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DSM_OPT

Demand Side Management: Operation Optimization Of Industrial Energy Systems

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1 Introduction

DSM_OPT addresses the operation optimization of industrial energy systems by deploying demand side management (DSM) measures, including energy efficiency (EE) and market demand response (DR). The former leads to natural gas and CO_2 emission savings, and the latter provides load flexibility for the enhanced integration of fluctuating renewable energy sources (RES) and a reduction in energy costs. The project covers both technology development and implementation in two existing industrial energy systems: the industrial-scale bakery "Albin Sorger 'zum Weinrebenbäcker' GmbH and "Stahl- und Walzwerk Marienhütte GmbH".

Within the program, the project contributes to the goals of *technology development*, *market development,* and *acceptance* of energy efficiency and DSM solutions. As part of the model region NEFI – New Energy for Industry, the project addresses the goals of *decarbonization of industrial energy systems*, *value creation by technology 'Made in Austria',* and *securing production sites and jobs by user involvement*.

Within the scope of the research project, two peer-reviewed scientific articles [1,2] and two contributions to conference proceedings [3,4] have been published, and one peer-reviewed scientific article is still under review [5]. Another manuscript for a peer-reviewed scientific article and a doctoral thesis are in progress. Since these publications cover the applied technologies, methodical approaches, and main results in a very concise and comprehensive manner, parts of their content are cited directly in this report.

1.1 Context

The transition to a climate-neutral energy system is one of the most pressing challenges of the 21st century. Industry, as one of the largest energy consumers, plays a crucial role in this transformation. Globally, industrial sectors account for approximately one-third of total energy consumption, a proportion that is expected to persist in the foreseeable future [6]. In Austria, industrial energy demand represents a similarly significant share [7]. As energy systems become increasingly dependent on volatile renewable energy sources (RES), the need for industrial flexibility is growing to ensure energy security and grid stability.

DSM is a critical mechanism to balance the fluctuations of renewable generation, and enables industries to shift their energy demand in response to electricity market signals or grid constraints, thereby contributing to a more efficient and resilient energy system. However, integrating DSM strategies into industrial production processes remains challenging due to operational constraints, limited market incentives, and the complexities of scheduling within energy-intensive industries [5].

The International Energy Agency has highlighted insufficient flexibility as a major obstacle to renewable energy expansion, emphasizing that grid reinforcements alone cannot resolve intermittency issues. Moreover, it is projected that Europe's flexibility demand will increase by 40 % by 2030. In Austria, the national balancing energy requirement is expected to reach approximately 4 TWh by the same year [8,9]. Moreover, electrification trends are expected to drive Austria's electricity demand up by 50 TWh by 2040, increasing the need for industrial demand side flexibility (DSF) [10]. Without sufficient flexibility, the integration of renewable energy could be severely hindered, leading to curtailment of renewable generation and inefficiencies in the energy system. Industrial facilities, due to their large energy demand

and existing control infrastructure, are well-positioned to contribute to DSM initiatives, provided that appropriate decision support tools and optimization strategies are available [11,12].

Digitalization plays a pivotal role in enabling DSM strategies. Advances in industrial simulation, big data analytics, and real-time sensor monitoring provide new opportunities to optimize production processes. The integration of digital decision support (DSS) tools into industrial operations can improve energy efficiency by 10-20 % and productivity by up to 25 % over five years [13,14]. These improvements are driven by the ability to predict energy market fluctuations more accurately and dynamically adjust production schedules accordingly.

In recent years, energy costs have risen, and the concept of "cost" has evolved to incorporate economic, social, and environmental factors. This shift has increased interest in sustainability and energy efficiency as key competitiveness factors. Traditional peak and off-peak pricing structures are becoming obsolete due to the variable nature of renewable generation. Consequently, industries require sophisticated decision-making tools that incorporate real-time market data, process constraints, and flexibility potentials [15–17].

1.2 Flexibility and Demand Side Management

Flexibility in energy systems operates at multiple levels, encompassing supply-side adjustments (e.g., flexible power plants), demand side modifications (e.g., load shifting), grid management (e.g., market structures and network expansion), and storage solutions (e.g., batteries and pumped hydro) [18]. Traditionally, flexibility has been achieved mainly through adaptable power generation, with hydro and thermal plants playing a central role [19]. However, with the increasing penetration of RES, supply-side flexibility is decreasing, leading to a growing "flexibility gap" [20].

In the context of energy consumption, flexibility refers to the ability of consumers to adjust their energy demand in response to market or system signals through internal measures [21]. The literature lacks a universally accepted categorization of flexibility. In the course of the DSM_OPT project, we adopted the classification framework proposed by Sethi and Sethi (1990) [22], which distinguishes between three hierarchical levels, each with subcategories, to evaluate flexibility potentials (see Chapters 2.2 and 3.2). To enhance applicability, the original terminology has been adapted, categorizing flexibility into component level, system level, and overall system level:

1. Component Level (Machines/Equipment)
    - Machine flexibility: Refers to the ability of a machine or piece of equipment to perform various operations without requiring extensive effort to switch between tasks.
    - Material flow flexibility: Describes the range of possible material or product pathways within the production process, reflecting the system's ability to efficiently shift, integrate, and process different products or raw materials.
    - Operational flexibility: Refers to the capability of producing a product through different manufacturing approaches, such as altering the sequence of operations or substituting specific process steps.
2. System Level (Production Systems)

- Process flexibility: Denotes the ability to manufacture different products without requiring significant reconfigurations or incurring high costs.
- Product flexibility: Relates to the effort required to introduce new products or replace existing ones within the production system.
- Routing flexibility: Describes a system’s capability to produce products using alternative manufacturing routes.
- Volume flexibility: Refers to the ability of a system to operate economically at different utilization levels.
- Expansion flexibility: Indicates the potential to increase the capacity and performance of a system.

3. Overall System Level (Production Site)
   - Program flexibility: Assesses whether a production site can operate unattended for a certain period.
   - Production flexibility: Describes the entire product portfolio that can be manufactured at a given site without requiring additional modifications.
   - Market flexibility: Captures the ability of a production site to respond to changing market conditions.

DSF is emerging as a crucial solution, providing a cost-effective means to counterbalance these fluctuations through DSM strategies, which encompass both energy efficiency (EE) and demand response (DR) measures [23,24], see Figure 1.

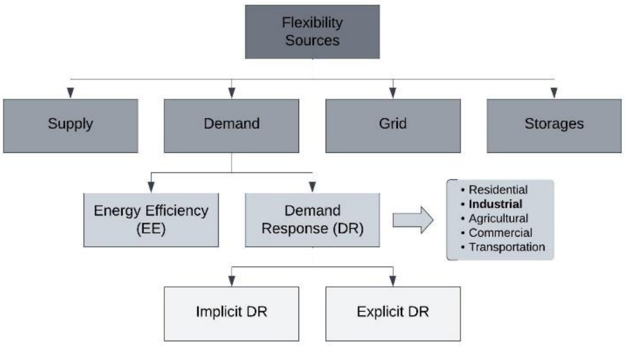


Figure 1: Demand response strategies for realizing flexibility [5]

DR programs fall into two categories: implicit (price-based) and explicit (incentive-based). Implicit DR encourages consumers to adjust their energy consumption based on fluctuating electricity prices, while explicit DR offers financial incentives for reducing or shifting loads in predefined timeframes, often orchestrated through flexibility markets [24]. Implementing DR in industrial settings presents challenges, as aligning energy-intensive processes with dynamic price signals requires advanced scheduling tools and robust IT systems. Direct load control, commonly used in smaller-scale applications, is less viable for large industries, where process constraints limit flexibility [25,26].

Recognizing the benefits of industrial DR, organizations such as the European Union and the International Energy Agency advocate for its expansion as a means of enhancing energy security and decarbonization [27–30]. Industries with energy-intensive operations, e.g., aluminum electrolysis or cement production, can be well-positioned to leverage flexibility to reduce costs and optimize resource use [27,30]. Studies have demonstrated cost savings ranging from 10 % to 34.2 % and power consumption reductions of 16.9 % to 20.7 % across different sectors [31].

Assessments of flexibility potentials typically distinguish between theoretical, technical, economic, and achievable potentials [32]. A study evaluating DR opportunities across Europe identified possible hourly load reductions of 93 GW and load increases of 247 GW in energy-intensive industries [26]. Economic modeling, such as simulations using the REMix energy system tool, has demonstrated the ability of DR to reduce overall energy supply costs by minimizing the need for peak power generation, resulting in substantial financial savings [33].

Despite its potential, DSM adoption in the industry remains limited due to technological, regulatory, and economic barriers. Many facilities lack the IT infrastructure required for real-time energy management, while regulatory uncertainties and concerns about production disruptions deter companies from implementing DSM measures [34]. Given the complexity of industrial processes, successful DSM deployment necessitates integrated decision-support tools that align energy optimization with production constraints, ensuring uninterrupted operations while enhancing efficiency [23,35]. Digitalization offers a promising avenue for integrating DSM into industrial operations, allowing businesses to dynamically adjust energy usage in response to market conditions.

1.3 Energy-intensive Industries

According to the International Energy Agency, the energy-intensive industrial subsectors account for more than two-thirds of industrial energy demand and emissions worldwide. Energy-intensive subsectors include iron and steel, aluminum, cement, chemicals, and petrochemicals, as well as pulp and paper [7]. The classification of the food industry remains debated in the literature, as it is unclear whether it falls under energy-intensive or -extensive industries. Nevertheless, both the iron and steel industry and the food industry are significant sectors in Austria and can contribute to making Austria's industry more sustainable and competitive.

The iron and steel sector is a significant driver of industrial energy consumption and carbon emissions, accounting for approximately 7 % of global CO_2 emissions in 2021 [36]. In 2018, global crude steel production reached 1.8 billion tonnes, with the predominant production pathway being the blast furnace-basic oxygen furnace (BF-BOF) process, which accounted for 71 % of output. In contrast, the electric arc furnace (EAF) method, which relies primarily on recycled steel scrap, is a more sustainable alternative. The EAF process emits significantly less CO_2—around 0.46 tonnes per tonne of crude steel—compared to the 2.20 tonnes emitted by the BF-BOF route [37]. The disparity is largely attributed to the feedstock differences, as BF-BOF relies on iron ore, whereas EAF utilizes scrap steel. Given its lower carbon footprint, EAF technology plays a crucial role in the decarbonization and electrification of steel production. The share of EAF-based steel production is expected to increase as the industry transitions towards more sustainable processes [36]. However, the EAF production route presents operational challenges, including significant power fluctuations and high peak demands due to its batch-wise operation [37]. The growing integration of renewable energy sources such as wind and solar, which are inherently variable, necessitates a thorough understanding of EAF energy consumption patterns across different forecasting horizons to optimize their utilization in industrial settings.

Within the Austrian industrial sector, food production accounts for 8 % of energy consumption [38] and more than 3 % of the emissions of climate-damaging greenhouse gases [39]. Bread, along with instant coffee, milk powder, French fries, and crisps, are among the most energy-intensive food products, which is due to the thermal processes involved in their manufacturing, which consume large proportions of the total processing energy [40]. The high energy intensity of baking processes is related to the low values of convective heat transfer coefficients through air (approx. 30 W/m_2K) [41]. However, both the energy consumption as well as the greenhouse effect of small bakeries are estimated to be twice as high compared to large bread factories [42]. Hence, the need for energy efficiency measures targeting not only large but also small bakeries, especially focusing on the baking process, is apparent. Therkelsen et al. (2014) [43] suggest to minimize oven operating time and reduce standing losses by implementing optimized baking scheduling. Likewise, it is stated that the scheduling of baking processes is a good practice opportunity that involves low implementation cost and is applicable at 90 % of the production sites [44]. They expect the CO_2-saving potential to be significant but clarify that further research is required for quantification. There have been efforts to tackle the scheduling problem in bakeries in the past by research groups from different fields, most of which focus on economic objectives and production time. Previous studies on optimal scheduling in baked goods production predominantly emphasize economic optimization. The work in DSM_OPT shifts the focus to energy efficiency and high acceptance levels among small-scale bakeries with low automation. Unlike broader studies that address entire production lines, this work concentrates on the most energy-intensive processes, optimizing them in greater detail.

1.4 Energy System and Forecast Modelling

Forecast modeling has become an essential tool for optimizing future outcomes, equipping decision-makers with the necessary insights to take informed actions [45]. Over the past decades, a variety of forecasting methods have been developed across scientific disciplines. However, the literature does not provide a universally accepted classification for forecasting approaches. Therefore, we propose a structured categorization of energy forecast modeling (see Figure 2) in this project.

One key distinction in forecast models is based on the availability of input information. From this perspective, we differentiate between perfect knowledge and non-perfect knowledge models. Perfect knowledge models assume full awareness of future input parameters, system states, or production plans within the forecasting horizon. This category includes deterministic models and scenario-based forecasts, where all relevant variables are predefined. Non-perfect knowledge models, on the other hand, operate under uncertainty, as future input parameters are unknown or stochastic. These models rely on historical data distributions or past observations, making them inherently subject to uncertainties.

Forecasting methodologies can be broadly categorized into physics- and mathematics-based models, statistical approaches, and machine learning techniques. Physics- and mathematics-based models are grounded in fundamental principles, such as thermodynamic laws and chemical or physical equations. Statistical approaches utilize probability distributions and regression techniques to identify patterns in historical data. Machine learning methods employ algorithms that learn from data to improve prediction accuracy, often outperforming traditional models in complex or highly variable systems. While different forecasting methods are suitable for different types of variables and time-series characteristics, no standardized guidelines exist for selecting the optimal method in a given context [46]. The quality and reliability of a forecast still depend significantly on the expertise of the model developer [47].

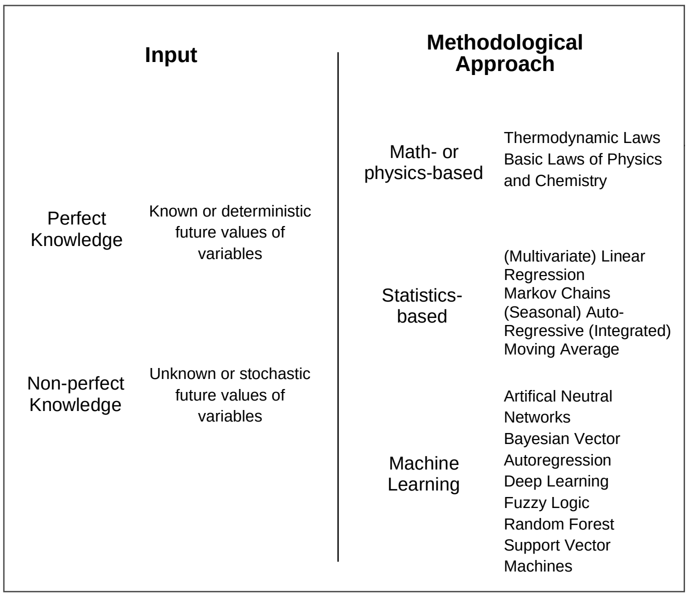


Figure 2: Forecast model classification scheme [1]

Another critical aspect of forecasting is the forecast horizon, which defines how far into the future predictions extend. Common classifications, such as “short-term,” “mid-term,” and “long-term,” lack precise definitions and vary across disciplines. In fields like photovoltaics, more specific terms—such as day-ahead, intra-day, or intra-hour forecasting—offer greater clarity and are particularly relevant for electricity consumption and market-driven forecasting [45] (see Figure 3).

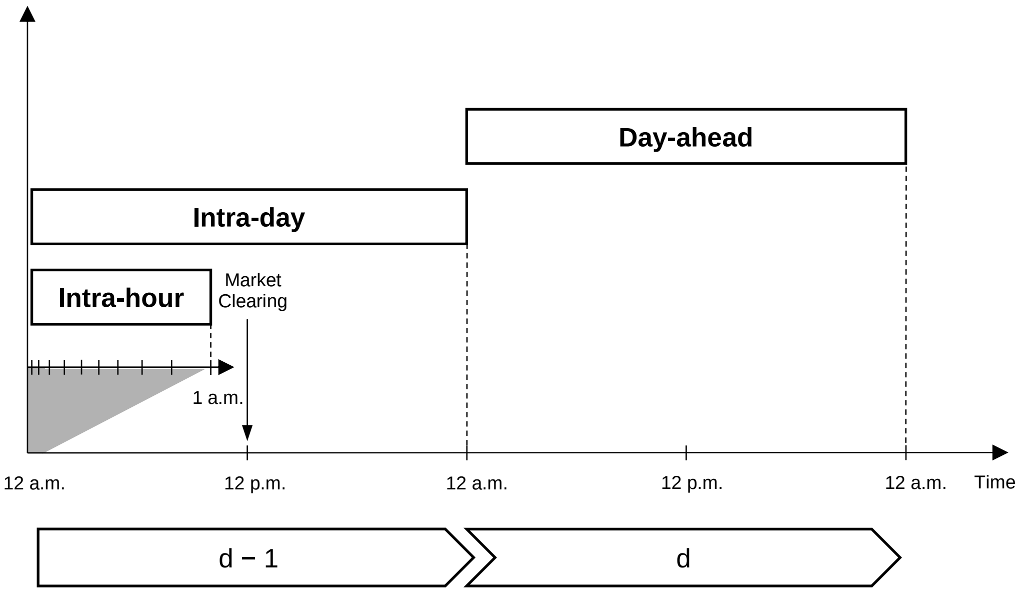


Figure 3: Impact area of different forecast horizons [1]

Closely related to the forecasting horizon is temporal resolution, which determines how frequently forecasted data points are generated within a given time frame. This resolution can range from milliseconds to several years, depending on the forecasting objective and application.

1.5 Operation Optimization

1.5.1 Mathematical Modeling of Optimization Problems

Integer Linear Programming (ILP) is a mathematical optimization technique where all decision variables are constrained to take integer values. It is widely used in combinatorial optimization problems, including scheduling, resource allocation, and network design [48]. ILP models consist of linear objective functions and constraints, making them computationally challenging, as solving ILP problems belong to the NP-hard complexity class [49]. Despite this, advances in branch-and-bound and branch-and-cut algorithms have improved their solvability.

Multi-objective optimization (MOP) is a fundamental approach for solving real-world problems that involve the simultaneous optimization of multiple, often conflicting, objective functions [50]. Unlike single-objective optimization, which yields a single optimal solution, multi-objective optimization does not produce a unique solution unless the exact preference or weighting of all objectives is predefined [51]. Instead, it results in a set of compromise solutions, known as Pareto-optimal solutions, where no solution is strictly better than another across all objectives [50]. These solutions illustrate the trade-offs between conflicting criteria, allowing decision-makers to select an outcome based on their specific priorities [51]. The nature of non-commensurable objectives in MOPs makes it essential to apply optimization techniques that effectively balance competing goals [41].

1.5.2 Optimization Problems in an Industrial Context

Unit Commitment (UC) refers classically to the optimization problem in power system operations that determines the schedule of generating units to meet electricity demand at the lowest cost while satisfying operational constraints [52,53]. These constraints include minimum up/down times, ramping limits, spinning reserves, and startup/shutdown costs [54]. The problem is typically formulated as a MILP model, where binary variables indicate whether a unit is on or off, and continuous variables determine power output levels [55]. UC plays a critical role in power market operations, balancing economic efficiency and grid reliability by ensuring an optimal dispatch of available generation resources [56]. Recent advances in renewable energy integration have made UC increasingly complex due to uncertainty and variability in wind and solar power, requiring sophisticated stochastic and robust optimization techniques [57].

