** The site becomes increasingly exposed to external energy markets, particularly electricity and hydrogen, while simultaneously reducing its reliance on internally generated work arising gases (WAGs). The operational flexibility provided by EAF and DRP, coupled with the ability to store large quantities of DRI, enhances the site's ability to respond to price fluctuations. However, constraints within the steelmaking system, production targets, and interdependencies among processes limit unrestricted optimization.
  - **Impact of Energy Policies:** The current network tariff scheme, which penalizes peak electricity demand, reduces cost-saving opportunities for electrification. This also discourages investments in electrolyzers, as high network costs increase operational expenses. Comparisons with neighboring countries, such as Germany and Belgium, reveal relatively higher costs in the Netherlands, making industrial electrification less competitive.
  - **Intermediate Role of Natural Gas:** Natural gas serves as a transitional energy carrier, bridging the gap between coal and hydrogen. The duration of this phase depends on the cost and availability of green hydrogen. Investments in natural gas infrastructure must be adaptable for eventual replacement with hydrogen-based systems to ensure long-term sustainability.

- **Systemic Implications for the Netherlands**
  - **Energy Carrier Demand:** The optimized transition plan highlights specific electricity, hydrogen, and natural gas consumption patterns, imposing demands on the Dutch energy system. Large-scale hydrogen adoption in Phase 3 necessitates a robust and affordable hydrogen supply chain.
  - **Policy and Market Considerations:** Tata Steel's transition pathway provides valuable insights for policymakers and investors, serving as a case study for decarbonizing energy-intensive industries. The existing network tariff structure must be revised to enable flexible and economically viable decarbonization efforts.
  - **Integration with the Broader Energy System:** These findings align with larger-scale studies, such as the DEMOSES project, assessing how Tata Steel's decarbonization aligns with national energy transition goals and its impact on grid operators, energy suppliers, and market dynamics.

Key Investment Considerations for Decarbonization

- **Phased Implementation:** The proposed configurations (Phases 1, 2, and 3) progressively reduce emissions:
  - **Phase 1:** 40% CO2 reduction by decommissioning coal-based processes and adopting natural gas and electricity.
  - **Phase 2:** 60% CO2 reduction with increased reliance on natural gas and electricity.
  - **Phase 3:** 90% CO2 reduction by transitioning to hydrogen-based systems.
- **Component Sizing:** Infrastructure sizing, particularly for EAF, DRP, and SAF, significantly impacts operational costs and flexibility. Sensitivity analysis indicates that oversizing the EAF by 75 MW can yield cost savings of up to €5 per ton of steel, depending on network tariff structures.
- **Hydrogen Ecosystem Development:** Hydrogen prices will critically influence steel production costs in Phase 3. The availability and affordability of hydrogen are key factors. If hydrogen prices exceed €3/kg, site-based electrolyzer investments may become cost-effective, reducing steel production costs by at least €10/ton. Additionally, to mitigate exposure to volatile electricity prices, Tata Steel could explore self-generation through wind or solar power or secure long-term power purchase agreements.

Comparing Key Findings with Other Studies

- Toktarova et al. (2020) reports CO2/ton ratios of 1.6–2.2 for the BF/BOF route, aligning with our estimate of 2.1 for the current configuration.
- The same study suggests DR/EAF ratios of 0.63–1.15, consistent with our Phase 2 ratio of 0.9.
- Boldrini, Koolen, Crijns-Graus, Worrell, & van den Broek (2024) finds that the H2/DRI/EAF route offers 3–27 times greater decarbonization potential than the BF/BOF/CCUS route, supporting our transition strategy.
- For steel production costs, Toktarova et al. (2020) estimates a 12–13% increase for the DR/EAF route, similar to our Phase 1 findings. Differences arise due to varying assumptions, such as their electricity price estimate of €35/MWh versus our detailed hourly projections by Tata Steel.

Conclusion Tata Steel's decarbonization pathway highlights the complexities of transitioning an energy-intensive industry while achieving climate goals. The transition results in a costlier yet more sustainable production system, increasing exposure to external market conditions. Achieving decarbonization targets requires:

- Strategic investments,
- Flexible operational practices,
- Supportive energy policies.

These efforts balance economic viability with environmental objectives, offering a blueprint for industrial decarbonization and serving as a foundation for broader systemic analyses.

Final remarks about the contribution of the model
This work encompassed multiple aspects, including:

- Understanding the steel-making processes.
- Examining the specific processes at Tata Steel's IJmuiden site.
- Distinguishing between important and non-important processes relevant to the main goals of this work.
- Acquiring data for both the design and validation of the model.
- Designing the model to reflect the current site's operations, optimize them, and facilitate the transition towards a green steel-producing site.

In addition to these aspects, the model had to meet specific requirements from Tata Steel's site, such as precise demand-side simulation and time constraints. Requirements were also imposed by the DEMOSES project, as the model needed to function as an optimization tool that receives energy prices and provides consumption patterns as an initial step, with specific time resolutions.

Another essential component of this work was addressing the research questions. Ultimately, the model successfully performed in this regard. However, in my opinion, the model itself and the methodology used to design it are more significant than the numerical results and answers to the research questions for the following reasons:

- The methodology and resulting model demonstrate that PyPSA is a useful and fit-for-purpose tool. When handled appropriately, it can provide valuable models for complex energy systems and sector coupling models. Initially, this was an open question and not a given.
- The full potential of PyPSA and Python was not entirely exploited in this study, as more complex functions, additional components, rolling horizon methods, and system plotting capabilities could be implemented.