Traditional Economic Cost Dispatch (ECD) determines the optimal power allocation across generation units at the lowest possible cost while satisfying system constraints [51,53,58]. However, power generation also produces atmospheric emissions, prompting the need for an environmental orientated dispatch, which minimizes pollutant release instead of cost [51]. Combined, Economic and Environmental Dispatch (EED) is a key challenge, especially in power system optimization, balancing cost efficiency and environmental responsibility. Since economic and environmental objectives are inherently conflicting, MOP techniques such as the weighting method, ε-constraint method, and goal programming are applied to find an optimal trade-off [51,58]. A major limitation of conventional EED approaches is their nonlinearity, making it difficult to find a global optimum using traditional methods [50]. Research has traditionally addressed DSM and dispatch problems separately, but recent studies explore them as complementary optimization stages, integrating supply flexibility and DSF. [59] While various emission reduction strategies include installing pollutant-cleaning technologies or upgrading equipment, these often require significant capital investment and long-term modifications [60]. In contrast, EED provides an effective alternative that is easy to implement and does not require additional infrastructure [61]. While EED has been extensively studied in the context of power system optimization, its application at the industrial process level remains largely unexplored. However, industrial facilities with high energy demand and operational flexibility offer significant potential for cost and emission optimization using EED principles. In an EAF, the energy mix between electricity and natural gas directly influences both operational costs and CO_2 emissions, making it a candidate for an integrated economic-environmental optimization approach. Similar to power system dispatch, industrial processes could dynamically adjust energy input based on price volatility and emission factors, taking into account process constraints contributing to both cost savings and decarbonization goals. Expanding EED methodologies beyond the power sector to industrial applications could enhance DSF, supporting a more sustainable energy system.

Optimal scheduling (OS) is a fundamental challenge across various industries and plays a crucial role in the future development and optimization of industrial energy systems and DSM [62]. This is particularly relevant for process industries, where increasing competition and tight profit margins necessitate efficient planning. Despite its importance, scheduling in many industrial facilities remains manual and heavily dependent on operator expertise and years of practical experience. However, achieving an optimal schedule is inherently complex, as each industry has distinct operational constraints and requirements [63,64]. From a computational perspective, scheduling problems are classified as NP-hard [62,65], meaning that finding an optimal solution is computationally demanding and, in many cases, impractical for large-scale systems [49]. In industrial applications, this complexity often makes exact solution methods infeasible, especially as the number of tasks, machines, and constraints increases. Exact approaches typically rely on implicit enumeration techniques, such as branch-and-bound, dynamic programming, or (M)ILP. While these methods work well for smaller problems, larger and more intricate scheduling tasks often require heuristic or metaheuristic approaches, artificial intelligence-based techniques (e.g., neural networks), or approximate MILP solutions, such as Lagrangian relaxation [62].

1.6 Project Scope and Structure of Work

The DSM_OPT project is dedicated to advancing DSM solutions for industrial applications. The project focuses on two key research areas: (1) the development of innovative technologies for DSM DSS and (2) the implementation and validation of these solutions in real-world industrial settings. The primary outcome of DSM_OPT is the development of a DSM DSS toolbox designed to support industrial process optimization. This toolbox consists of modular components, each targeting specific energy management strategies:

- EE: Identifying process optimizations that minimize energy consumption.
- TOU: Adjusting energy-intensive operations based on electricity tariff structures.
- Market DR: Leveraging flexibility in industrial processes to participate in electricity markets.

Two case studies serve as test environments for validating the DSM DSS toolbox, each representing distinct industrial sectors with unique energy consumption profiles and flexibility potentials. One case study focuses on Marienhütte (MH), an electric steel and rolling mill. The insights gained from this study will contribute to improving energy-efficient scrap recycling and advancing climate-neutral steelmaking processes. Another case study examines the bakery Sorger (BS), an industrial-scale bakery. The investigated approaches are expected to lower operational costs while maintaining a high level of production efficiency, demonstrating the potential benefits of DSM strategies in the food processing sector. To achieve its goals, DSM_OPT follows a structured work plan, presented in Figure 4. By implementing DSM methodologies in real-world industrial settings, DSM_OPT demonstrates tangible benefits:

- Cost savings: Optimized energy procurement reduces operation costs.
- Carbon emissions reduction: Enhanced energy efficiency and grid-integrated flexibility support Austria’s 2040 climate neutrality targets.
- Renewable energy integration: Improved scheduling allows industrial operations to align with fluctuating renewable generation.

The findings from DSM_OPT will serve as a foundation for scaling DSM strategies across multiple industrial sectors. As Austria progresses towards a flexible and decarbonized energy system, the project's outcomes will contribute to the national and European energy transition.

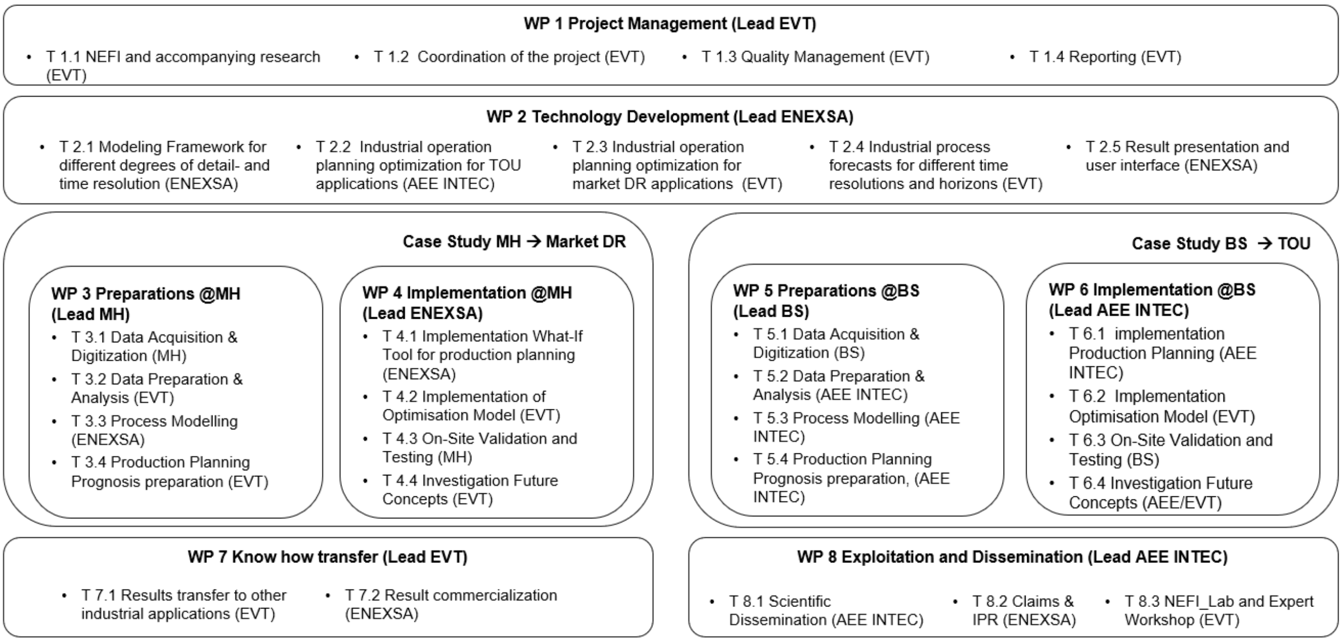


Figure 4: WP structure of DSM_OPT (from project proposal)

To comprehensively address the findings of DSM_OPT, this report is structured as follows. Chapter 2 presents a detailed use case of an industrial-scale bakery, covering process descriptions, flexibility analysis, optimization approaches, and implementation aspects. Similarly, Chapter 3 focuses on EAF steel production, detailing DSM DSS software infrastructure, process models, and optimization strategies. Building on these case studies, Chapter 4 explores the transferability of findings to other energy-intensive industries, including iron and steel, non-metallic minerals, chemicals, and pulp & paper, assessing cross-industry DSM potential. Chapter 5 outlines the feature development and implementation plan, addressing key technological and operational aspects. Finally, Chapter 6 provides a conclusion and an outlook on future research directions.

2 Use case: Industrial-scale Bakery

2.1 Process Description

In an industrial bakery, numerous factors influence the production process, and production pathways vary depending on the product. For instance, a traditional bread roll undergoes a proofing phase after dough preparation, during which it is stored in a proofing cabinet before being baked or frozen for later baking. Other products, such as cakes, do not require proofing and are baked immediately, whereas certain items, like doughnuts, are fried instead. In addition to product-specific variations, external factors such as seasonal fluctuations (e.g., ambient temperature) and short-term influences (e.g., public holidays) must be considered, as they impact production volume, product range, and the consumption of energy and other resources. Consequently, production planning is inherently complex and is primarily based on the long-standing experience of bakers rather than the systematic use of digitalization and automation. Figure 5 shows the process flow diagram of the investigated industrial-scale bakery. Daily production is scheduled based on a predefined baking list, which is generated for the following day's production. As a result, oven operation times and the utilization of other dough-processing machinery vary daily. After receiving the production plan for the day, dough preparation and mixing of the various recipes start in an order determined by product-specific quality constraints and the experience of the bakers. Depending on the product, different production lines (automated, semi-automated, manual) are employed to form the dough before either continuing proofing in the interim storage or being baked or cooled. Multiple kinds of ovens, directly and indirectly, gas-fired as well as wood-fired, are available to meet the requirements of different products. The baking process itself is influenced by product type, the final state of the product (pre-baked, frozen semi or fully baked), oven pre-heating requirements, and baking duration. Additionally, interim freezer storage can also handle production peaks. Finally, packaging and delivery take place on schedule.

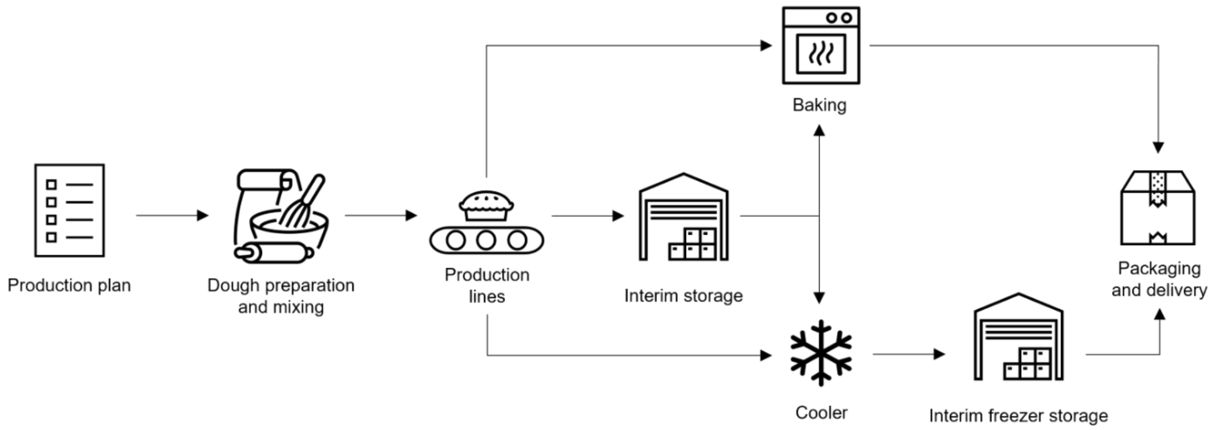


Figure 5: Production process in industrial-scale bakery

Key constraints in production planning include the required delivery time and the daily operational schedule of ovens and dough preparation equipment. The relative energy consumption of various equipment is illustrated in Figure 6. The majority of energy consumption (82 %) is attributed to different oven types. This finding aligns with the literature, as Lampropoulos et al. (2013) [66] report that baking consumes the most energy in baked goods production, and Behrangrad (2015)) [67] indicates that the baking process can account for 26–78 % of the product-specific energy consumption. A detailed examination of the baking process, looking at the mean energy consumption divided into energy spent in the oven operating modes (stand-by, heating-up, baking), shows that 42 % of total operating time is spent in standby mode, consuming 17 % of the total energy, which reveals potential for energy efficiency improvements. Cooling processes account for approximately 11 % of total energy use, while the remaining 7 % are associated with dough preparation machinery and other equipment.

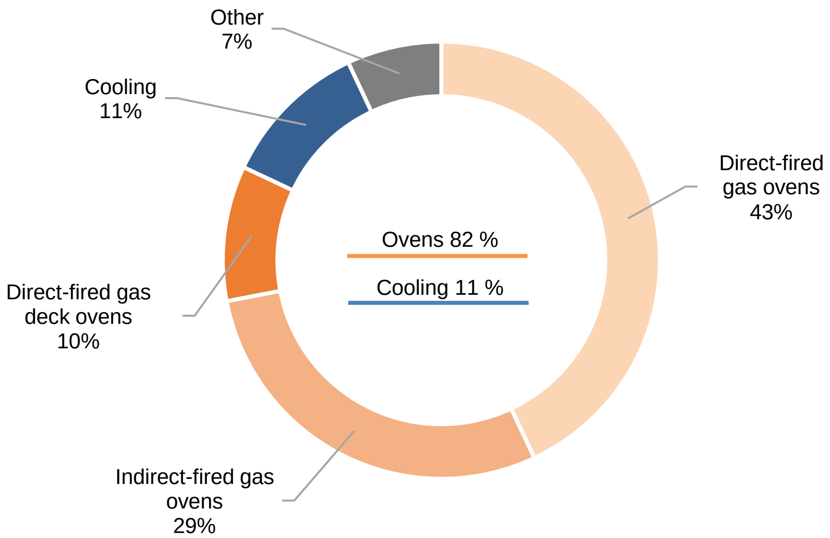


Figure 6: Energy demand distribution of industrial-scale bakery [4]

2.2 Flexibility Analysis

In general, to be able to implement DSM measures, flexibility potential must be available. The flexibility of consumers refers fundamentally to their ability to adjust their energy consumption through internal measures in response to market or system signals. A flexibility analysis was carried out for the Sorger bakery to uncover existing potential: Firstly, the component level is analyzed. This means that individual machines, such as dough preparation machines or ovens, were scrutinized. Next, flexibility is analyzed at the system level. Here, the ability of the system to produce different products without major effort, to add new products to the range, and to optimize the production process plays a key role.

Machine flexibility in the industrial bakery presents a mixed picture. In the event of a failure in the dough preparation machinery, the only alternative is manual processing, which is not a viable solution on an industrial-scale. For ovens, machine flexibility is limited, as substituting one oven type for another often leads to compromises in product quality, given that the specific baking environment significantly influences the final product. In contrast, the existing proofing interrupters offer a high degree of flexibility, as their temperature settings can be easily adjusted. This allows for a seamless transition between their use as proofing interrupters and deep freezers.

Regarding material flow and operational flexibility, strict adherence to product recipes is essential to ensure that baked goods meet the required quality standards. This includes both the necessary processing steps and predefined dough parameters, such as consistency and temperature. Producing an optimal dough requires manual adjustment of water quantity and temperature, as these factors depend heavily on flour characteristics and ambient temperature. In this regard, the expertise of experienced bakers plays a crucial role. As a result, material flow and operational flexibility are significantly constrained (Table 1).

Table 1: Qualitative evaluation of flexibilities at the component level in the industrial-scale bakery [4]

	Machine flexibility	Material flow flexibility	Operational flexibility
Dough preparation machines	-	-	-
Ovens	~	-	-
Cooling	+	-	-

At the system level (Table 2), various flexibility potentials were identified within the industrial bakery. The product portfolio is diverse, and different baked goods can be produced with minimal changeover time. The exact assortment varies seasonally and in response to holidays. Dedicated production lines are designed to switch between products within minutes, with the sequencing influenced by factors such as allergens and organic vs. non-organic classification. The integration of new products is generally feasible without significant modifications. Consequently, product and process flexibility are present. A certain degree of routing flexibility was identified for ovens, as multiple ovens of the same type are available and are not fully utilized at all times. Another source of routing flexibility lies in the option to include or exclude cooling in the production process. For most products (except bread), different levels of completion are possible at the time of delivery—pre-baked/frozen, pre-proofed, raw/frozen, or fully baked. This enables storage to decouple the dough preparation from the baking process. Volume flexibility is necessary but only feasible within certain limits, as the product range fluctuates seasonally, particularly for special baked goods during holidays (e.g., Easter, All Saints' Day). The limiting factor is workforce availability, necessitating special shifts and temporary hiring during peak periods. As a result, expansion flexibility at both sites is considered minimal.

In the production process, few processes are automated, with many steps performed manually. However, program flexibility remains absent due to the need for direct supervision. In terms of production flexibility, a broader product range is produced, and during peak seasons, standard products may be temporarily removed from the lineup to accommodate the production of seasonal specialties. This adaptability indicates that production flexibility is present. The bakery can theoretically adjust production daily in response to sales data from bakery branches, offering the potential for market flexibility. However, adjustments are typically evaluated every week, particularly when determining whether to discontinue a seasonal product.

Table 2: Qualitative evaluation of flexibilities at the system and overall system level in the industrial-scale bakery [4]

		Industrial-scale bakery
System level	Process flexibility	+
	Product flexibility	+
	Routing flexibility	+
	Volume flexibility	~
	Expansion flexibility	-
Overall system level	Program flexibility	-
	Production flexibility	+
	Market flexibility	+

2.3 Process Models

As elaborated in the previous chapter, the baking process was targeted for optimization, and hence, the process parts were modeled. The objective was to develop models that describe the energy consumption of the oven under different operational states, including stand-by, heating-up, cooling-down, and baking. The oven's stand-by mode, heating-up phase, and cooling-down phase were modeled using measured data, capturing the relationship between runtime, temperature, and energy consumption. For the baking process itself, measured data was utilized to construct a look-up table containing product-specific energy demands, temperature profiles, and baking durations. These models allowed for an accurate representation of the energy required to carry out a specified baking schedule, providing insights into potential energy savings through optimized scheduling and operational adjustments. By integrating these part models, a comprehensive energy consumption model was developed, which serves as a foundation for implementing an optimization-based energy-efficient DSM strategy in the bakery. The resulting model facilitates data-driven decision-making by allowing bakery operators to assess the impact of scheduling changes based on an optimized production sequence (see Chapter 2.4).

2.4 Optimization

A two-stage optimization methodology for achieving optimal scheduling of baking processes was developed in the programming language Python. Following recommendations from two prior studies [43,44] on baking scheduling, the optimization focuses on both energy efficiency and a balanced load profile. Prioritizing energy consumption and peak load over traditional cost-based functions emphasizes sustainability.

- <u>Stage 1</u>: Distribution of baking orders to the ovens and determination of the optimum baking sequence for each oven. Optimization stage 1 is discussed in Chater 2.4.1.

- <u>Stage 2</u>: Determination of the optimum operating time for each oven, taking energy supply from renewable energy sources into account. This step was realized as an outlook to pave the way for a potential electrification of the baking process in the future. Optimization stage 2 is discussed in Chapter 2.4.2.

2.4.1 OS of the Baking Ovens

In stage 1 the optimizer aims to achieve an efficient load profile by distributing baking jobs optimally across ovens and sequencing jobs to minimize energy used in heating and stand-by between jobs. The production list containing all products to be baked in the respective shift serves as the input data for the scheduling problem. Deadlines for all products on the list may be given as an optional constraint. From this data, an optimal production plan containing the allocation of products to the available ovens and the times when baking jobs are to be started is generated. The problem is formulated as a partitioning problem and, hence, an ILP problem, which is solved with linear optimization techniques provided by PuLP [68]. The variables of the optimization problem x_{ij} are associated with the permutation p_i and the oven o_j respectively and can either be equivalent to 0 or 1. If x_{ij} takes the value 1, then the associated permutation p_i of baking jobs is selected to be realized in oven o_j. This means that no other permutation can be realized in this oven, consequently all other x_{ij} associated to oven o_j take the value 0. The objective function E_{tot} for minimizing total energy consumption is defined as:

$$E_{tot}(x_{ij}) = \sum_{j=1}^{N} \sum_{i=1}^{n} x_{ij}\, E(o_j, p_i)$$

$E(o_{j,}p_i)$ represents the total energy consumed by oven o_j for baking job sequence p_i. N is the total number of ovens, and n is the total number of possible baking job sequences. The integer-valued coefficients x_{ij} are chosen to minimize E_{tot}. To set the maximum number of ovens available N, the following constraint is imposed:

$$\sum_{j=1}^{N} \sum_{i=1}^{n} x_{ij} \leq N$$

Additionally, a constraint ensures that each product P_k appears exactly once in a job sequence:

$$\forall\, k \text{ } if \text{ } P_k \in p_i: \sum_{j=1}^{N} \sum_{i=1}^{n} x_{ij} = 1$$

Here p_i denotes a baking job sequence containing a product P_k.

To calculate the total energy, one year of measurements of the six parallel gas-fired wagon ovens was analyzed using the pattern search functionality of the software Visplore [69]. This data was utilized to fit oven heat-up rates, stand-by energy demand as well as the period for cooling down. Additionally, the start- and end temperatures, as well as the duration and energy demand of the different baking processes following the same baking program throughout the year, were extracted, and through statistical evaluation, a look-up table was created. The lookup table contains the average product-specific quantities for each baking program and is used as the database for the scheduling problem.

Due to computation time limitations needed for real-world application, the generation of possible permutations of baking sequences was precomputed based on the following constraints:

1. Cascadic baking temperatures: The start temperature T_{k+1}^{s} of a recipe P_k in any eligible permutation p_i of the baking sequence has to be higher or equal to the end temperature T_k^{e} of the preceding recipe P_{k+1}.
$$\forall\, P_k \in p_i : T_k^{e} \ \leq T_{k+1}^{s}$$
2. Product-specific deadlines: Deadlines t_k^{d} can be chosen for every product P_k individually. Only permutations p_i of the baking sequence adhering to all deadlines concerning their respective baking duration $t(p_i)$ are eligible for optimization.
$$\forall\, P_k : t(p_i) \leq t_k^{d}$$

To save computation time, the precomputing of baking sequences, permutation calculation, is carried out in a structured way, performing eligibility checks on all possible base permutations containing only two recipes and consequently building on the set of eligible permutations by adding one recipe after the other performing all checks and only keeping viable permutations in the set of permutations eligible for optimization.

The compute time performance of an optimal scheduling tool significantly affects its applicability, especially when using linear programming. The computation time scales poorly due to the exponential growth of possible job permutations as the number of baking jobs increases when utilizing the standard procedure of optimizing the full problem, considering every permutation of the sequence containing all baking jobs. The problem is aggravated when considering parallel production since all permutations of all possible partitions of the set of baking jobs have to be considered. To address this problem, the set of baking jobs to be considered is split up into subsets or chunks. These subsets are chosen so that all baking jobs share a similar baking temperature to reduce the need for heating up between baking. Each chunk was then optimized independently and hence reduced the total computational complexity, yielding shorter runtimes. This chunking approach improves the scalability of the solution by reducing the number of permutations considered.

The computation times for a chunked and an un-chunked (single) scenario of a set of short single baking jobs without imposing product-specific deadlines were investigated to test under maximum computational complexity. The results, see Figure 7, highlight the significant performance gains achieved by the chunking method compared to the single scenario approach. For this study, the maximum number of baking jobs per chunk was set to 9, which leads to a clear drop in the computation time for 19 baking jobs since, at this point, the number of necessary chunks is increased to 3 due to the limit of baking jobs per chunks. The size of the single chunks being smaller results in a faster computation time overall. This pattern continues for higher numbers of baking jobs. In the bakery, optimal scheduling techniques must account for varying production volumes between shifts. For example, the average number of baking jobs during the day shift is 20, consisting of five distinct recipes, while the night shift averages 39 jobs with 16 distinct recipes. The results depicted in Figure 7 indicate that computation times for the day shift fall within acceptable limits without chunking due to multiple identical baking jobs being treated as one long baking job. However, for the night shift, the complexity of scheduling makes optimization infeasible without chunking, highlighting the necessity of this technique for operational application in high-demand scenarios. Overall, the computation time predictions generated within the scope of this study aligned well with the observed data and may serve as a good indicator in case the production volume changes in the future.

During application on site, additional factors impact computation time. The specific combination of baking jobs to be processed can lead to a higher or lower number of permutations to be processed due to their respective baking temperatures impacting the number of eligible permutations of the baking sequence due to the temperature staging constraint. To speed up the optimization, repeated baking jobs are treated as a single job with a longer duration and higher energy demand during optimization. The effect of the grouping is twofold: On the one hand, a lower number of baking jobs reduces the complexity of the scheduling problem by limiting the number of eligible permutations of the baking sequence the algorithm needs to consider. On the other hand, the maximum baking time per oven is exceeded with lower numbers of distinguishable baking jobs if the duration of those baking jobs is longer, which again results in a lower number of eligible permutations of the baking sequence. A similar effect takes place due to deadlines defined for specific products, also reducing computational complexity. The effect varying baking temperatures have on computation time is minor compared to the effect of grouping baking jobs of the same type and product-specific deadlines, resulting in an overall slightly lower computation time in practice compared to the computation times evaluated for the theoretical study.

Overall, this investigation underscores the importance of tailoring optimization models to specific operational conditions, such as workload variations between shifts, and demonstrates how techniques like splitting the optimization problem into separate chunks can address computational challenges in real-time DSM deployment.

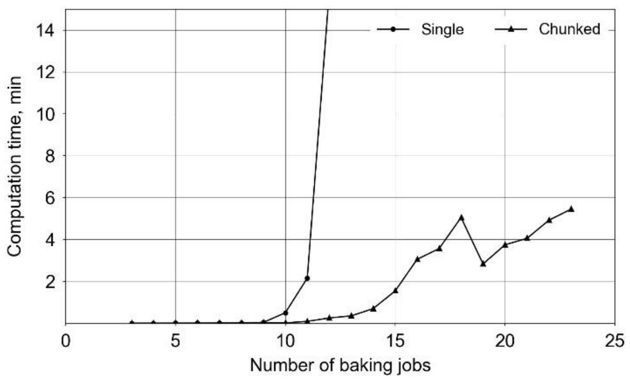


Figure 7: Comparison of computation time for single and chunked baking jobs

The optimization model was applied to evaluate its performance using measured data from the years 2023 and 2024. A set of 21 standard production days (no weekends or holidays) was chosen, covering all seasons to account for seasonal differences in production volume and product portfolio. For each day, both the day shift and night shift were analyzed, and the energy consumption, energy cost, CO_2 emissions, and timespan of the original production schedule were compared against the optimized production schedule. The results show clear improvements in terms of energy consumption, total oven runtime, and the associated quantities (Table 3). The day shift typically has a lower production volume, on average 20 baking jobs consisting of 5 distinct recipes. The night shift, on the other hand, has a mean production volume of 39 baking jobs consisting of 16 distinct recipes. The difference in production volume results in a corresponding difference in energy consumption, production timespan, and the associated performance indicators. It also entails a higher computation time for optimizing the night shift of an average of 190 seconds as compared to the mean computation time for optimizing the day shift of one second on average. For both shifts, significant savings could be achieved, see

Table 4.

Table 3: Evaluation of optimization performance for standard production (day and night shift)

		Day shift				Night shift			
		Measured		Optimized		Measured		Optimized	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Energy consumption	kWh	582.1	216.5	331.7	217.5	1 109.9	266.4	774.1	238.4
Production timespan	Min	944.4	423.6	429.5	290.2	1 807.0	475.6	1 030.9	341.4
Energy costs	EUR	33.4	12.5	18.6	12.1	63.7	15.4	43.5	13.5
Emissions	kg CO_2 equ.	143.9	53.5	82.1	53.8	27.4	65.8	191.6	59.0

Table 4: Savings achieved by optimal scheduling for day and night shift

Savings in % for	day shift	night shift
Energy consumption	43	30
Production timespan	55	43
Energy costs	44	32
Emissions	43	30

In Figure 8, the comparison of optimized versus not optimized production is depicted for one exemplary night shift. The original schedule uses all available ovens, and approximately 25 % of the overall energy consumption is dedicated to stand-by energy, whereas the optimized schedule leads to a higher oven utilization, and only two ovens are necessary, which also cuts out the stand-by energy as such. Additionally, arranging the baking jobs according to their temperature level offers a reduction of heating energy of approximately 10 %. The results have to be seen as the theoretical potential, which can be reached if the optimized schedule is implemented by the bakery staff.

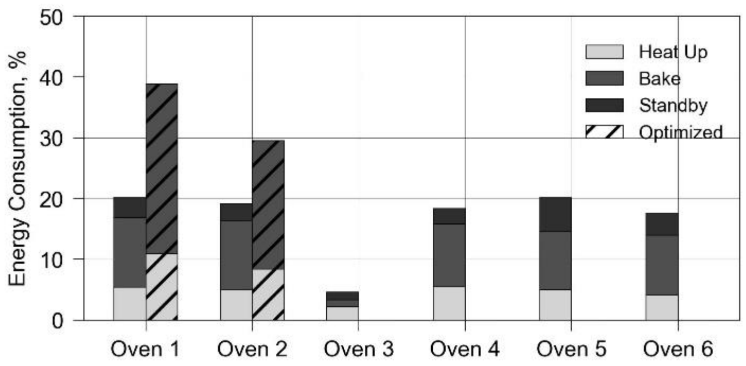


Figure 8: Original vs. optimized energy consumption for use case 1 (baking ovens)

The results show a potential to reduce energy consumption by 30 % on the night shift and by 43 % on the day shift, as well as reduce the total runtime of the ovens by 43 % on the night shift and by 55 % on the day shift, without impacting product quality.

2.4.2 Load Shifting for Optimal PV Integration

The second stage of optimization aims to find the optimal times for each oven to start to execute the baking job sequences assigned to them in stage 1 considering a background load profile. This background load profile may consist of contributions like energy consumption originating from cooling, room heating or compressed air production. For the optimization process the total load p_{tot} is calculated by adding the background load profile p_{bg} to the sum of all N time shifted single oven load profiles p_j.

$$p_{tot}(t, t_{start}) = p_{bg}(t) + \sum_j^N p_j(t + t_{start}^j)$$

Note, that here t_{start} is a vector consisting of all oven start times t_{start}^j. In order to choose t_{start} in an optimal fashion, different objective functions $\mathrm{C}(t_{start})$ were investigated. On the one hand a squared variation of the load profile was considered to penalize large fluctuations in the load profile:

$$\mathrm{C}_1(t_{start}) = (p_{tot}(t_{i+1}, t_{start}) - p_{tot}(t_i, t_{start}))^2$$

where t_i and t_{i+1} are consequent time steps. On the other hand the maximum:

$$\mathrm{C}_2(t_{start}) = \max_i p_{tot}(t_i, t_{start})$$

was utilized to put a special focus on reducing the peak load. The following linear yielded the best results:

$$\mathrm{C}(t_{start}) = \alpha(p_{tot}(t_{i+1}, t_{start}) - p_{tot}(t_i, t_{start}))^2 + \beta \max_i p_{tot}(t_i, t_{start})$$

Here, α and β are weighting factors, which were chosen to be $\alpha = \frac{1}{2}\beta$ for the optimization of the results shown in Figure 9. The optimization itself was implemented using the SciPy [70] implementation of the Nelder-Mead. This method provides the possibility to optimize nonlinear functions without requiring derivatives. While it shows linear convergence properties only, this method can be considered robust - a highly desirable property for practical applications. For this application, an iterative process called the optimizer using randomized initial conditions and a randomized initial simplex was implemented. Finally, the best optimization result is returned.

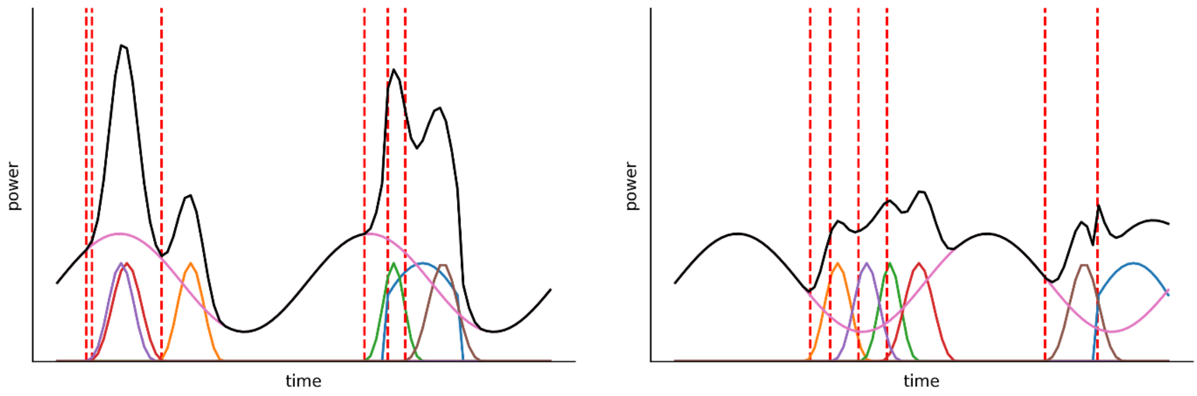


Figure 9: Starting times (dashed red lines) of six surrogate single oven load profiles (colored) considering a surrogate background load profile (brown) and the total load (black) before (left) and after (right) optimization

In Figure 9, on the left, the initial state for optimization with randomly chosen t_{start} is shown. The total load exhibits significant peaks due to the disadvantageous timing of the single oven load profiles. The right plot shows the timings after optimization. In this example, the maximum load was reduced by 46 %, and the squared variation of the curve was reduced by 86 %.

In the following, the application of the stage 2 optimization tool to shift the load profile of baking ovens to periods of high photovoltaic (PV) power generation is discussed. The analysis was conducted using the simulation of different PV sizes using the Python library PVLib [71]. Oven load profiles were derived from real production plans, optimized using the optimal scheduling tool, and then assumed to be electrified. This approach provides insight into the potential of load shifting to enhance self-consumption of PV energy, reducing reliance on grid electricity and increasing sustainability in bakery operations (Figure 10).

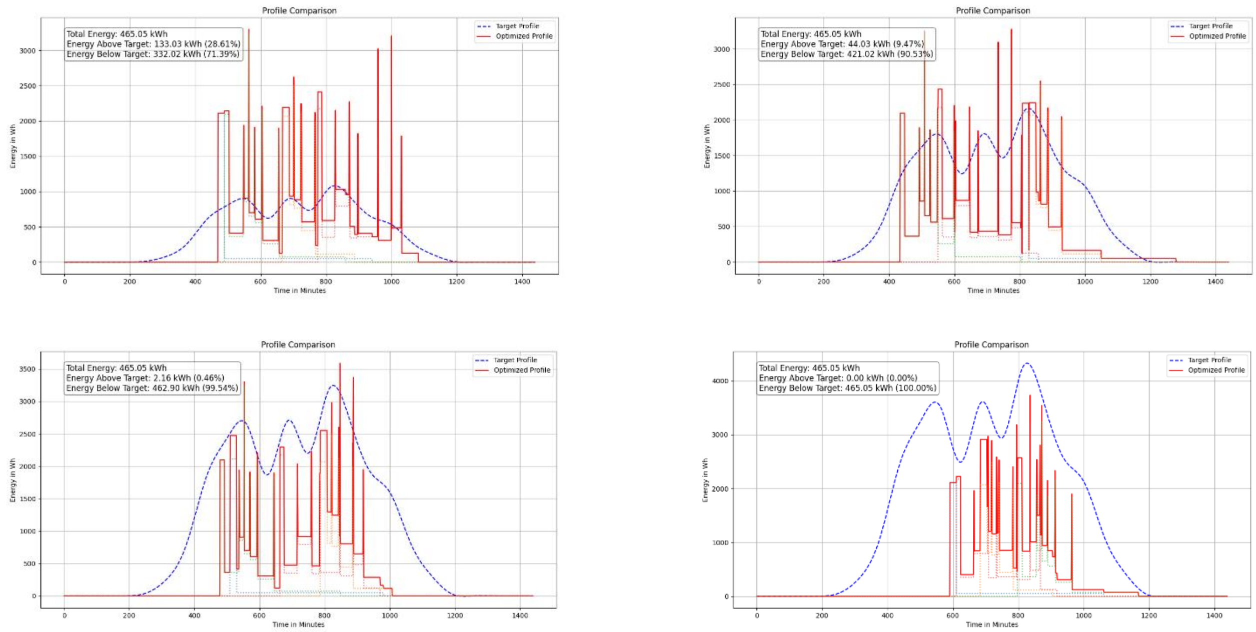


Figure 10: Load Shifting of optimal oven load profiles depending on different PV sizes

The results underscore that deploying effective DSM strategies requires addressing operational constraints, computational challenges, and user acceptance. Combining optimization with interactive tools can bridge gaps in the automation and digitalization of industrial production plants.

2.5 Implementation and Testing

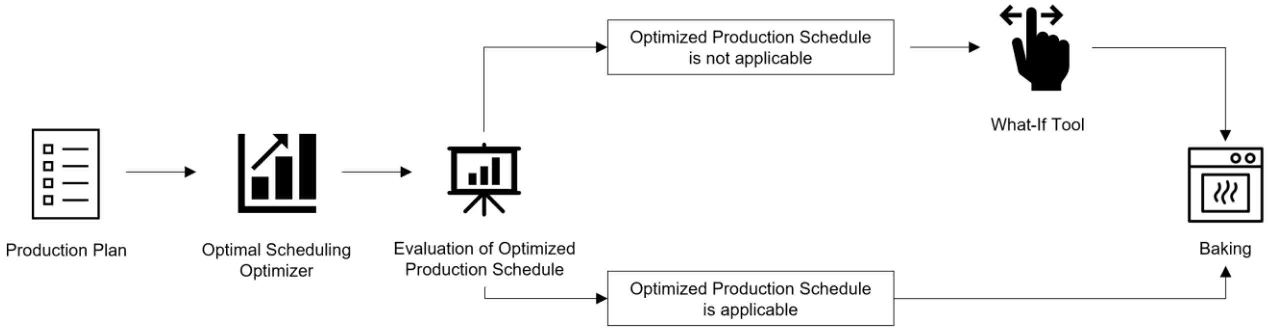


Figure 11: Workflow of baking scheduler

The baking schedule optimizer was implemented and tested in the bakery. During the first validation period, additional constraints stemming from interactions with the rest of the highly product-specific production chain, like fermentation times, became apparent, and the involvement of bakers in manually operating the ovens introduced challenges due to interference of their other duties with the execution of the optimized baking schedule. To overcome this barrier, a what-if option (What-if tool) was integrated into the optimizer tool. This feature allows bakers to adjust the optimized schedules according to their work routines while tracking the energy efficiency of each change to the original plan. The workflow of the updated baking scheduler is illustrated in Figure 11. During the second validation period, the combination of the optimal scheduler and the what-if tool was confirmed to be a viable solution for integrating advanced DSM strategies into production sites with low levels of automation. This approach demonstrated how interactive optimization could bridge the gap between theoretical energy-saving models and the practical constraints of manual operations. Additionally, the team at the bakery noted the double benefit of the optimizer-what-if combination as an educational tool for the bakery staff concerning energy efficiency.