The developed model sits between highly process-focused models, such as those created in ASPEN (which are used at Tata Steel and other industries for in-depth process simulation and optimization), and simplified economic models like Excel sheets used by economic and asset development departments.

- Process-focused models excel at simulating and optimizing the physical aspects of individual processes but lack an overarching perspective on energy consumption, costs, and system-wide interactions, which this model provides.
- Simple Excel models, on the other hand, are too static, lack optimization and system analysis capabilities, and fail to capture the interactions between processes in large systems. While useful for preliminary cost estimations, they are insufficient for serious decision-making and evaluating configurational changes.

This model bridges the gap between these two extremes. In the new era of sector coupling, renewable energy integration, and fluctuating energy costs, particularly hourly electricity price variations, models like this will be crucial for:

- Understanding the full picture of an energy-related system, where the primary objective may not be energy efficiency but overall cost savings.
- Exploring the interactions between system processes dynamically under different scenarios involving external price fluctuations or internal configurational changes.
- Testing the sizing and design of new components within the existing system.
- Making informed decisions by comparing the marginal costs of different configurations with the CAPEX of new components or modification costs for existing ones.
- Identifying system bottlenecks and performing sensitivity analyses to determine which bottleneck will emerge next after addressing the current one.

- Supporting decision-making for contracts with energy suppliers, such as gas or electricity providers, by determining the price points at which market participation or internal generation becomes more beneficial.
- Optimizing the gas network system at the site by determining where to direct produced gases, taking into account potential configuration changes such as fewer WAGs in the future or more volatile electricity prices.
- Establishing optimal operational strategies for the site under extreme scenarios (as explored in the verification section), allowing for rapid response to plant failures or process shutdowns.
- Suggesting the best maintenance periods for different plants by analyzing when energy prices are expected to be high or when storage levels allow for minimal operational disruption.

Given the above considerations, designing this model was a complex task that had to satisfy numerous requirements. Ultimately, its capabilities exceed initial expectations. While the model may have limitations, potential inefficiencies, or room for further optimization, its approach to modeling this complex hybrid energy system at a steel production site is of significant importance. The methodology and approach used to answer the research questions are, in many ways, more valuable than the numerical results themselves.

The model successfully addresses the research questions by:

- Accurately reflecting the current site configuration and optimizing it for cost efficiency.
- Proposing a detailed transition pathway for the site.
- Analyzing the impacts of these transitions under various external price scenarios and different configurational settings (e.g., EAF size, network costs, and electrolysis on-site).

Although the results provide probable trends and insights into the site's future, they are based on numerous assumptions, as explained in this work. Consequently, the methodology and approach used to generate these insights are more important than the specific numerical outcomes.

A key contribution of this work is that for Tata Steel's IJmuiden site, given a known configuration with precise operational characteristics and known or estimated external commodity prices, a researcher using this model can:

- Explore all of the model's described capabilities.
- Gain valuable insights into the site's future potential based on current knowledge and expected trends.

The model was developed using PyPSA (an open-source tool), and its design methodology is documented in detail in this report. This ensures that such a model can be replicated for any steel-making site or for a general energy-intensive industrial system. The model documentation and details belong to Tata Steel and are also part of the DEMOSES project, as Tata Steel contributes to this initiative by using or providing the model.

In conclusion, the core and most significant contribution of this work is the development of this model and its demonstration of potential applications in answering key research questions. The uncertainty and assumptions inherent in the model's inputs mean that the approach and methodology are more crucial than the absolute numerical results.

Recommendations for Tata Steel

Based on the findings of this study and insights gained during the project, the following recommendations are suggested for Tata Steel's transition towards a sustainable and optimized operation:

Utilizing the Model for Strategic Decision-Making:

- This model, or an extended version of it, should be used to gain a comprehensive view of the site's future energy consumption patterns. Tracking both energy generation (self-generated electricity or waste gases) and energy consumption points will allow for improved integration and optimization of energy flows.
- The model should be applied to various scenarios with different external input prices to determine the upper and lower production cost limits for steel in the coming decades. This will help assess whether the steel price remains competitive in Tata Steel's target markets.
- The operational costs of different transition pathways and new components are provided by the model. By comparing cost savings from investment decisions with capital expenditures (CAPEX) over a specific time horizon, the financial viability of each investment can be assessed.

Key Findings from the Model:

- Decarbonization will increase steel production costs, even without considering transition-related investment costs. It is not recommended to transition faster than competitors due to economic viability concerns.
- Price responsiveness will be critical for cost savings, given electricity price fluctuations. Effective bidding strategies and demand-side flexibility should be a top priority. Without this, participation in the day-ahead electricity market may be unprofitable.
- The model suggests optimal sizes for new components to ensure a smooth transition and minimize bottlenecks. Sensitivity analyses should be conducted around these values, incorporating the exact characteristics of existing and new plants.
- The configurations outlined in this study can achieve a **90% CO_2 reduction**. To reach full carbon neutrality, **Carbon Capture, Utilization, and Storage (CCUS) technologies** may be required for specific processes.
- **Electric Arc Furnace (EAF) oversizing** can offer cost savings. This should be compared with CAPEX to determine the optimal EAF size. The same applies to components like **SAF (Submerged Arc Furnace) or DRPs (Direct Reduction Plants)**, though expected savings may be lower than those from EAF oversizing.
- **Hydrogen electrolysis becomes cost-effective** at hydrogen prices above €3/kg. These values should be compared with CAPEX for electrolyzer installation before making investment decisions.