3 Use case: EAF Steel Production

3.1 Process Description

The production site is divided into two main areas: the steel mill and the rolling mill. The facility primarily relies on two energy sources: electricity, which accounts for approximately two-thirds of consumption, and natural gas, which contributes the remaining one-third. The steel mill consists of the EAF, the ladle furnace, ladle heaters, the continuous caster, and the dedusting system as auxiliary equipment (Figure 12). The process begins with the melting of steel scrap in the EAF, which exhibits significant power peaks due to multiple melting phases. After the refining stage, the molten steel is tapped into a refractory-lined ladle and transported to the ladle furnace for secondary metallurgical treatment. The ladle furnace also serves as a buffer, compensating for timing discrepancies between the EAF and the continuous casting process. In continuous casting, the transition from liquid to solid steel occurs, and the solidified strands are cut into billets. Most equipment in the steel mill is connected to the dedusting system, with the EAF's different operational phases significantly influencing dedusting requirements. The rolling mill begins where the steel mill ends. Here, the billets are reheated in the pusher furnace to a rolling temperature before being processed in the rolling lanes to achieve the desired dimensions. The final products are either cooled on a cooling bed as bars or wound into coils. Additionally, coils can be further processed in the recoil plant, where they are rewound into larger coils ranging from 3 to 5 tons.

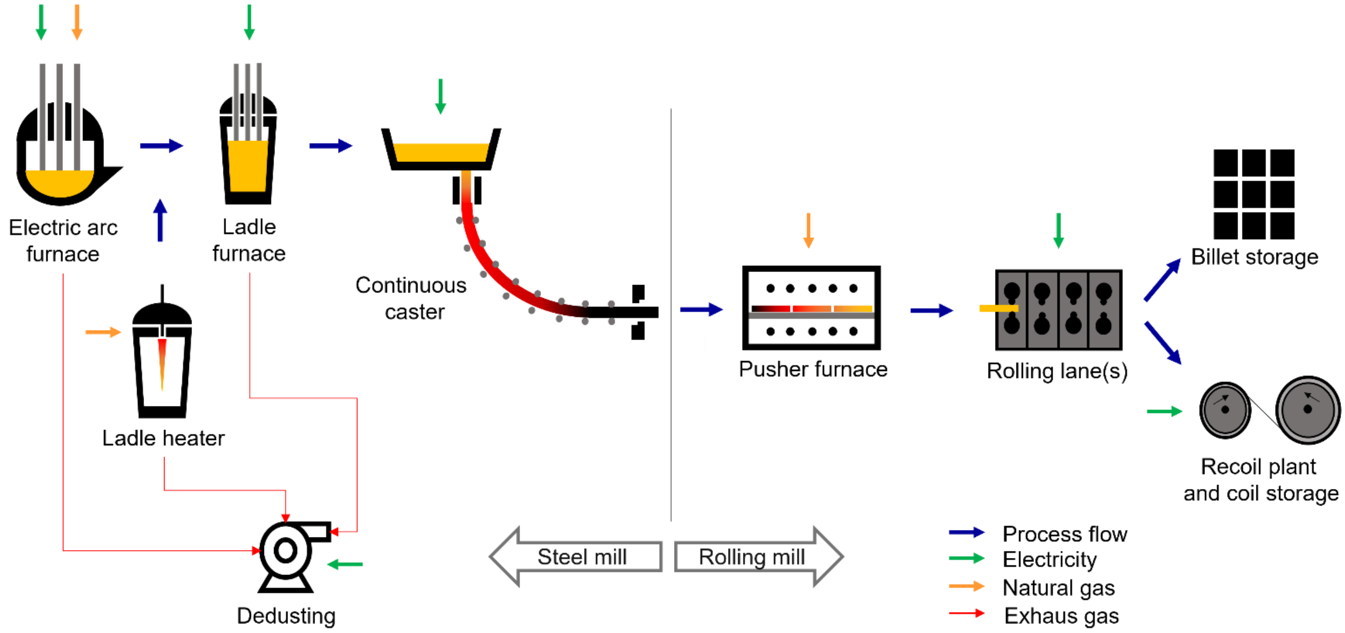


Figure 12: Process flow diagram at MH's plant

The plant components displayed in Figure 12 account for approximately 85 % of the total energy demand at the site. Other auxiliary systems, social buildings, and other non-production-related facilities are not considered in the following flexibility analysis. A relative distribution of the plant's energy consumption is illustrated in Figure 13. The EAF is by far the most energy-intensive unit, consuming 49 % of the total energy demand, followed by the pusher furnace (19 %) and the rolling mill (7 %).

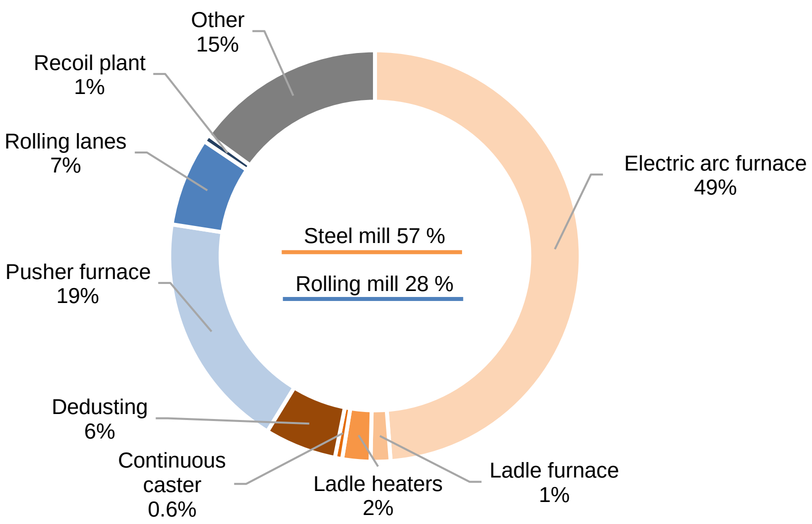


Figure 13: Energy demand distribution of electric steel mill [4]

3.2 Flexibility Analysis

As shown in Table 5, flexibility at the component level within the electric steel plant is highly constrained due to process requirements and operational constraints. Each unit fulfils a specific function—for example, the EAF is solely responsible for melting steel scrap and cannot perform secondary metallurgical treatments. Similarly, other units such as continuous casting, dedusting systems, the pusher furnace, the rolling mill, and the recoil plant cannot take on additional tasks or substitute for other equipment. As a result, machine flexibility is considered nonexistent. The evaluation of material flow system flexibility also reveals significant limitations, primarily due to the linear structure of the production process and the temporal and spatial dependencies within the steel mill. Any modification to the process has far-reaching implications for downstream operations, often leading to higher costs or reduced production efficiency. While some studies suggest that the EAF offers flexibility potential due to its relatively simple start-up and shutdown behavior [72,73], these analyses often overlook its impact on material flows. In reality, interrupting an ongoing charge prolongs the process duration and, even for short delays, can create supply issues in the subsequent continuous casting stage [74]. Additionally, heat losses due to cooling of the molten steel must be considered, potentially increasing specific energy consumption [75]. Beyond energy efficiency concerns, product quality deterioration due to altered heating and cooling conditions must also be taken into account [76]. Consequently, material flow within the steel mill is neither spatially nor temporally flexible. Although the steel mill and rolling mill are decoupled through intermediate billet storage, which theoretically allows for greater flexibility in material flows toward the pusher furnace and rolling mill, it is generally more energy-efficient to process billets directly after continuous casting. This reintroduces a direct temporal dependency between these process stages. Similarly, the recoil plant is theoretically decoupled, but its current utilization rate rarely allows for material flow adjustments. Regarding operational flexibility, no flexibility potential is present. The sequence of process steps is fixed to ensure the required steel and product quality. For example, the refining phase in the EAF can only begin once the entire batch of steel scrap has been fully melted.

Table 5: Qualitative evaluation of flexibilities at component level in the electric steel plant [4]

	Machine flexibility	Material flow flexibility	Operational flexibility
Steel mill			
Electric arc furnace	-	-	-
Ladle furnace	-	-	-
Continuous caster	-	-	-
Ladle heaters	-	-	-
Dedusting	-	-	-
Rolling mill			
Pusher furnace	-	~	-
Rolling lane(s)	-	~	-
Recoil plant	-	~	-

At the system level of the steel mill, no significant flexibility potential was identified. Process flexibility is virtually nonexistent, as the site exclusively produces reinforcing steel. Changing the steel grade would require not only adjustments to the input materials but also modifications to process control in the EAF and ladle furnace, directly impacting dedusting system regulation, ladle logistics, and casting parameters in the continuous caster. Similar constraints apply to product flexibility, as introducing new steel grades or substituting materials would require substantial process modifications. Routing flexibility is also absent, as no alternative production routes or redundant equipment exist at the site. The steel mill's equipment, particularly the EAF, cannot be operated economically at varying productivity levels. While it is technically possible to partially fill the furnace, this would result in higher specific costs and failure to meet production targets. In the rolling mill, however, process flexibility exists, as it can produce both bars and coils in various dimensions. The necessary setup times for rolling mill adjustments are already factored into cost calculations. Theoretically, modifications to production sequencing are also possible, provided that delivery deadlines are met. The introduction of new products depends on the feasibility of adapting the rolling stands and must be assessed on a case-by-case basis. Routing flexibility, however, is not present, as no alternative production routes exist. Volume flexibility may be feasible within certain limits as long as delivery commitments are met. However, operating at very low utilization levels is likely uneconomical since the pusher furnace must still heat billets to the required rolling temperature, resulting in a disproportionately high specific energy demand. Additionally, reducing rolling mill utilization would necessitate lower utilization in the steel mill, which is not economically viable due to factors such as labor costs and the discontinuous operation of continuous casting. The rolling mill and recoil plant, however, are not significantly affected by fluctuating utilization levels.

Due to the low degree of automation and reliance on operator expertise [77], unattended operation is nearly impossible, making program flexibility very low to nonexistent. In terms of production flexibility, the site can manufacture bars and coils in predefined dimensions, but producing additional product types would require additional modifications.

Beyond the flexibility categories defined by Sethi and Sethi (1990) [22], further flexibility potentials were identified. The EAF operates with both electricity and natural gas, allowing for adjustments in the energy mix within certain limits. This flexibility potential could be leveraged in day-ahead electricity markets to reduce costs or lower CO_2 emissions. Another flexibility potential lies in ladle logistics, specifically the transport and preparation of molten steel ladles within the steel mill. Typically, three to four ladles are in circulation, transferring molten steel from the EAF to the ladle furnace and then to the continuous caster. To prevent thermal shock when transferring molten steel, ladles must reach precise target temperatures at specific times. This temperature control is managed through ladle heaters. Additionally, ladles require periodic maintenance after a certain number of uses. Currently, ladle logistics and maintenance decisions are largely manual and operator-driven.

Table 6: Qualitative evaluation of flexibilities at system and overall system level in the electric steel plant [4]

		Steel mill	Rolling mill	Electric steel plant
System level	Process flexibility	-	+	
	Product flexibility	-	~	
	Routing flexibility	-	-	
	Volume flexibility	-	~	
	Expansion flexibility	n.a.	n.a.	
Overall system level	Program flexibility			-
	Production flexibility			~
	Market flexibility			n.a.

3.3 DSM DSS Software Infrastructure

The requirements for a decision support system (DSS) toolbox for demand side management in industrial companies can be summarised into four fields:

- Data transfer: data transfer between the company's data archive and the forecasting model, triggering model execution
- Model: a digital twin of the plant to calculate forecasts
- Calculation: a service to execute the model(s)
- Human-machine communication: graphical user interface for inputs and results presentation

As a central module for the modeling framework, ENEXSA developed the software package Data Processing Service (DPS). DPS is designed as a workflow automation tool. It connects to industrial data archives and automates data pre- and post-processing as well as model execution. For data transfer, interfaces to the most common industrial data sources (OSI PI, OPC, ODBC, InfluxDB) were developed. There is also the possibility to load data from text files as a general option. Those interfaces allow read and write access to the specified data sources. For a minimized user effort for the configuration of the data handling and calculation sequence, a graphical user interface was developed (Figure 14).

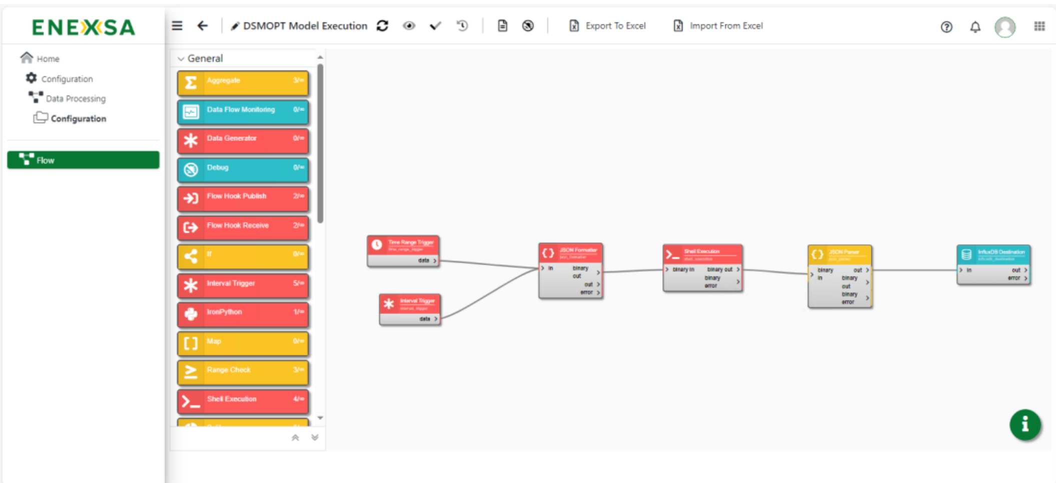


Figure 14: Exemplary workflow in the DPS

Forecasting model calculations can be carried out either using ENEXSA's in-house developed Distributed Calculation Service (DCS) or by calling software via shell execution. Both options can be automatically triggered from the DPS.

The DCS is highly parallelized and can be used as a local and a cloud service. Currently, the DCS includes workers to run EBSILON models (thermodynamic simulation), models stored as ONNX files, genetic optimization models, and Python models. An optimization framework was created for the genetic solver to build the model. The Python worker can either use pure Phyton or create pip or conda environments. Conda is a Python environment specifically designed for engineering, scientific, and data science tasks.

Shell execution does not have the parallelization capabilities and easy data exchange of the DCS. However, it provides more flexibility in running different software tools and permits a broader range of data types for input and output. Any software that can be called via the command line with additional arguments can be linked via this interface. Input and output data are exchanged using JSON files.

Which of the two model execution methods is more appropriate depends on the input and output data, the type of model, and how often the model must be executed. In general, interactive DSM forecasting models are simpler and do not require complex equations solvers or optimizers. Therefore, DCS and command line execution work fine for them. Automatic DSM forecasting models tend to have more complex models that have more dependencies on other software tools and solvers and require more customization of input and output data. Therefore, the command line interface is better suited for them.

3.4 Process Models

In this section, the aggregates and their corresponding process models of the electric steel plant are described, which serve as energy demand and consumption forecast models and build the foundation for the DSM DSS toolbox.

EAFs rank among the largest electricity consumers in industrial grids, making accurate energy demand forecasting crucial for grid stability and cost efficiency. High-resolution energy demand predictions enable industrial operators to optimize electricity procurement, avoid peak load charges, and implement DSM strategies without disrupting production. [73,78] However, forecasting EAF energy consumption is particularly challenging due to [37,79,80]:

- The stochastic nature of EAF operations, where batch processes introduce variability.
- The complexity of the steelmaking process, which involves multiple interacting parameters.
- Uncertainties in batch-specific parameters, such as material composition and process dynamics.

The EAF analyzed in this study accounts for approximately 60 % of the total energy consumption in the electric steel mill and is exclusively used for reinforcing steel production. As it is the largest consumer in the plant combined with extreme operational behavior, a special interest lies in modeling this aggregate. The furnace operates with three graphite AC electrodes, consuming 85 % of the total energy, while three additional gas burners contribute the remaining 15 %, improving temperature distribution and melting efficiency. As the first unit in the process chain, the EAF's batch-based operation dictates the timing of all downstream processes. Each operational cycle, or "heat", consists of several phases. It begins with preparation, followed by the charging and melting of three steel scrap baskets. Scrap selection for baskets 2 and 3 occurs dynamically while the melting process is already underway. Once melting is complete, the process enters the fining phase, where pulverized coal and additives are introduced to form foam slag, which absorbs impurities. In the final tapping phase, the foam slag is removed, and the molten steel is transferred into a preheated, refractory-lined ladle for transport to the next processing stage. The tap-to-tap time defines the total duration of one heat, with minimal energy consumption occurring during the preparation and tapping phases. Figure 15 presents a representative energy demand curve for two heats, while Table 7 summarizes key parameters such as scrap masses, phase durations, and energy consumption shares. The first basket contains the largest scrap mass (47.4 %) and accounts for the highest energy consumption (31.6 %), whereas the second basket typically has the smallest mass (24.1 %). A notable 20.8 % of total energy consumption occurs during the fining phase, where metallurgical properties are adjusted.

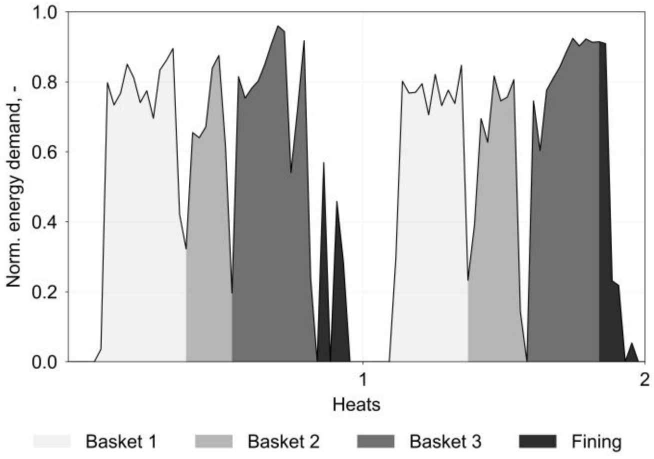


Figure 15: Representative energy demand for two heats of the investigated EAF [1]

Table 7: Average scrap mass, duration, and energy consumption of different operational EAF phases of the investigated EAF (normalized, in %) [1]

	Scrap Mass [%]	Duration [%]	Heat-Based Energy Consumption [%]
Preparation	-	5.2	0.2
Basket 1	47.4	29.0	31.6
Basket 2	24.1	16.2	19.6
Basket 3	28.5	18.2	25.7
Fining	-	25.2	20.8
Tapping	-	6.2	2.1

Two grid connection capacity monitoring approaches—a one-step and a multi-step Long Short-Term Memory (O-LSTM NN, M-LSTM-NN) neural network—are assessed for intra-hour energy demand forecasts. Both neural network models are structured with three layers, each containing up to 90 nodes. They were implemented in Python using Keras, a high-level API of the TensorFlow library. Hyperparameter optimization was performed via GridSearch, and both models share the following key characteristics: a linear activation function, Mean Squared Error (MSE) as the loss function, and the ADAM optimizer. The O-LSTM NN predicts one-minute-ahead energy demand based on 90 historical timesteps, using only real measured values as input. The model updates dynamically: after measuring the next actual value (T+1), it shifts the time window forward (T−88 to T+1) to predict the next step, effectively rolling along the real-time axis (Figure 16A). To extend the forecast horizon, the M-LSTM NN follows an iterative approach. Initially, it operates like the O-LSTM NN, but instead of using only real values, it feeds its previous predictions as inputs for each subsequent step. This method allows forecasting up to 60 minutes (Figure 16B). However, since multi-step predictions depend on prior forecasted values, errors accumulate over time, reducing accuracy as the horizon lengthens [81].

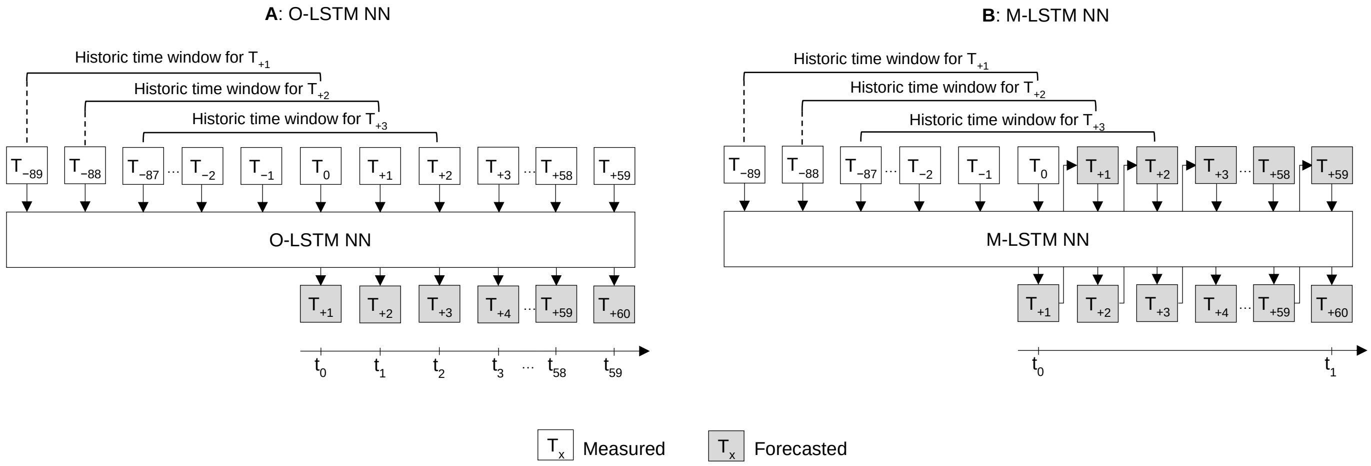


Figure 16: Model execution flow of O-LSTM NN (A) and M-LSTM NN (B)

The O-LSTM NN approach proves effective in modeling energy demand with high precision, particularly for applications requiring a maximum guard function (see Figure 17). Evaluations show that the model maintains a relative Root Mean Squared Error (rRMSE) ranging from 0.73 % to 16.29 % for 15-minute intervals, while the Mean Absolute Percentage Error (MAPE) varies between 0.18 % and 17.71 %. These results indicate that the O-LSTM NN provides reliable short-term forecasts, capturing rapid demand fluctuations with reasonable accuracy.

The M-LSTM NN approach faces challenges in accurately capturing the operational phases of the furnace (Figure 18), with an average MAPE ranging from 9.26 % to 30.59 %. If a reaction time of less than one minute is sufficient to prevent grid capacity exceedance, the O-LSTM NN is preferable due to its higher accuracy. However, if a longer forecast horizon is needed, the M-LSTM NN is the better choice despite its lower accuracy. This approach is only effective if forecasting starts at the initiation of one heat, as it cannot account for varying break lengths or provide meaningful predictions when started mid-heat. While the O-LSTM NN can represent breaks between heats, it remains limited to its one-minute forecast horizon.

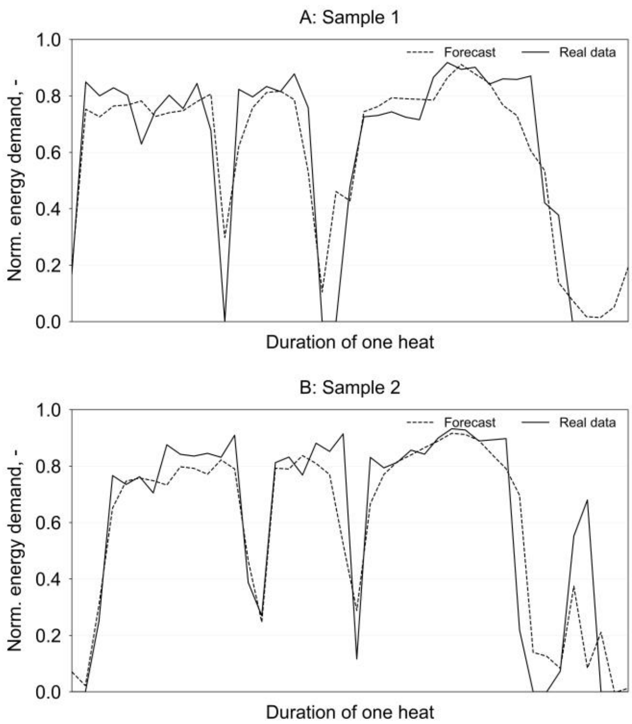


Figure 17: Energy demand forecast of Sample 1 (A) and 2 (B) with O-LSTM NN [1]

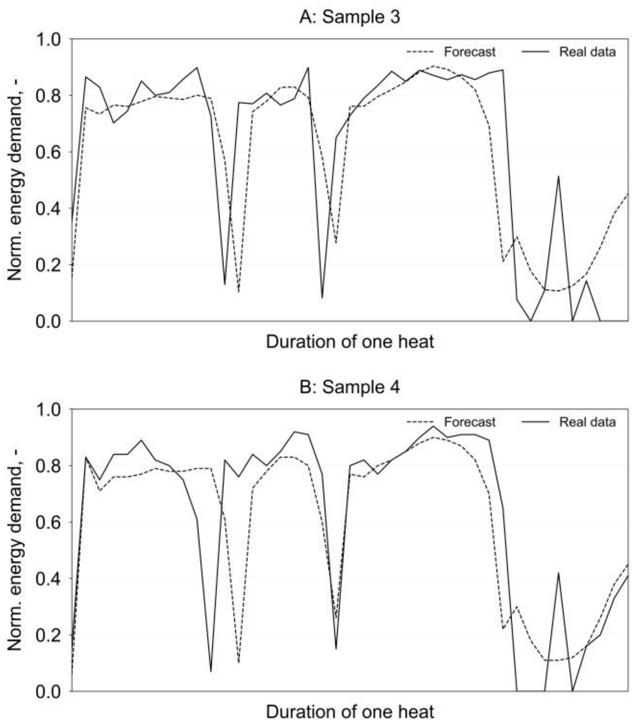


Figure 18: Energy demand forecast of Sample 3 (A) and 4 (B) with M-LSTM NN [1]

A hybrid model combining statistical and stochastic methods has been developed to forecast energy consumption for day-ahead electricity procurement within a 36-hour forecast horizon, aligning with the day-ahead market's requirements. The workflow for this model is illustrated in Figure 19. Since the energy demand per heat depends largely on the inserted scrap mass, forecasting future scrap masses is a crucial step. This is achieved using a SARIMA model, which integrates an Auto-Regressive (AR) and Moving Average (MA) approach. SARIMA models are defined by seven key parameters: (p, d, q) (P, D, Q)s, where p represents the auto-regression order, d denotes integration order, and q specifies the moving average order. The seasonal components (P, D, Q) follow the same logic, with s indicating the seasonal period [82]. Once the scrap mass forecast is obtained, total energy demand is estimated via linear regression, correlating scrap mass with energy consumption. The predicted total energy is then distributed across operational phases based on historical data (Table 7). Heat duration and start/end times are similarly derived from the scrap mass prediction. For energy-intensive operational phases—such as the three melting phases and fining—a Markov chain sequence is generated at a 1-minute resolution, modeling fluctuating energy demand typical for EAF operations. The resulting sequence is then segmented into separate demand curves for electricity and natural gas. Since natural gas consumption follows a consistent pattern, a third-order polynomial fit is applied to construct its demand curve. Finally, a resampling algorithm aggregates the generated 1-minute demand curves into hourly energy consumption values, forming the basis for electricity procurement in the day-ahead market. The model is implemented in Python (PyCharm 2023.3.4), utilizing NumPy, pandas, and statsmodels.

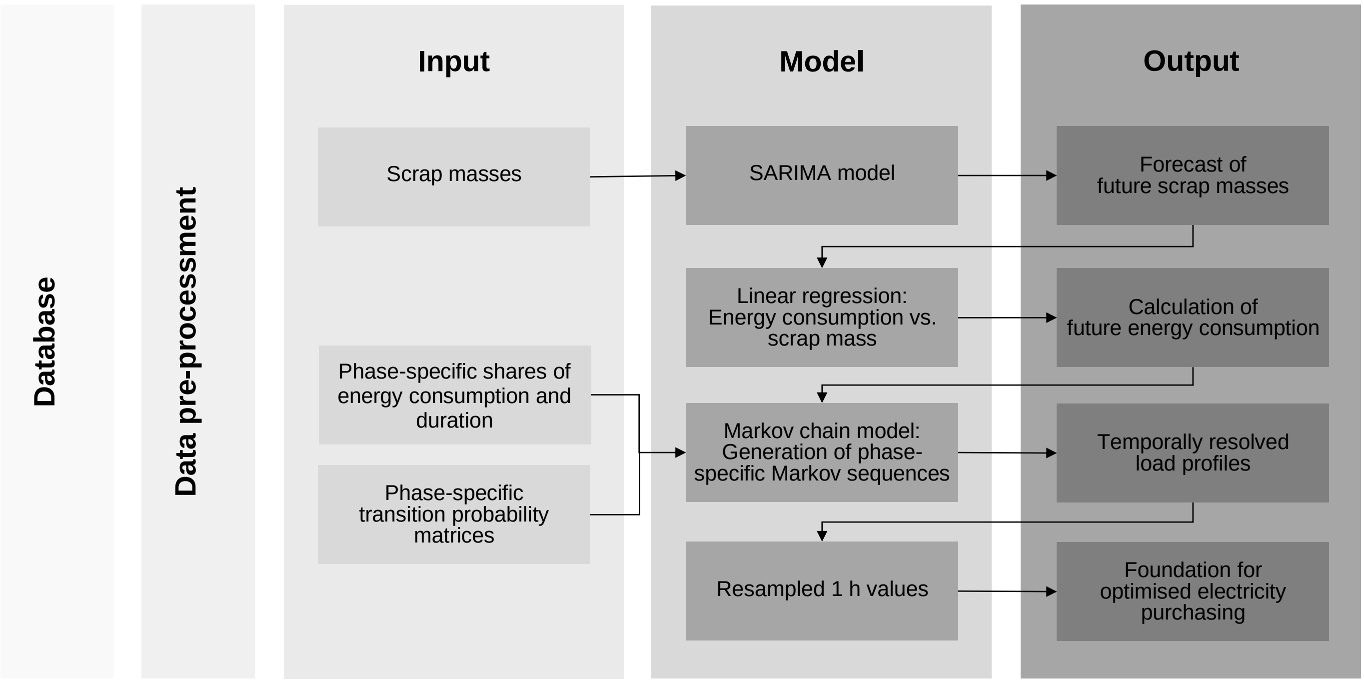


Figure 19: Workflow of statistic-stochastic model [1]

Alongside the quantitative assessment of the combined statistical-stochastic model, a monetary evaluation was conducted to gauge its practical impact on electricity procurement strategies. Comparing electricity purchases based on the standard load profile with those using the forecast model revealed notable advantages: an average cost reduction of 0.21 % across all samples and a significant decrease in energy balancing needs (2.21 % of actual consumption with the forecast model vs. 12.12 % with the standard load profile).

The ladle furnace functions similarly to the EAF but operates on a much smaller scale and exclusively uses electricity. Its primary role is to maintain the temperature of molten steel before it reaches the continuous caster, acting as a buffer in the process chain. Additionally, it facilitates secondary metallurgical treatment, refining the steel's composition. Due to its stochastic operating behavior, the ladle furnace is also modeled using a Markov chain, similar to the EAF, to capture stochastic energy consumption patterns.

The continuous caster transforms molten steel into solidified billets, ensuring a steady, continuous operation with a stable energy demand. Since interruptions can severely disrupt production, a critical constraint is that the caster must never run out of liquid steel. Its energy consumption is modeled based on historical data, reflecting its relatively constant load profile.

The steel mill operates five ladle heaters used for preheating and maintaining ladle temperatures. These include two standing ladle heaters for maintenance tasks, two lying ladle heaters, and one booster fire for additional heating capacity. As part of DSM_OPT, the plant is implementing OxyFuel ladle heaters to improve energy efficiency (the booster fire has used a natural gas-oxygen combination ever since). Data measurements with the new OxyFuel ladle heaters indicate significant natural gas savings (Table 8). The direct emission factor is 2.75 kg CO_2/Nm^3, while the indirect factor ranges from 3.13 to 3.44 kg CO_2/Nm^3. As a result, the implementation of OxyFuel technology enables an annual reduction of 54.3 t in direct CO_2 emissions and 61.8 to 67.9 t in total CO_2 emissions (including indirect effects). A data-driven approach is applied to derive representative gas demand curves, differentiating between operational heating modes (lying and booster) and maintenance tasks (standing).

Table 8: Comparison of the natural gas consumption of the original and oxyfuel ladle heaters

	Natural gas savings, %	CO_2 savings direct, t/a	CO_2 savings indirect, t/a (lower bound)	CO_2 savings indirect, t/a (upper bound)
Standing ladle heater #1	81.2	10.0	11.4	12.5
Standing ladle heater #2	66.0	16.3	18.6	20.4
Lying ladle heater #1	49.9	12.4	14.1	15.5
Lying ladle heater #2	52.2	15.6	17.7	19.5
Booster fire	0.0	0.0	0	0
Sum	-	54.3	61.8	67.9

The dedusting system operates whenever the EAF, ladle furnace, or ladle heaters are in use, regulating air extraction based on the current operating phase of the EAF. Since its energy demand is directly linked to these production units, it is modeled using historical values to reflect actual plant operation and load variations.

The pusher furnace is modeled using an XGBoost Regressor. Model inputs are the input billet temperature, the day of the week, and the time of the day. The model's time granularity is 1 minute. The gas consumption of the next minute is calculated from the time series of the last 120 minutes of the three input variables. If a longer forecast is to be created, the model must be run recursively again and again, including the predicted data in the input. Figure 20 shows the model results. The raw prediction results show a scatter. The results are smoothed using different window sizes (centered window, window size 9 or 19) to better match the measurement data.

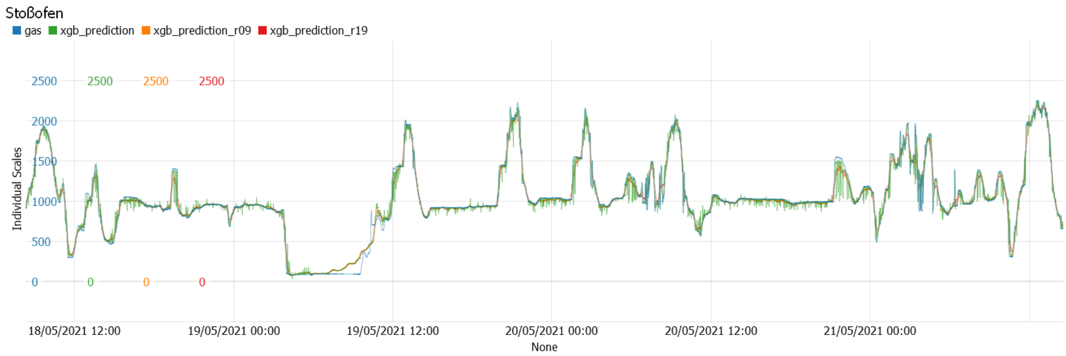


Figure 20: Pusher furnace surrogate model results

The rolling line model is a hybrid model. Rolling times are calculated using physical relationships: The time required to roll the billet is calculated from the billet volume, the dimension to be rolled, and the rolling speed. The takt is the time between the start of two consecutive billet rolling processes. It is the sum of the rolling time and the interbillet time. The interbillet time is the time between the end of rolling one billet and the start of rolling the next billet. Figure 21 shows a comparison of the measured takt and the estimated takt.

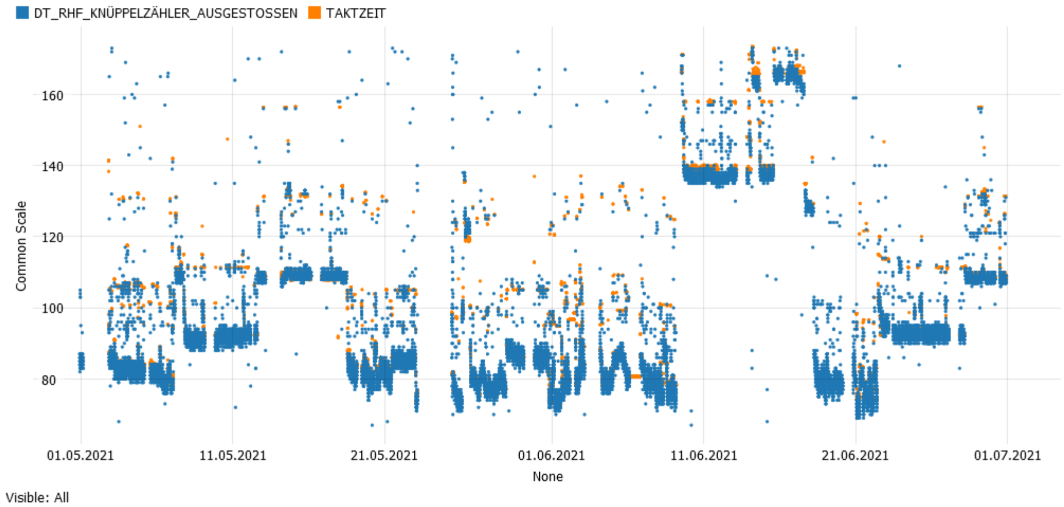


Figure 21: Measured takt (blue) vs. modelled takt (orange)

Power consumption is assumed to be constant during and between rolling operations. The power consumption measurement data supports this assumption. Power consumption P_{pred} while processing one billet is calculated by a multivariate regression model. Historic measured data was used as training data. Input parameters are the product diameter D, the rolling speed v, and the hot billet temperature T:

$$P_{pred} = -23677.93 + 26.48 \cdot Z + 645.53 \cdot v + 1339.39 \cdot D - 0.68 \cdot T \cdot v - 1.30 \cdot T \cdot D + 22.03 \cdot v \cdot D$$

The time series of measured versus predicted values and the parity plot are presented in Figure 22 and Figure 23.