Additional Considerations and Strategic Recommendations:
Rethinking Production Philosophy:

- The traditional goal of maximizing production volume may need to be reconsidered. With increasing energy price volatility and a greater reliance on electricity and hydrogen, an alternative approach could be to **produce only when the marginal cost of steel is below a certain threshold relative to its market price**.
- This shift in operational philosophy would reduce the site's capacity factor, which is uncommon in the steel industry but may become necessary as new energy carriers take precedence.

Securing Strategic Energy Supply Agreements:

- Coal (for some years), natural gas, and hydrogen will continue to play key roles during the transition.
- Long-term supply contracts should be established under **favorable terms** to ensure the availability of these energy carriers at competitive prices. The model's energy demand forecasts should support contract negotiations.

Exploring Secondary Steelmaking Options:

- The potential for reducing primary steel production by increasing **secondary steelmaking** (e.g., incorporating more scrap in EAFs) should be assessed.
- The model should be adjusted to evaluate different scenarios under varying energy and market conditions to determine optimal secondary steelmaking strategies.

Maximizing Site Operational Flexibility:

- The site should be designed to prioritize steel production **under favorable energy conditions** rather than aiming for maximum production at all times.
- Investments in **flexibility-enhancing technologies** (e.g., EAF oversizing or on-site electrolyzers) should be considered to capitalize on energy price fluctuations.

Preparing for the Hydrogen Transition:

- Hydrogen integration should be accelerated by investing in **hydrogen infrastructure**, including storage and supply chains, particularly for **Phase 3** operations.
- Tata Steel should collaborate with government and industry stakeholders to establish a **robust hydrogen ecosystem** that ensures an affordable and reliable hydrogen supply.

Optimizing Electricity Use and Network Costs:

- Tata Steel should engage with policymakers and grid operators to **restructure network costs** that currently penalize flexible operations. Advocacy for **industrial decarbonization policies** that support grid stability is essential.
- On-site **renewable energy generation** (e.g., solar or wind) and **energy storage solutions** should be explored to reduce dependency on grid electricity and mitigate exposure to price volatility.

Strengthening Collaboration with External Stakeholders:

- Partnering with **policymakers, energy providers, and researchers** will be critical in influencing energy policies and market mechanisms that support industrial decarbonization.
- Participation in initiatives like the **DEMOSES project** should continue to ensure Tata Steel's transition strategy aligns with the broader energy transition in the Netherlands.

Investing in Digitalization and Advanced Monitoring Systems:

- Advanced monitoring and control systems should be implemented to **optimize energy consumption and production efficiency** in real-time based on the model's outputs for shorter simulation horizons.

Developing Industry-Wide Standards for Hydrogen and Green Steel:

- Collaboration with other steel producers should be pursued to establish **benchmarks and certification standards** for hydrogen use and **green steel**. This will facilitate **market acceptance** and potentially enable premium pricing for sustainable steel products.

Engaging with End-Users:

- Tata Steel should build partnerships with downstream industries to **promote green steel adoption** and establish **demand-side commitments** that incentivize decarbonization investments.

By implementing these recommendations, Tata Steel can position itself as a leader in sustainable steel production while effectively addressing the economic and operational challenges associated with the energy transition.

Further Research

To build on the findings of this study and address additional challenges and opportunities in Tata Steel's energy transition, the following research avenues are recommended:

- **Explore Alternative Solvers and Computational Efficiency:**
  - Investigate the use of different optimization solvers to analyze their impact on computation times and solution accuracy. This can help determine the most efficient solver for large-scale simulations involving complex energy and material flows.
  - Benchmark the current solver against alternatives, focusing on scalability for extended scenarios or increased model complexity.
- **Develop a Bidding Strategy for Electricity Markets:**
  - Convert the site's demand profile into an electricity market bidding strategy to enable better integration with the electricity market, optimizing costs while ensuring operational flexibility.
  - Combine this approach with rolling horizon techniques and shorter simulation periods, while maintaining yearly evaluations to reflect long-term planning and operational adjustments.
- **Integrate Maintenance and Disruption Planning:**
  - Add maintenance scheduling and the potential for unforeseen disruptions to specific plants within the model. Simulating and optimizing under such scenarios would improve resilience and reliability.
  - Develop strategies to prioritize operations of critical units during disruptions or maintenance periods to minimize production and cost impacts.
- **Include CAPEX and Oversizing Costs:**
  - Extend the model to incorporate capital expenditures (CAPEX) for various configurations and oversizing options to provide a more comprehensive economic evaluation.
  - Perform cost-benefit analyses of oversizing specific components, such as EAFs or electrolyzers, to evaluate trade-offs between upfront costs and operational savings.
- **Shift Optimization Focus:**
  - Optimize for profit maximization instead of cost minimization, taking into account potential revenue streams from the steel market.
  - Perform multi-objective optimization for parameters like energy use, emissions, flaring, or production flexibility to provide a more nuanced approach to decision-making.
- **Incorporate Energy Storage and Renewable Integration:**
  - Add the option of on-site energy storage systems, such as batteries or hydrogen storage, to increase flexibility in electricity consumption.
  - Evaluate the potential for on-site renewable energy generation (e.g., solar, wind) and its integration with the broader energy system, considering the site's energy needs and the fluctuating nature of renewables.
- **Analyze Scrap Availability and Recycling Pathways:**
  - Investigate the potential impact of increased scrap availability on production strategies and decarbonization pathways.
  - Develop scenarios that prioritize recycled steelmaking, incorporating external market dynamics, energy prices, and environmental regulations.
- **Evaluate Policy and Regulatory Impacts:**
  - Explore the implications of different policy scenarios, such as changes to carbon taxes, emissions trading schemes, or subsidies for hydrogen and renewables.