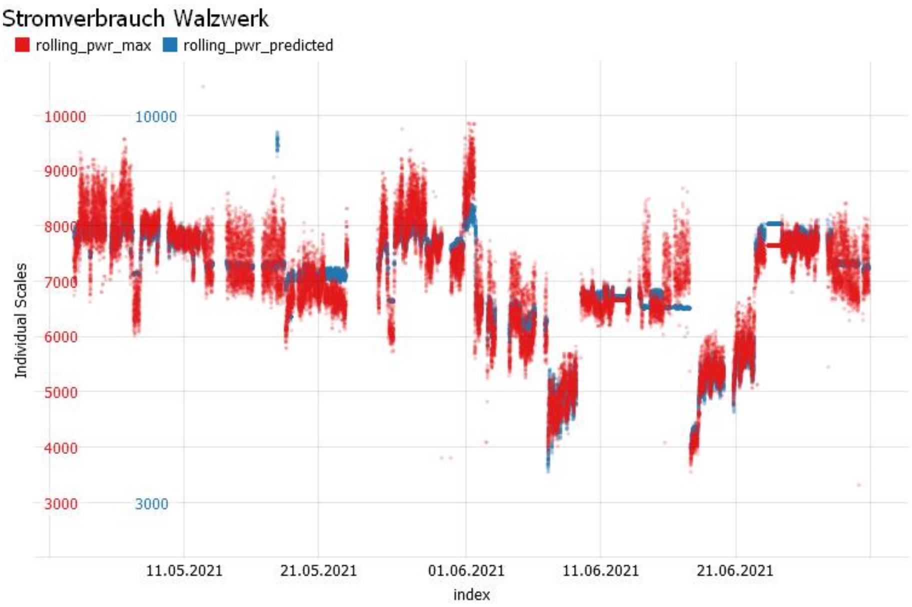


Figure 22: Time series of measured and predicted rolling power

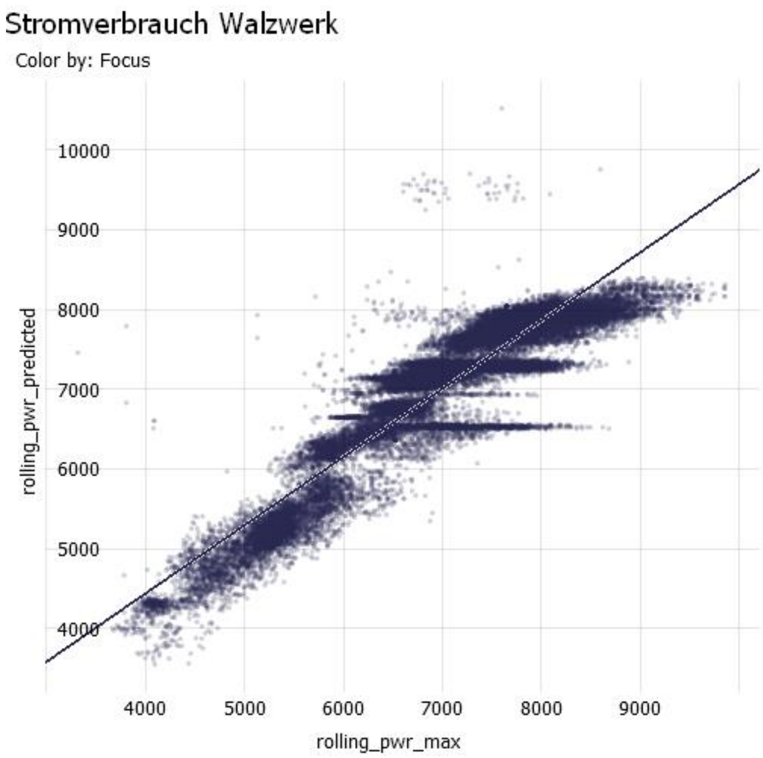


Figure 23: Parity plot between measured and predicted rolling power

The following minor consumers were modeled using lookup tables for the different operating modes. Historic values provide the data for the lookup tables.:

- Recoil plant
- Steel mill low-voltage consumers
- Rolling mill low-voltage consumers

Two key insights emerge: Forecast accuracy declines with longer horizons, and different methods deteriorate at varying rates. Despite these challenges, this research enhances the understanding of forecasting performance in the context of industrial energy management, particularly for grid capacity monitoring and electricity procurement. Improved day-ahead scheduling not only reduces costs but also alleviates grid stress, supporting energy conservation and CO_2 reduction through enhanced efficiency.

Using the process models, the overall plant model for interactive and automatic DSM DSS considering process constraints was created. All models that were created can be executed using the DSM DSS toolbox described in Chapter 3.3.

3.5 What-if Tool

A Python interactive DSM DSS forecasting model was built. The production plans for the entire plant are retrieved from the company's ERP system or are specified by the user (in the case of using the What-if tool). A forecast of electricity and natural gas consumption is created from these production plans. The major challenge in creating the overall model was modeling the material flows (scrap, molten iron, billets) together with the interaction of the individual processes. The model also considers the shift system of the employees as well as necessary maintenance work and plant vacations.

Figure 24 shows the internal and external data flow of the model. External data is drawn from relational database systems (RDBMS) or provided by the user via the user interface. Time series results are stored in a time series database (TSDB). The internal resource and energy flows that link the individual processes are also mapped. The order in which the process models are executed is determined based on these linkages.

The billet storage separates the steel mill and the rolling mill in two logical units. Both submodels work independently of each other. The steel mill model places all the billets produced in the billet storage. The rolling mill model then removes the appropriate billet (based on the time it was stored) from the storage. The plant model schedules the individual processes.

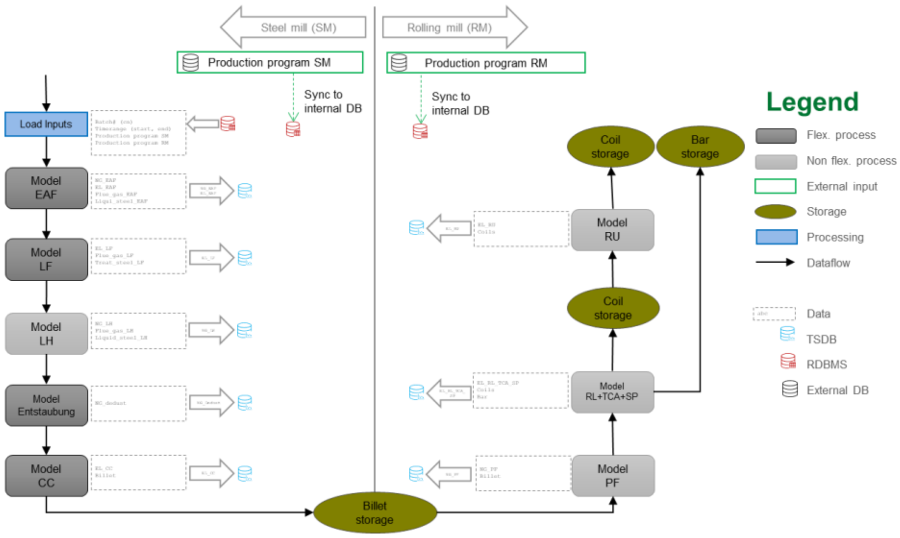


Figure 24: External and internal data flow of the model

The process models then calculate the time series of energy consumption. The temporal granularity of the time series output can be flexibly adapted. The model includes an interface to export the resulting time series to InfluxDB, an SQLite database, or a JSON file, which can be processed by the DPS.

The What-If tool is an interactive DSM functionality. The user can manually specify a production backlog and calculate the energy consumption of the individual plant components. To facilitate the creation of case studies, it is possible to retrieve data for past periods from the ERP database. The what-if tool was implemented in MS Excel. An add-in establishes the connection to the calculation server and the databases.

Figure 25 shows the MS Excel Add-in and the spreadsheet to fetch past data from the ERP. “Start” and “end” in lines 12 and 13 describe the period over which the data is to be retrieved. The results are written to a cell area, which is specified in line 16. Multiple different periods can be fetched at once, and a separate column must be created for each period. By clicking the “Submit” button in the Add-in, the queries are sent to the server; by clicking the “Get Results" button, the results are written to the cells specified in line 16.

Figure 26 shows the fetched production backlog data for the rolling mill. This can be adapted according to the user's requirements. This input data is then used to calculate the time series, which are shown in Figure 27. The results data can be visualized using the MS Excel chart tools. Input data submission and result data fetching work analogously to retrieving data from the ERP.

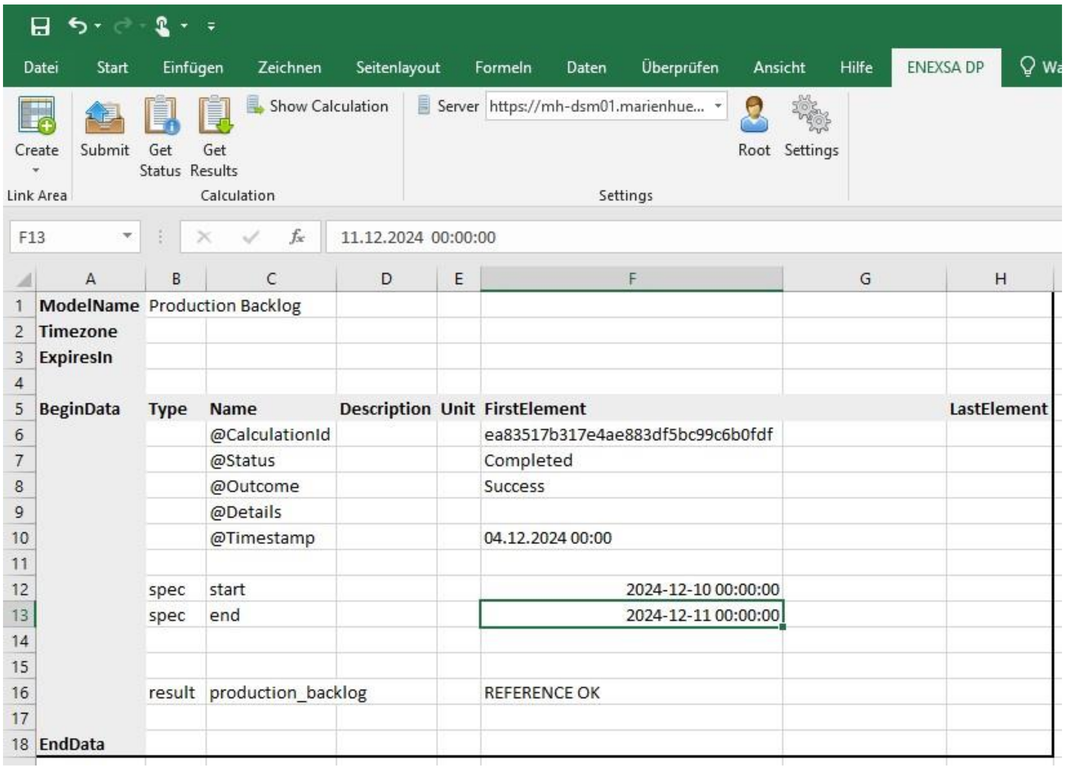
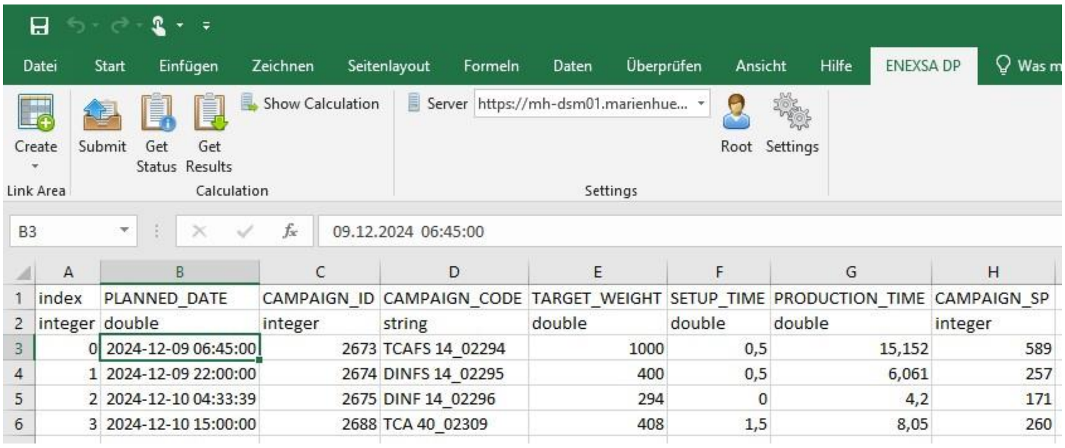


Figure 25: MS Excel Add-in and spreadsheet to fetch historic production backlog data



	A	B	C	D	E	F	G	H
1	index	PLANNED_DATE	CAMPAIGN_ID	CAMPAIGN_CODE	TARGET_WEIGHT	SETUP_TIME	PRODUCTION_TIME	CAMPAIGN_SP
2	integer	double	integer	string	double	double	double	integer
3	0	2024-12-09 06:45:00	2673	TCAFS 14_02294	1000	0,5	15,152	589
4	1	2024-12-09 22:00:00	2674	DINFS 14_02295	400	0,5	6,061	257
5	2	2024-12-10 04:33:39	2675	DINF 14_02296	294	0	4,2	171
6	3	2024-12-10 15:00:00	2688	TCA 40_02309	408	1,5	8,05	260

Figure 26: MS Excel Add-in with an exemplary production backlog for the rolling mill

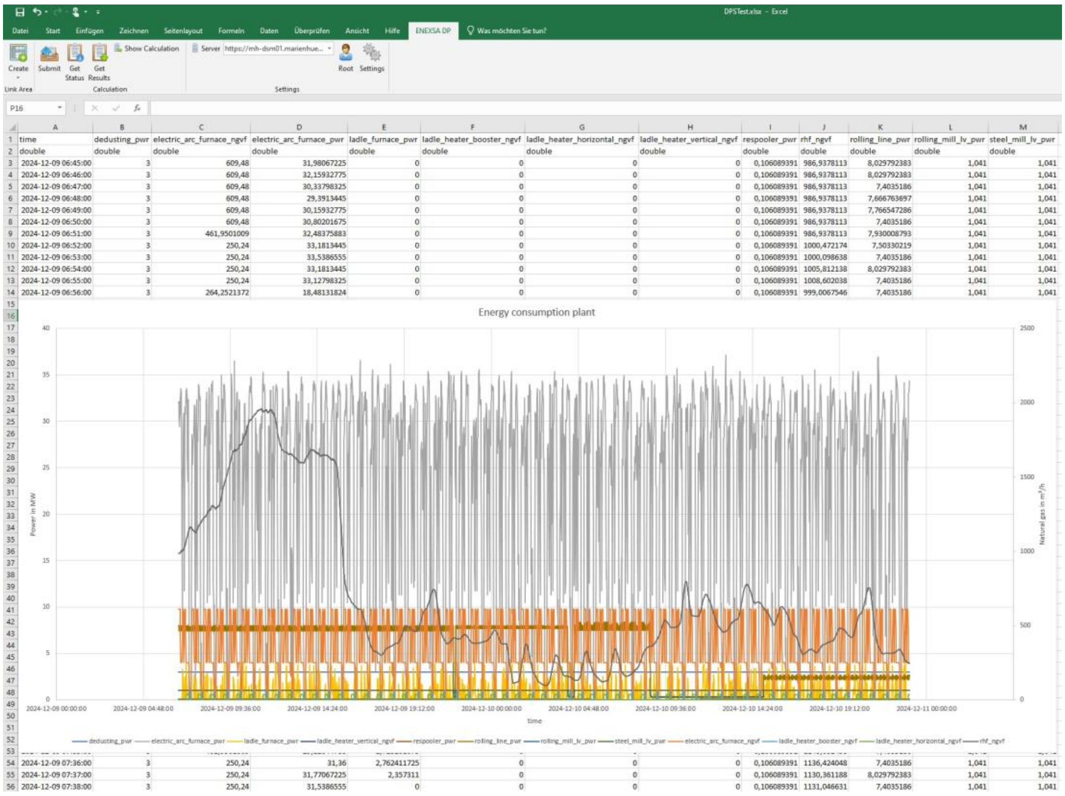


Figure 27: Result time series and visualization

3.6 Optimization

Based on the insights of the flexibility analysis from Chapter 3.2, optimization models were created accordingly, including:

- EED combined with UC of the EAF
- OS of the rolling mill

3.6.1 EED/UC of the EAF

As the EAF is the largest electricity consumer in an electric steel plant and one of the largest consumers in the power grid, it plays a key role in DSM. The literature frequently highlights the EAF's high flexibility potential, suggesting that it can serve as a valuable source of demand side flexibility due to its straightforward on/off operation [29,72,73]. However, most studies do not account for the impact of EAF operating times on downstream processes in an electric steel mill, thereby only assessing a theoretical flexibility potential.

In this study, we investigated the possibility of a combined UC and EED MOP for an EAF to flexibilize the energy mix ratio between electricity and natural gas for every heat in the investigated time sample. The analysis was carried out using real production data from 2024, based on which 36-hour samples were created to target the optimization horizon of the day-ahead market. The energy mix ratio is defined as the amount of electricity divided by the sum of electricity and natural gas. In original production, the average ratio is 86 %. It is possible to increase the ratio to 100 %, which would mean a purely electricity-driven operation of the EAF.

The optimization model is formulated as an ILP in Python, utilizing the PuLP library and the Gurobi solver. The first objective function minimizes energy costs—covering electricity, natural gas, CO_2 costs, grid charges, and taxes. Therefore, the energy prices are known beforehand. The second objective function aims to reduce CO_2 emissions, which are connected to the use of electricity and natural gas. The process constraints ensure that only one heat is produced at a time, that the heats do not overlap, and that the total amount of raw steel produced within a given timeframe matches the original production plan. With this, we make sure that the logistics and timing of downstream processes are not influenced. Additionally, we considered the relationship between heat duration and energy mix, recognizing that longer heat durations are required as the share of electricity increases.

Figure 28 presents the results of the UC/EED EAF optimization for different weighting factors of the objective functions. The upper section of each subplot represents the original production scenario, where the energy mix ratio remains relatively stable throughout the observation period of 36 hours. When the weighting factor between the objective functions is varied, it becomes evident that ecologically focused optimization runs (which aim to minimize CO_2 emissions) result in greater fluctuations in the energy mix ratio between heats compared to economically focused optimization runs (which seek to minimize energy costs). In the case where the weighting factor is set to 1.0, indicating a full focus on economic optimization, the ratio remains highly stable, with the highest possible share of natural gas due to the current price conditions, which favor natural gas over electricity, even when factoring in CO_2 costs from the emissions trading system.

The results highlight the inherent conflict between economic and environmental objectives (

Table 9). An environmentally focused optimization reduces CO_2 emissions by 1.60 %, but this comes at the expense of a 1.46 % increase in energy costs, as electricity is currently more expensive than natural gas and also remains linked to CO_2 emissions (293 g CO_2 / kWh). Conversely, an economically focused optimization that favors the use of natural gas (440 g CO_2 / kWh) reduces energy costs by up to 5.18 % but at the cost of a 1.15 % increase in CO_2 emissions.

The future development of energy prices will be a decisive factor in determining whether further research in this area is warranted. Since EAF operation is partially automated, implementing heat-wise regulation of the energy mix ratio would require new process control schemes and testing series beforehand to ensure product quality. Additionally, factors such as the CO_2 intensity of electricity, dependence on increasing availability of renewable electricity generation, and rising CO_2 prices may significantly alter the economic and environmental trade-offs in the future.