  - Assess how these policies would influence site operations, investment decisions, and competitiveness in the global steel market.

- **Integrate Market Dynamics for Steel and Byproducts:**
  - Include market dynamics for steel products and potential revenue streams from byproducts (e.g., slag, gases) to refine profit analysis.
  - Simulate how market demand fluctuations might influence operational strategies and energy consumption patterns.

- **Expand the Scope to Include Broader System Impacts:**
  - Analyze how Tata Steel's energy consumption patterns influence and are influenced by the broader energy system in the Netherlands, including grid stability and market interactions.
  - Use the insights to propose infrastructure or policy changes to support industrial decarbonization while maintaining energy system resilience.

- **Incorporate Advanced Decision-Making Tools:**
  - Develop machine learning models to predict energy prices, optimize bidding strategies, and support real-time decision-making.
  - Employ predictive analytics to assess the impact of operational changes or market conditions on production efficiency and costs.

By addressing these areas, further research can refine and expand the scope of the current model, providing actionable insights for Tata Steel and contributing to broader efforts in industrial decarbonization.

6 Reflection

When I started this master thesis project, I was excited by the topic. The idea of building a comprehensive model to describe a large energy system and analyze the impacts of its transition perfectly aligned with my interests and academic background. However, as I progressed, I quickly realized the complexity of the task at hand. I needed to balance three key, and sometimes conflicting, objectives. First, I had to perform scientific research that adhered to my program's requirements, answered the research questions, and contributed novel insights to the field. Second, I was working within the framework of Tata Steel, which meant the outcomes had to be practical and useful for the company's future applications. Third, the model had to comply with the DEMOSES project requirements to serve as a satellite model, contributing to the overarching goals of coupling various energy models across the Netherlands. Balancing these three dimensions proved to be one of the most challenging aspects of the project. Excelling in one area often created difficulties in the others.

The initial stages of the project were particularly challenging. Understanding the operations of a steelmaking site, which is a highly complex system, required substantial effort. I had to identify which processes were most relevant to my model and decide the depth of detail needed for their representation. This task was compounded by the unfamiliar terminology and technical details of the steel industry, which took time to fully grasp.

Another significant challenge was selecting the appropriate tool for the optimization model. While I knew the model would focus on optimization, the choice of the tool was not clear initially. Options included Linny-R, manual formulation of the optimization problem, or PyPSA. Tata Steel's preference leaned towards PyPSA due to its strengths in modeling energy systems, but it was not guaranteed to suit the specific requirements of my project. Additionally, I needed to invest time to learn PyPSA thoroughly enough to modify its core functionalities, as its default design primarily focuses on electricity grids and simpler energy systems. My initial plan involved a dual effort: first, gaining a deep understanding of the site's operations and steelmaking processes, and second, building progressively more complex models in PyPSA until I could confidently model the real site.

Obtaining operational data from the site presented its own set of challenges. Tata Steel, being a large company with specialized teams for each process, required me to connect with the right individuals to access specific data. This was a time-consuming process, often delayed by organizational complexities, which added pressure to an already tight timeline.

One of the later challenges I faced was determining the right point to stop developing the model and shift focus to analyzing the results and aligning the work with my thesis goals. As I gained more experience with PyPSA and built a solid base for the site's key processes, new ideas and challenges often arose—some from my own curiosity and others from discussions with industry professionals. While the enthusiasm for continuous improvement was motivating, it required discipline to resist overextending the scope of the model and instead focus on delivering a well-rounded thesis.

Through this process, I learned to find the right balance between achieving my academic goals, meeting the company's expectations, and fulfilling project requirements. One key takeaway was the importance of leveraging meetings with highly skilled professionals. When I was well-prepared with clear questions, these meetings often provided valuable insights that saved me hours of work. Conversely, I realized the cost of attending such meetings unprepared, which taught me the importance of efficient preparation and time management.

Participating in the DEMOSES project meetings was another enriching experience. Listening to the diverse approaches of individuals from different sectors and backgrounds toward a common problem gave me a broader perspective on collaborative problem-solving. These discussions highlighted how interdisciplinary efforts can lead to innovative solutions.

Lastly, I had the chance to observe and experience the differing viewpoints of the scientific community and the industry. Even when addressing similar problems, universities and industries often approach solutions differently. Academia emphasizes thoroughness, exploration, and long-term insights, while industry prioritizes efficiency, cost-effectiveness, and speed. Even within the R&D department of a large company like Tata Steel, there is a noticeable focus on producing results that are practical and implementable. Despite these differences, I found that exchanging practices and perspectives between the two worlds can lead to mutual benefits.

In conclusion, this project not only allowed me to enhance my technical skills and subject knowledge but also helped me grow as a professional by teaching me the importance of balance, preparation, and collaboration. These lessons will be invaluable as I move forward in my career, navigating complex projects that involve diverse stakeholders and competing demands.

A Appendix A: Cost Inputs Data (Confidential - Only for the Committee version)

In this section, the confidential version of this report includes detailed analytical data on price inputs, such as average values and duration curves for each scenario. However, in this public version, specific data on prices and scenarios cannot be disclosed, as they are considered sensitive information.

B Appendix B : Sensitivity analysis for other parameters except cost

The following figures illustrate the minimal variations in CO_2 emissions, natural gas consumption, and total electricity consumption across the four price scenarios and the four transition configurations. These variations are negligible, and as such, are excluded from the main text for brevity. This analysis supports the conclusion that these parameters are predominantly determined by the configuration of the site rather than by external price fluctuations. The configuration-driven nature of these parameters underscores the significance of technological and operational choices in shaping the site's energy and emissions profile.

B.1 Sensitivity Analysis

Current

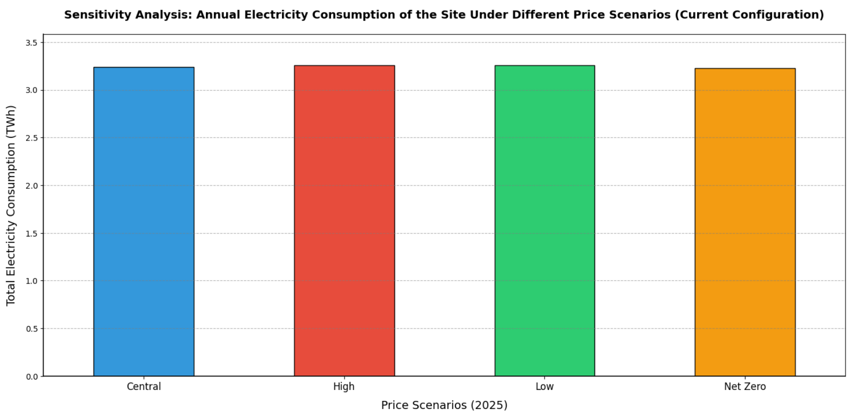

Figure 139: Sensitivity analysis of the total electricity consumption of the site under 4 different price scenarios for the current configuration.

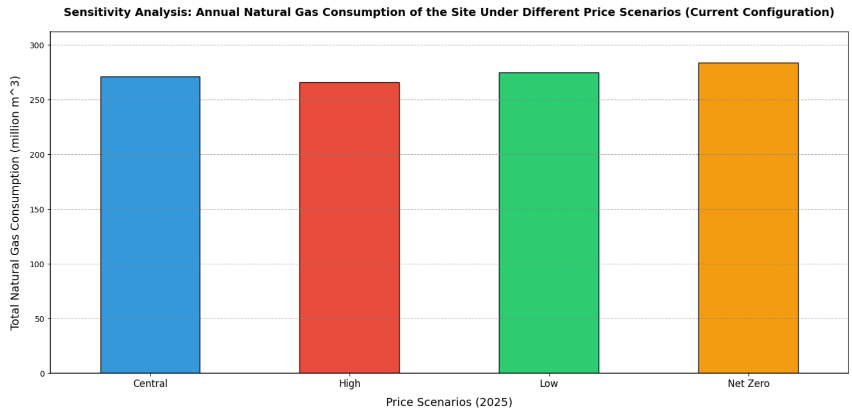

Figure 140: Sensitivity analysis of the total natural gas consumption of the site under 4 different price scenarios for the current configuration.

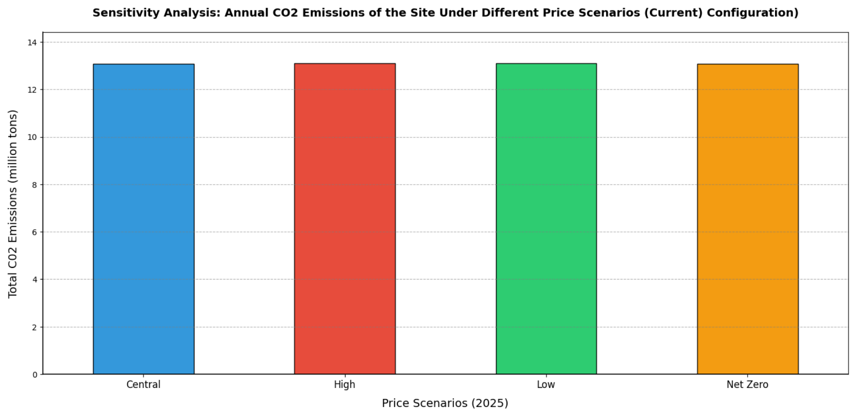

Figure 141: Sensitivity analysis of the total CO2 emissions of the site under 4 different price scenarios for the current configuration.