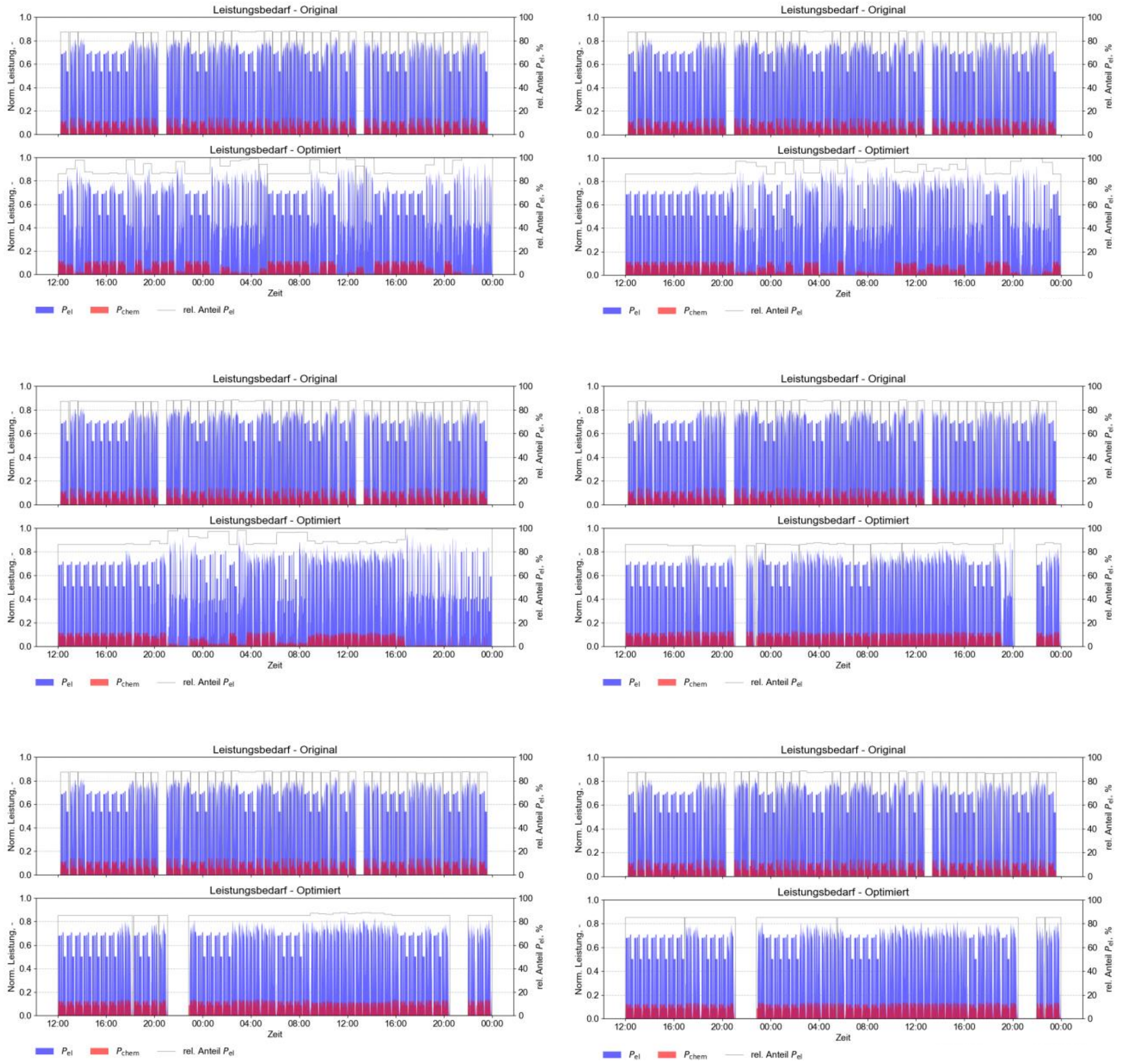


Figure 28: Energy consumption (electricity in blue, natural gas in red, ratio between electricity and natural gas in black) depending on the weighing factor (from top left to bottom right: 0, 0.2, 0.4, 0.6, 0.8, 1.0)

Table 9: Cost and CO_2 changes regarding different weighting factors between objective functions for the UC/EED EAF optimization

Weighting factor	Optimization focus	Cost changes	CO_2 changes

%	-	%	%
0	Environmental	+ 1.46	- 1.60
10		+ 0.08	- 1.65
20		+ 0.00	- 1.65
30		- 0.32	- 1.57
40		- 0.43	- 1.57
50	Balanced	- 0.80	- 0.86
60		- 4.52	+ 0.46
70		- 4.88	+ 0.74
80		- 5.15	+ 0.96
90		- 4.64	+ 1.08
100	Economic	- 5.18	+ 1.15

3.6.2 OS of the Rolling Mill

The rolling mill is the second-largest electricity consumer at the facility, following the EAF, and accounts for approximately 9 % of the total energy demand. The process begins with billets, produced in the steel mill, which are reheated in a pusher furnace before being continuously rolled into rods or coils. The rolling mill consists of multiple sections, each containing several vertical and horizontal rolling stands. The number of rolling stands a billet passes through depends on the target product diameter. When switching between different diameters, set-up times are required to adjust the rolling stands accordingly.

Production is scheduled based on an order list, covering a planning horizon of several weeks to a few months. The available production data for the rolling mill includes energy consumption measurements for each rolling stand, which were aggregated to determine the total energy demand. Additionally, detailed specifications for scheduled jobs—such as diameter, product type, length, and quantity—were analyzed over 11 weeks from April to June 2024. The data analysis focused on deriving specific energy consumption values for different product diameters (8 to 40 mm), which serve as key input parameters for scheduling optimization. Notably, the specific energy demand is directly influenced by product diameter, as smaller diameters require more intensive rolling work, leading to higher energy consumption (see Figure 29).

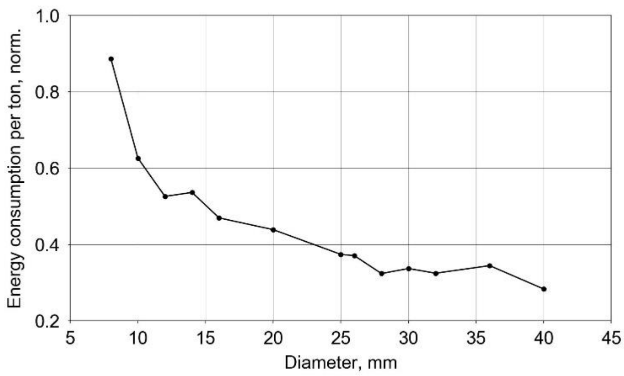


Figure 29: Relationship between the product diameter and the specific energy requirement [5]

An optimization model was developed in Python using PuLP to determine the optimal job scheduling in the rolling mill. The objective is to minimize electricity costs while meeting production constraints by balancing energy demand with fluctuating electricity prices over different mid-term horizons (one to eleven weeks). The model is formulated as a time-discrete ILP, where the objective function minimizes the total energy cost across all campaigns:

$$C_{tot}(x_{ci}) = \sum_{c=1}^{C} \sum_{i=1}^{T} x_{ci}\, cost(t_i)$$

where x_{ci} is a binary variable indicating whether campaign c starts at time t_i, and $cost(t_i)$ represents the electricity price. Constraints ensure that each campaign is scheduled exactly once and that only one campaign runs at a time, as parallel production is not possible:

$$\forall\, c\colon \sum_{i=1}^{T} x_{ci} = 1$$

$$\forall\, [t', t'']\colon \sum_{c=1}^{C} \sum_{i=t'}^{t''} x_{ci} \leq 1$$

The model incorporates setup times for diameter changes, as well as weekly downtimes and maintenance periods. To assess the potential for DR applications, the model was tested with spot market electricity prices from April to June 2024. Additional scenarios included historical prices (2021–2023) and simulated day-ahead prices for 2030 and 2040, based on Loschan et al. (2023) [83] and the Ten-Year Network Development Plan (TYNDP) [84].

The influence of different optimization horizons was analyzed using 2024 Central European day-ahead electricity prices (Table 10). Cost savings ranged from 5.73 % to 7.17 %, with the highest savings observed for a one-week horizon (7.17 %). However, as the optimization horizon increases, average cost savings tend to decrease. Conversely, cost variability follows the opposite trend: shorter horizons (e.g., one to two weeks) exhibit higher fluctuations, with a standard deviation of 5.65% for a one-week horizon, whereas longer horizons stabilize results, reaching the lowest variability of 0.41 % at nine weeks. This suggests that shorter horizons may yield higher savings but with greater uncertainty, whereas longer horizons lead to more predictable outcomes.

Table 10: Cost savings for different optimization horizons for Scenario 2024 [5]

Optimization horizon	**Cost savings**	**Standard deviation of cost savings**
weeks	Mean, %	%
1	7.17	5.65
2	6.49	2.62
3	6.10	3.05
4	6.39	2.41
5	5.73	2.62
6	6.10	1.88
7	5.91	0.81
8	5.87	0.61
9	5.87	0.41

10	5.93	0.81
11	6.33	-

The load-shifting potential was evaluated for the 11-week 2024 scenario using the optimized production schedule. Table 11 presents the overall, positive, and negative shift potentials, expressed as percentages of the original weekly energy consumption.

- Positive shift indicates increased energy use in the optimized schedule compared to the original plan.
- Negative shift represents reduced energy demand.

Results show significant weekly variations: The highest overall shift potential occurs in Week 0 (38.84 %), driven by a strong positive shift (39.53 %) and a minimal negative shift (-0.69 %). In contrast, Week 9 exhibits the largest negative shift (-46.16 %), resulting in the lowest overall shift (-39.98 %). Positive shift occurs every week, ranging from 0.98 % (Week 3) to 20.92 % (Week 6), indicating consistent opportunities to shift energy usage to more favorable periods.

Table 11: Weekly load shift potential [5]

Week	**Overall shift potential**	**Positive shift potential**	**Negative shift potential**
-	% of original weekly energy consumption		
0	38.84	39.53	-0.69
1	0.40	4.16	-3.76
2	-9.11	3.45	-12.56
3	-20.13	0.98	-21.11
4	-1.20	3.60	-4.80
5	7.12	18.01	-10.89
6	17.86	20.92	-3.06
7	-10.04	14.49	-24.53
8	-8.46	7.09	-15.55
9	-39.98	6.18	-46.16
10	-3.70	11.28	-14.98

Figure 30 compares the energy consumption of the original and optimized production plans for the 2024 scenario. The original plan prioritizes minimizing setup times by scheduling consecutive orders with similar diameters, reducing operational complexity and failure risks. In contrast, the optimized plan adjusts the production sequence to align with electricity price fluctuations, leveraging volatile energy costs for economic benefits. The results highlight significant flexibility potential through load shifting and cost reduction in a mid-term timeframe. However, a key challenge is identifying a suitable market framework for this flexibility. The futures market lacks the required temporal resolution for industrial operations, while the day-ahead spot market often provides too short-term price signals for effective planning. Additionally, energy price forecasting over mid-term horizons remains a challenge, as reliable predictions are scarce and often come at a cost.

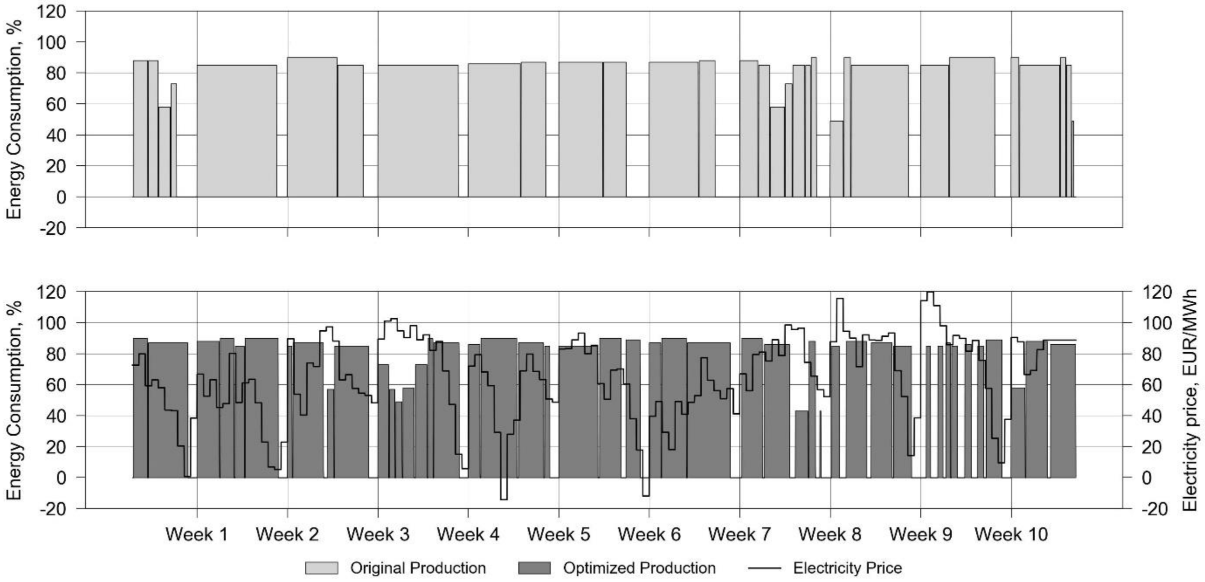


Figure 30: Original vs. optimized energy consumption for rolling mill [5]

The influence of electricity price characteristics on cost savings was analyzed using historical day-ahead prices (2021–2024) and forecasted prices for 2030 and 2040 based on the TYNDP scenario-building process [84]. Table 12 summarizes the results.

Table 12: Cost savings for different scenarios [5]

Scenario	Electricity price		Cost savings
-	Mean, EUR/MWh	Standard deviation, EUR/MWh	%
2021	61.91	22.54	4.31
2022	183.29	56.73	5.19
2023	91.56	35.02	4.70
2024	64.64	41.47	6.33
2030	60.70	15.17	3.68
2040	59.64	24.04	4.58

The mean electricity prices vary significantly across the scenarios, reflecting the market conditions of each year. The highest average price occurred in 2022 (183.29 EUR/MWh), coinciding with the largest price volatility (standard deviation: 56.73 EUR/MWh). In contrast, the lowest average prices are forecasted for 2030 (60.70 EUR/MWh) and 2040 (59.64 EUR/MWh), with reduced price fluctuations due to factors such as enhanced flexibility options, European market integration, decreased fossil fuel dependency, expanded grid infrastructure, and digitalization [85,86]. Cost savings through optimized scheduling show a positive correlation with price volatility. The highest savings (6.33%) occurred in 2024, with a mean price of 64.64 EUR/MWh and a standard deviation of 41.47 EUR/MWh. Similarly, the second-highest savings (5.19 %) are observed in 2022, driven by high price volatility. In contrast, 2030 yields the lowest savings (3.68 %), likely due to its stable price forecasts. Nevertheless, cost savings are achievable even in scenarios with relatively stable electricity prices through optimal scheduling optimization.

The computation time of the optimizer was analyzed for different temporal resolutions to assess its feasibility for real-world applications. Comparing 15-minute and 1-hour resolutions, the 15-minute resolution consistently yielded better results, achieving 0.56 % higher cost savings on average. This underscores its ability to capture finer fluctuations in electricity prices and optimize production schedules more effectively. The optimizer was tested on a system with an AMD Ryzen 5 PRO 4650U processor and 16 GB RAM. For an 11-week optimization horizon, the 1-hour resolution required approximately 1 minute 45 seconds, while the 15-minute resolution took significantly longer, averaging around 1 hour. While higher temporal granularity enhances optimization accuracy, it also increases computation time. However, even with a 15-minute resolution, a 1-hour computation time remains feasible for practical applications. Further reductions in temporal resolution require a careful trade-off between optimization accuracy, computational feasibility, and practical relevance.

3.7 Implementation and Testing

The DSM DSS toolbox, as described in Chapter 3.3, was set up on MH premises. DPS triggers data transfer (read and write) and model execution. Using DPS, the DSM DSS can run in online mode (the model is automatically executed with the current operating data at periodic intervals) and offline mode (interactive what-if mode, the user provides the required input data).

Figure 31 shows the software infrastructure that is set up for MH's DSM DSS. Data flow between the individual software modules is indicated by arrows. The yellow arrows describe the online functionality, and calculations are triggered hourly based on the current operating status. The green arrows indicate the data flow in the offline functionality (or the what-if tool). Both interactive and automated DSM models can be run with this setup in DPS. The DPS flows for both functionalities are shown in Figure 32 and Figure 33.

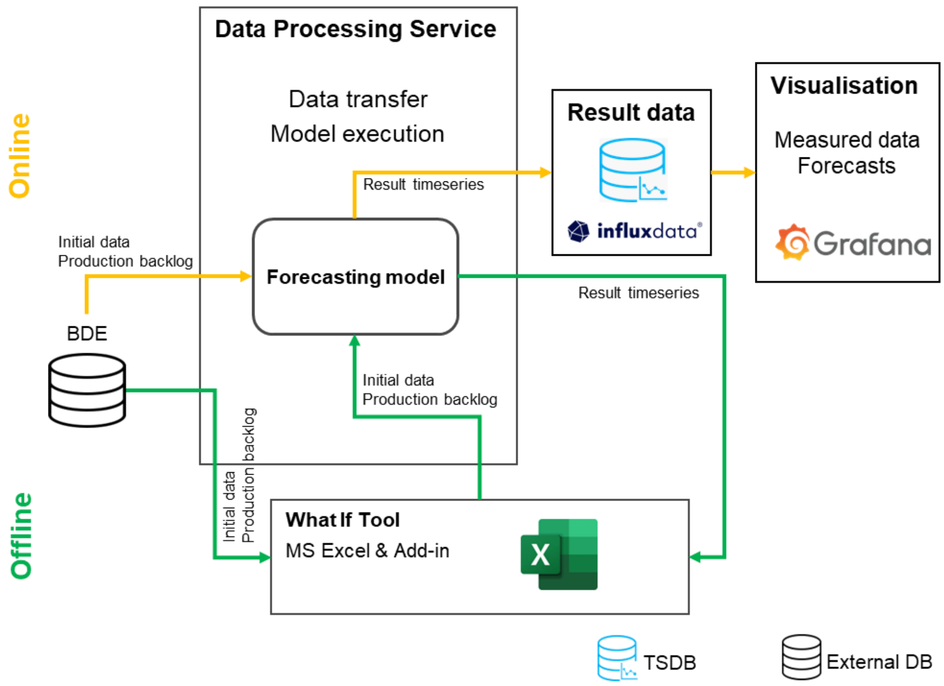


Figure 31: Software infrastructure for the DSM DSS at MH

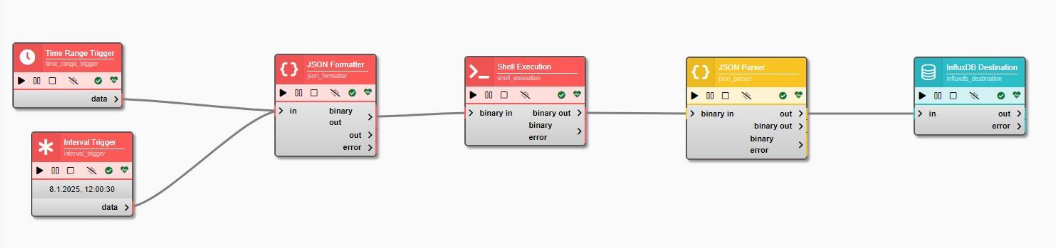


Figure 32: DPS flow for the online functionality

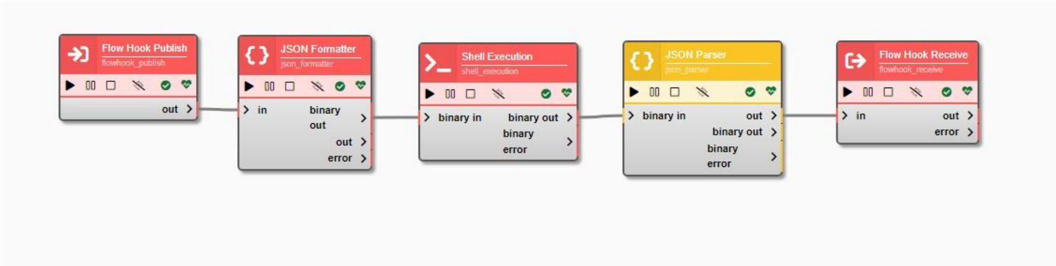


Figure 33: DPS flow for the offline functionality

The what-if tool is based on MS Excel and a customized Add-in that connects DPS with MS Excel. The user can fetch the operating state of the plant for a desired period from the MH’s enterprise resource planning database (BDE) and display it in an MS Excel spreadsheet. The input data can then be adapted to the user's desires, and a calculation run can be triggered via the MS Excel Add-in. After the calculation, the time series are transferred to MS Excel and can be displayed according to the user's requirements.

In addition to model execution, the online functionality also includes saving and visualizing the forecast result data. The database connection was configured for display in Grafana, and the necessary queries were created. In the default setting, the data for the last 12 hours and the next 72 hours are displayed. The forecasted consumption for the next 6, 12, 24, 48, and 72 hours is also shown. The individual time series were grouped according to the structure of MH’s energy system: total electricity and substations (Figure 34), electricity substations 4 (Figure 35) and 5 (Figure 36), and natural gas consumption (Figure 37).