Phase 1

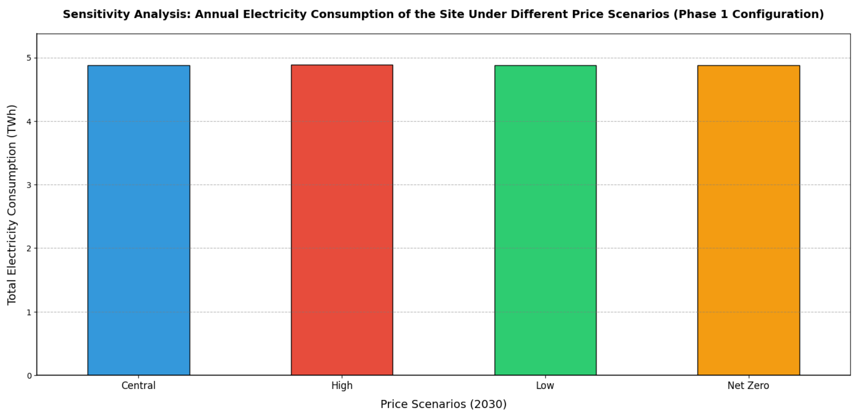

Figure 142: Sensitivity analysis of the total electricity consumption of the site under 4 different price scenarios for the Phase 1 configuration.

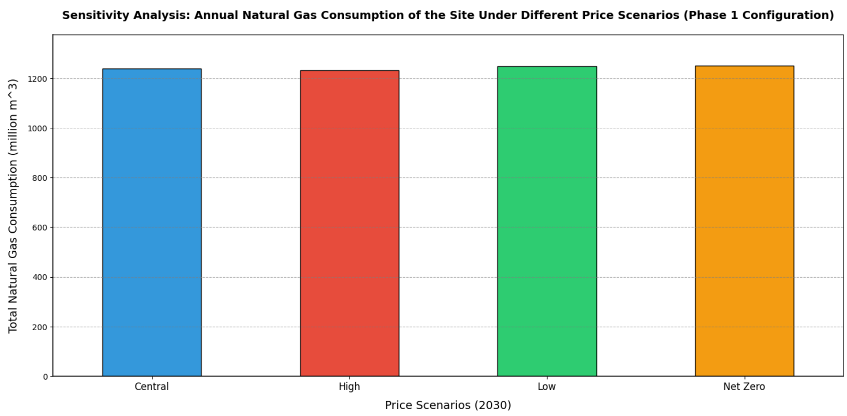

Figure 143: Sensitivity analysis of the total natural gas consumption of the site under 4 different price scenarios for the Phase 1 configuration

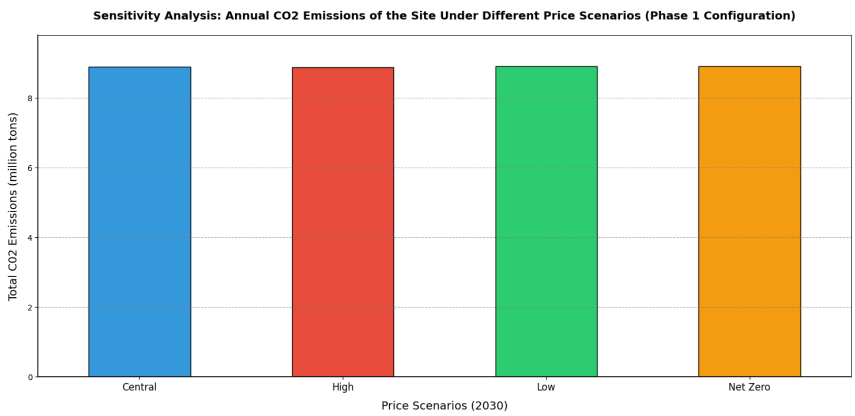

Figure 144: Sensitivity analysis of the total CO2 emissions of the site under 4 different price scenarios for the Phase 1 configuration.

Phase 2

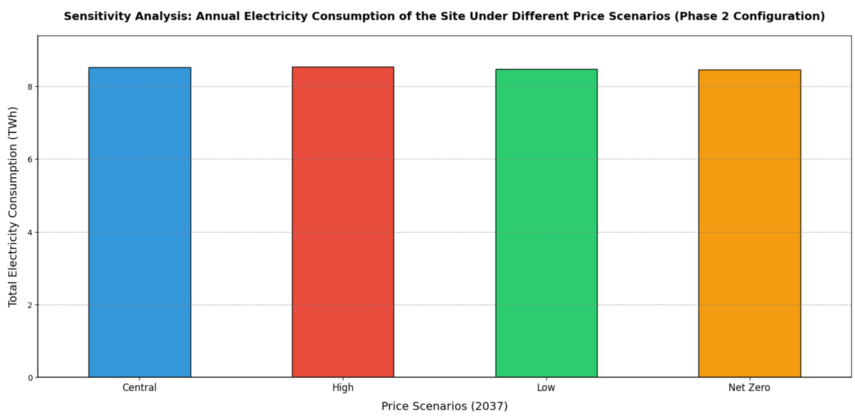

Figure 145: Sensitivity analysis of the total electricity consumption of the site under 4 different price scenarios for the Phase 2 configuration.

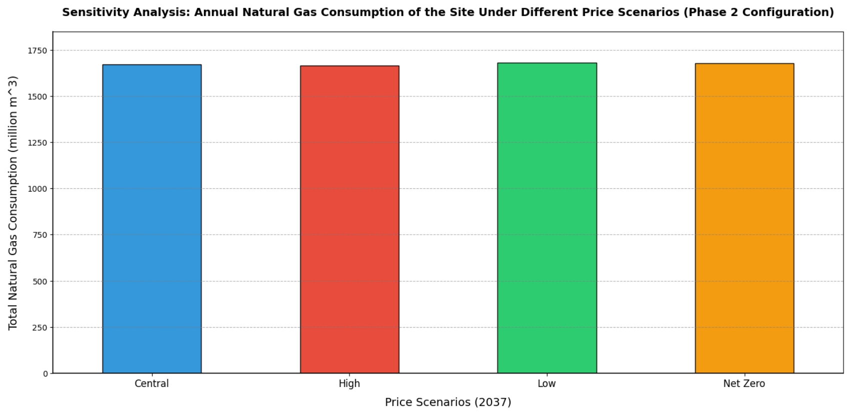

Figure 146: Sensitivity analysis of the total natural gas consumption of the site under 4 different price scenarios for the Phase 2 configuration.

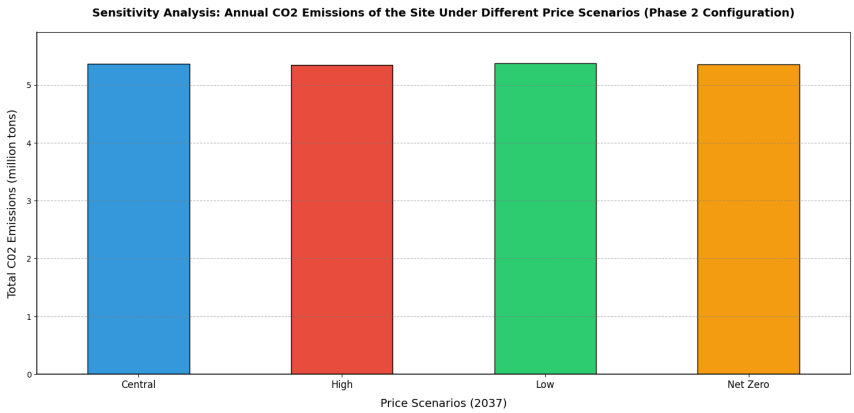

Figure 147: Sensitivity analysis of the total CO2 emissions of the site under 4 different price scenarios for the Phase 2 configuration.

Phase 3

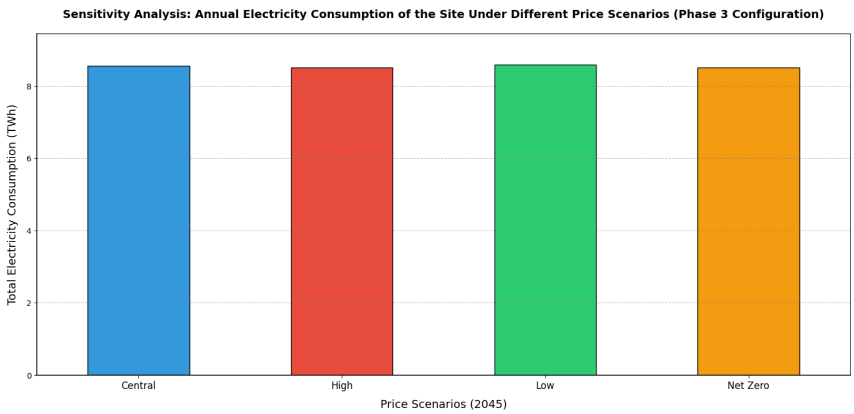

Figure 148: Sensitivity analysis of the total electricity consumption of the site under 4 different price scenarios for the Phase 3 configuration.

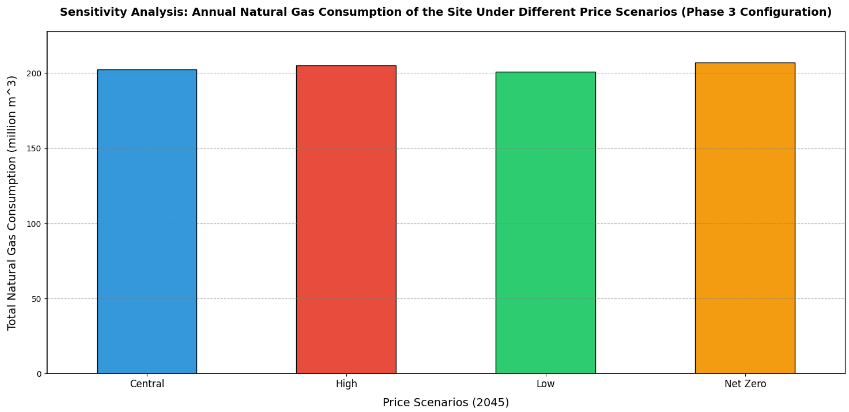

Figure 149: Sensitivity analysis of the total natural gas consumption of the site under 4 different price scenarios for the Phase 3 configuration.

Figure 150: Sensitivity analysis of the total CO2 emissions of the site under 4 different price scenarios for the Phase 3 configuration.

References

Bieda, B., Grzesik, K., Sala, D., & Gaweł, B. (2015). Life cycle inventory processes of the integrated steel plant (isp) in krakow, poland—coke production, a case study. *The International Journal of Life Cycle Assessment*, *20*, 1089–1101.

Boldrini, A., Koolen, D., Crijns-Graus, W., & van den Broek, M. (2024). The impact of decarbonising the iron and steel industry on european power and hydrogen systems. *Applied Energy*, *361*, 122902.

Boldrini, A., Koolen, D., Crijns-Graus, W., Worrell, E., & van den Broek, M. (2024). Flexibility options in a decarbonising iron and steel industry. *Renewable and Sustainable Energy Reviews*, *189*, 113988.

Burchart-Korol, D. (2013). Life cycle assessment of steel production in poland: a case study. *Journal of Cleaner Production*, *54*, 235–243.

Dutta, G., Sinha, G. P., Roy, P., & Mitter, N. (1994). A linear programming model for distribution of electrical energy in a steel plant. *International Transactions in Operational Research*, *1*(1), 17–29.

E-Bridge. (2024). *Electricity cost assessment for large industry in the netherlands, belgium, germany and france: Final report.* Retrieved from https://www.rijksoverheid.nl/documenten/rapporten/2024/04/03/e-bridge-report-electricity-cost-assessment-for-large-industry-in-the-netherlands-belgium-germany-and-france-full-report (Accessed: 2025-01-14)

Hasanbeigi, A., Morrow, W., Sathaye, J., Masanet, E., & Xu, T. (2013). A bottom-up model to estimate the energy efficiency improvement and co2 emission reduction potentials in the chinese iron and steel industry. *Energy*, *50*, 315–325.

He, H., Guan, H., Zhu, X., & Lee, H. (2017). Assessment on the energy flow and carbon emissions of integrated steelmaking plants. *Energy Reports*, *3*, 29–36.

Highs. (2024). Retrieved 2024-11-09, from https://highs.dev/

Hilpert, S., Kaldemeyer, C., Krien, U., Günther, S., Wingenbach, C., & Plessmann, G. (2018). The open energy modelling framework (oemof)-a new approach to facilitate open science in energy system modelling. *Energy strategy reviews*, *22*, 16–25.

Hörsch, J., Hofmann, F., Schlachtberger, D., & Brown, T. (2018). Pypsa-eur: An open optimisation model of the european transmission system. *Energy strategy reviews*, *22*, 207–215.

IEA. (2023). *https://www.iea.org/countries/the-netherlands.* https://www.iea.org/countries/the-netherlands. (22/01/2024)

Kim, J., Sovacool, B. K., Bazilian, M., Griffiths, S., Lee, J., Yang, M., & Lee, J. (2022). Decarbonizing the iron and steel industry: A systematic review of sociotechnical systems, technological innovations, and policy options. *Energy Research & Social Science*, *89*, 102565.

Larsson, M., Wang, C., & Dahl, J. (2006). Development of a method for analysing energy, environmental and economic efficiency for an integrated steel plant. *Applied Thermal Engineering*, *26*(13), 1353–1361.

Linny-R. (2022). *Linny-r.* https://sysmod.tbm.tudelft.nl/linny-r.html. (2024-11-09)

linopy. (2024). https://linopy.readthedocs.io/en/latest/. (2024-11-09)

Liu, C., Xie, Z., Sun, F., & Chen, L. (2017). Exergy analysis and optimization of coking process. *Energy*, *139*, 694–705.

Parzen, M., Abdel-Khalek, H., Fedotova, E., Mahmood, M., Frysztacki, M. M., Hampp, J., ... others (2023). Pypsa-earth. a new global open energy system optimization model demonstrated in africa. *Applied Energy*, *341*, 121096.

Pypsa. (2024). Retrieved 2024-11-09, from https://pypsa.readthedocs.io/en/latest/index.html

Ren, L., Zhou, S., & Ou, X. (2023). The carbon reduction potential of hydrogen in the low carbon transition of the iron and steel industry: The case of china. *Renewable and Sustainable Energy Reviews*, *171*, 113026.

Tatasteelijmuiden. (2024). Retrieved 2024-18-09, from `https://www.tatasteelnederland.com/en/About-us/tata-steel-ijmuiden`

Toktarova, A., Karlsson, I., Rootzén, J., Göransson, L., Odenberger, M., & Johnsson, F. (2020). Pathways for low-carbon transition of the steel industry—a swedish case study. *Energies*, *13*(15), 3840.

Venkataramana, R., Gupta, S., Kapur, P., & Ramachandran, N. (1998). Mathematical modelling and simulation of the iron ore sintering process. *Tata Search*, *5*, 25–30.

Wang, R., Jiang, L., Wang, Y., & Roskilly, A. P. (2020). Energy saving technologies and mass-thermal network optimization for decarbonized iron and steel industry: A review. *Journal of Cleaner Production*, *274*, 122997.

worldsteel.org. (2024). Retrieved 2024-18-09, from `https://worldsteel.org/data/top-producers/`

Zhang, Q., Wei, Z., Ma, J., Qiu, Z., & Du, T. (2019). Optimization of energy use with co2 emission reducing in an integrated iron and steel plant. *Applied Thermal Engineering*, *157*, 113635.