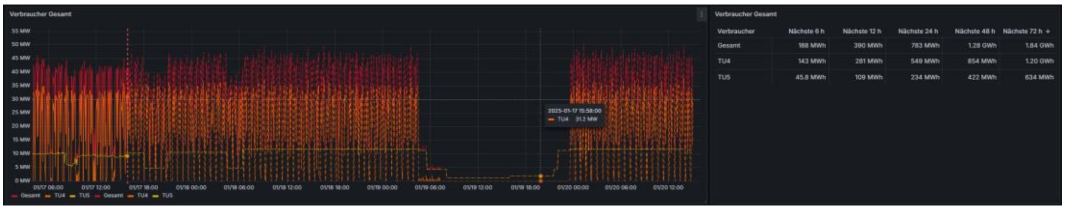


Figure 34: Result representation of total electricity consumption and the consumption of the two main substations

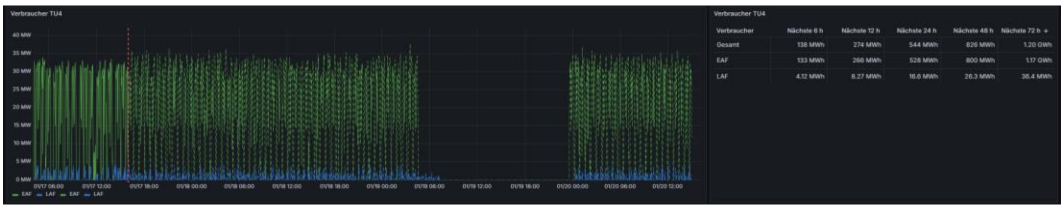


Figure 35: Electricity consumption at substation 4 and its consumers

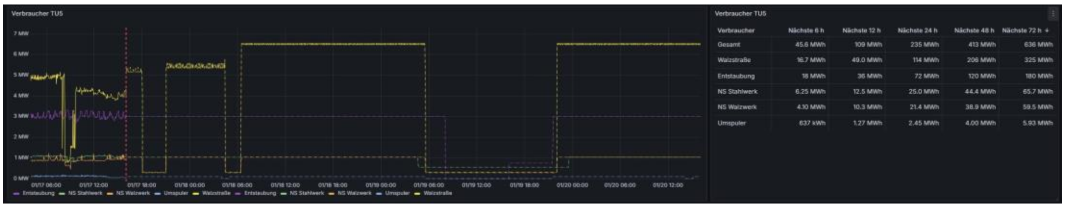


Figure 36: Electricity consumption at substation 5 and its consumers

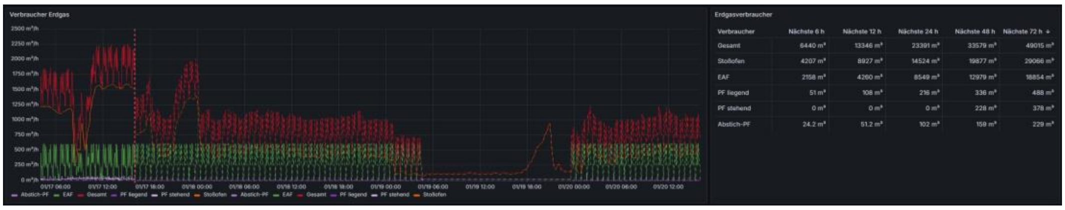


Figure 37: Total natural gas consumption and consumption of individual consumers

4 Know how Transfer to other Industry Sectors

For evaluating the result transfer potential, we started with a general requirement analysis, followed by the evaluation of the applicability of the current solutions and knowledge in other energy-intensive sectors, concluding with highlighting the expected required adaptions.

4.1 Requirements Analysis

As the focus in the project DSM_OPT lay on implementation, challenges regarding that, and the fact that the industry is highly heterogeneous, the requirement analysis focuses on the general demands to make Decision Support possible. These demands are mainly about data availability, processing, and handling. These include:

- Availability of installed data measurement equipment
- Continuous data measurement in a temporally resolved manner of all relevant process parameters, including:
    - Energy-related parameters (power, natural gas, coal, etc.)
    - Physical process variables, which correlate with the energy demand (e.g., temperatures, oxygen, additives, etc.)
    - Time-related parameters regarding the process (batch durations, transport times, etc.)
- Storage of production data
- General information about the production, like production schedules or shift models
- Access to data

These requirements ensure that a realistic representation and tracking of the production process is possible. Furthermore, sufficient data supports the success of finding correlations, relations, and dependencies in the process chain during data analysis. At this point, it must also be said that a finer temporal resolution increases the comprehensibility of the process but also the amount of stored data. An optional requirement beforehand is the visualization of the necessary production parameters, as the interpretability of the data is facilitated. The industry-specific characteristics and applicability of the developed tools and methods are discussed in Chapter 4.2.

4.2 Evaluation of Applicability

For the evaluation of applicability, in the first step, relevant energy-intensive sectors and their processes are identified and described as we aim to find the processes with the greatest leverage regarding operation optimization and demand side management measures. In the next step, we introduce appropriate key performance indicators (KPIs) to identify similar processes and characteristics to those considered in the project DSM_OPT. In addition to the characterization, the developed KPIs can be used to identify and describe the flexibility potential of the investigated processes.

4.3 Energy-intensive Industries and Process Identification

In literature, the line between energy-intensive and -extensive industry sectors is not clearly defined and depends on the respective (inter-)national legislation and interpretation. In most cases, the criterion for the distinction between energy-intensive and -extensive is an economic one, e.g., if the share of energy costs of total costs exceeds a certain threshold. Based on the possibility of criteria, we decided to take the following industry sectors as energy-intensive into account:

- Iron and steel
- Non-metallic minerals and building materials
- Chemicals and petrochemicals
- Pulp and paper

4.3.1 Iron & Steel

Although one use case of DSM_OPT is located in the iron and steel industry, a closer look is taken as the industrial sectors not only differ from one another but also exhibit major differences within them. Approximately 7 % of global greenhouse gas emissions (reference year 2021), equivalent to 2.6 Gt CO_2, are caused by the iron and steel industry. The production of crude steel can be divided into primary production via blast furnaces (BF-BOF, share of 71 % in 2019) and secondary production via electric arc furnaces (EAF; share of 28 % in 2019). The main raw material for primary production is iron ore, while steel scrap is used as input material for secondary production [36]. In terms of energy consumption (and subsequently greenhouse gas emissions), secondary production is far more sustainable, as the BF-BOF route consumes between 4.900 and 5.900 kWh / t crude steel, while the scrap-based EAF route consumes 600 to 1.200 kWh / t crude steel. [87,88]. In terms of process technology, the two routes differ primarily in the first process steps (Table 13). In the BF-BOF route, the coke is first produced in the coke oven. The iron ore is then sintered with coke in the sintering plant. The resulting material is melted in the blast furnace in a complex chemical sequence of reactions. In contrast, in the EAF route, steel scrap is melted in an electric arc furnace with the addition of additives. The subsequent further processing of the pig iron depends on the steel quality to be produced and can include the following process steps: Secondary metallurgical treatment in the ladle furnace, desulphurization, oxygen blowing process, and vacuum treatment. Nowadays, crude steel is mostly cast in continuous casters and then rolled in rolling mills.

Table 13: Key processes in the iron and steel industry

Process	Operation Mode
Coking Plant	Continuous
Sintering Plant	Continuous
Blast Furnace	Continuous
Electric Arc Furnace	Batch
Ladle Furnace	Batch
Desulphurization	Batch
Converter	Batch
Vacuum Oxygen Degasser	Batch
Continuous Casting	Continuous
Rolling Mill	Continuous

4.3.2 Non-metallic Minerals and Building Materials

In this section, the production processes of mainly cement are discussed, as the processes and aggregates, e.g., lime, bricks, and concrete, are quite similar or are products made from cement. More detailed information about the process characteristics of these products can be found in Table 14. Cement production requires approximately 830 to 1.100 kWh / t cement. Fuel (and subsequently heat) energy represents about 90 % of this total specific energy consumption (SEC), and the share of electrical energy is only about 10 %. The electrical energy consumed in the conventional cement-making process is typically 95 to 110 kWh / t cement. [89] The main process steps are:

- Raw material extraction
  The limestone is mainly mined in the form of big rocks and is transported to the raw milling facilities.
- Grinding and crushing
  The grinding and crushing of the limestone rocks is the first step of the actual cement manufacturing process and grounds the rocks into smaller stones. It comprises approximately 25 % of the total electric energy consumption.
- Preheating and precalcinating
  The heat required for this step often gets recuperated from the off-gases of the main clinker production step itself (from the rotary kiln). Due to the heat input, the calcium carbonate decomposes to lime and CO_2.
- Clinker production
  The actual clinker production happens in a rotary kiln, where the material is heated up to 1.450 °C. This process step is the most energy-intensive stage in cement production, accounting for about 90 % of total thermal energy use [90].
- Clinker cooling
  During clinker cooling, the heat is recovered for preheating. Required energy demand (electricity) in these steps arises for the operation of the cooling fans.
- Clinker grinding

About 40% of electrical energy demand is consumed for clinker grinding. So, it can be regarded as one of the major steps in cement processing in terms of electrical energy consumption. Thereby, the nodules of clinker are ground into fine powder under the addition of gypsum.

- Cement storage and packaging
  The final step of storing and packing might not be available in some industrial setups as they export clinkers directly.

Figure 38 shows the energy carriers commonly used in each step in cement manufacturing and underlines the subordinate role of electricity (in absolute numbers) in the production process.

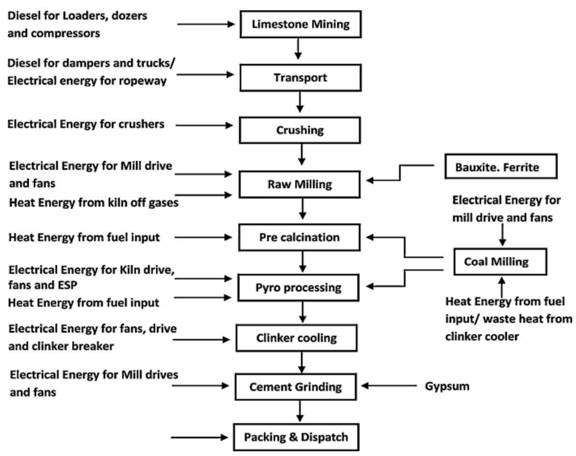


Figure 38: Energy flows in cement production [89]

Table 14: Key processes in the non-metallic minerals and building materials industry

Commodity	Process	Operation Mode
Brick, cement, lime	Crusher	Continuous
Brick	Pressing (Rolling Mil) & Forming	Batch/Continuous
Brick	Dryer	Batch/Continuous
Brick	Tunnel Furnace	Continuous
Cement, Glass, Lime	Material Mil (raw & clinker)	Batch
Cement	Rotary Kiln	Continuous
Cement	Cooler	Continuous
Glass	Tub Oven	Continuous
Glass	Glass Shaping Unit	Continuous
Glass	Chiller	Continuous
Lime	Lime Kiln	Continuous

4.3.3 Chemicals & Petrochemicals

The chemical and petrochemical sector consumes approximately 35 EJ of final energy per year worldwide, which represents more than 30 % of the global industry energy use [91]. This industry sector gains its importance as a supplier for many other production areas. In comparison, this sector is strongly heterogeneous due to the fair number of substances that are produced. The most important commodities, their process steps, and process operation modes are presented in Table 15. As can be seen, continuous processes dominate this sector, clearer than in the other industry sectors that have been discussed so far.

Table 15: Key processes in the chemical and petrochemical industry

Commodity	Process	Process Operation
Ammonia	Primary & Secondary Reformer	Continuous
Ammonia	CO Converter & CO_2 Separator	Continuous
Ammonia, Chlorine, Ethylene, Oxygen, Polyethylene, Urea	(Turbo) Compressor	Continuous
Ammonia, Ethylene	Boiler	Continuous
Ammonia, Urea	Synthesis Reactor	Continuous
Chlorine	Ion Exchanger	Continuous
Chlorine	Heating Unit	Continuous
Chlorine	Electrolyzer	Continuous
Chlorine, Oxygen	Chiller	Continuous
Chlorine, Urea	Evaporator	Continuous
Ethylene	Steam cracker	Continuous
Ethylene	General Quenching Unit	Continuous
Ethylene	Distillation	Continuous
Ethylene	Hydrogenation	Continuous
Oxygen	Molecular Sieve Unit	Continuous
Oxygen	Rectification Column	Continuous
Polyethylene	Tubular Reactor	Continuous
Polyethylene	Separator	Continuous
Polyethylene	Extruder	Continuous
Polyethylene	Dryer	Continuous
Urea	Falling Film Heat Exchanger	Continuous

4.3.4 Pulp & Paper

The pulp and paper industry can be divided into two sections: pulping and paper manufacturing. The specific energy consumption depends heavily on the type of pulp or paper produced, ranging overall from 400 to 2.700 kWh / t electricity and 3.300 to 5.100 kWh / t heat [92]. The main process steps during pulp and paper manufacturing include [93,94] (Table 16):

- Raw material preparation
  The raw material gets prepared as big logs are getting debarked and chipped.
- Fiber Separation
  The fibre separation happens in digesters to digest the lignin. Digesters can be batch-operated or continuous. Moreover, there can be mechanical or chemical (Kraft or Sulphite pulping) pulping processes, depending on the type of paper produced (e.g., mechanical pulping for softwood and the production of newspaper or tissue paper).
  Figure 39 shows a combined Kraft pulp and paper-making process, as it is an extensively used method in papermaking and is energy-intensive. Therefore, it offers potential for optimization, which partly has already been investigated in various studies.
  In the Kraft process, NaOH and Na_2S are added to hydrolyze the ligning under the influence of heat. The pulp then gets washed, and the black liquor forms. It can be burned and act as an energy provider for the recovery boiler. Back to the main fibre line, the pulp goes through oxygen delignification.

This step is where the processes tend to be different depending upon the type of technique used.

- Bleaching / Whitening
  Several chemicals and reactions are used to make the paper white (ozone, chlorine, chlorine dioxide).
- Papermaking
  The ultimate process that turns the slurry into paper. Drying constitutes the major energy consumption.

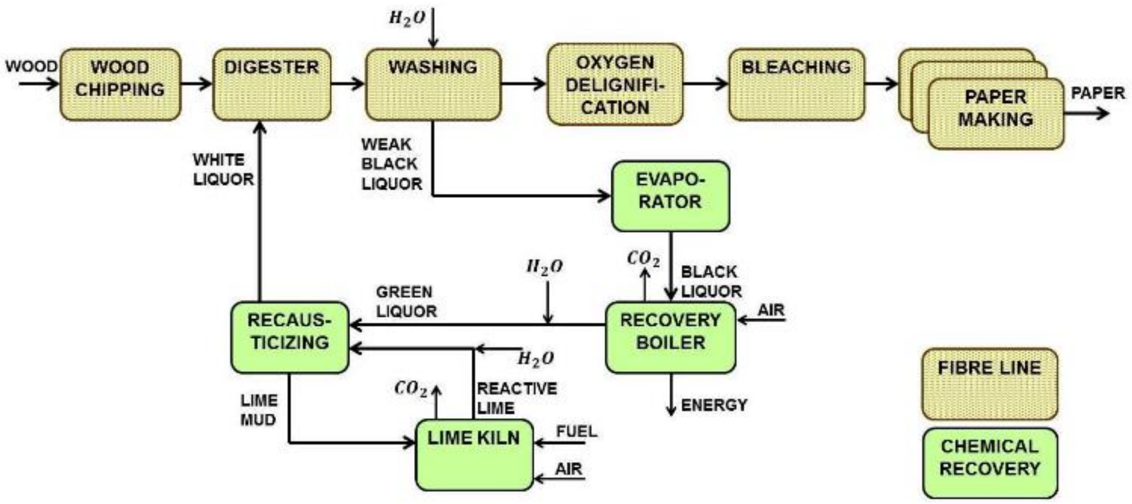


Figure 39: Process scheme of a combined Kraft pulp and paper-making process [94]

Table 16: Key processes in the pulp and paper industry

Process	***Operation Mode***
Debarker	Continuous
Chipper	Continuous
Pulper & Digester	Batch/Continuous
Pulp Refiner	Continuous
Washing & Screening	Continuous
Evaporator	Continuous
Oxygen Delignification	Continuous
Bleach Plant	Continuous
Lime Kiln	Continuous
Stock Preparation	Continuous
Pressing & Forming	Continuous
Dryer	Continuous
Calendaring	Continuous

4.4 Key Performance Indicators

To identify similar processes to those considered in project DSM_OPT, the KPIs in three different categories are used:

- Energetic KPIs, such as typical nominal power (thermal and electrical), can be measured, determined, or calculated for almost all industrial processes.
- KPIs for the characterization of the operation can be determined for almost all processes. However, they describe the mode of operation as well as the (time-related) main and secondary requirements of the process. In addition, these KPIs provide important findings for identifying and determining flexibility potentials as well as for identifying interdependencies between the individual processes.
- Process-specific KPIs describe process-specific parameters that cannot be determined for all processes. For example, the flow rate of a process can only be determined for those processes in which a mass or volume flow is present (e.g., pumps, mills, rotary kilns).

An overview of relevant KPIs for the process comparison, their classification, and a short description are shown in Table 17. As examples for the process-specific KPIs, KPIs are given, which are also relevant for the processes considered in the project DSM_OPT. Process-specific KPIs are, for example, the maintenance status. It describes the number of production cycles a ladle in the electric steel mill has undergone. This makes it possible to assess whether it is efficient to use the ladle again or send it for maintenance.

Table 17: KPIs for process comparison

Classification	Parameter	Unit	Description
Energetic KPIs	Energy consumption (1) (thermal, electrical)	kWh	Average energy consumption of a process/aggregate.
	Typical nominal power (1)	kW	Typical nominal power of a process/aggregate.
	Time-resolved load profiles	kW	Time-resolved load profiles of a process/device.
Characterization of the operation	Operating mode	-	Processes can be operated in a continuous and/or batch mode.
	Operating time (start, end) (1)	Time-stamp	The time window in which the process is active - e.g., begin / end of the working day.
	Power on-time	h, min	Duration of a process/aggregate must be in operation within the operating time – if the operation time is equal to the power-on time, then there is no flexibility.
	Power off-time	h, min	The duration of a process/aggregate must be off within the operating time.
	Ramp-up time or energy consumption	h or kWh	Time or energy is required until the process is at the nominal operating point.
	Ramp down time or energy consumption	h & € or kWh	Time or energy is required until the process is completely turned off.
Examples of process specifics KPIs	Maintenance status (1)	n	Indicates how many production cycles a unit has undergone, e.g., ladles in an electric steel mill.
	Ratio of energy carriers (1)	kW : Nm³ / h	Ratio of energy carriers if an aggregate is supplied by more than one energy carrier (e.g., electric arc furnace).
	Temperature level (begin, end) (1)	°C	Temperature level at the beginning/end of the process, e.g., baking ovens.

4.5 Cross-Industry Demand Side Management Potentials

The processes optimized in the project DSM_OPT are:

- EED and UC of the electric arc furnace to exploit economic advantages due to volatile energy prices on short-term markets (market DR).
- OS of the rolling mill to minimize operation costs by shifting energy-intensive production tasks to times when there is overproduction due to renewables (TOU).
- OS of baking ovens to minimize energy consumption through decreasing heat-up rates and standby times (EE).

Based on these processes, especially the concept of load shifting (in the form of optimal scheduling and unit commitment) is important for the process comparison. The first step was to identify the main processes in the energy-intensive industry (Table 13 to Table 16). In the next step, the processes are compared to the characteristics of the optimized processes in DSM_OPT and answering the following main questions support in assessing the process' suitability:

- Has this process a great share of energy consumption? Is it a large lever?
- How are the process dependencies of the up and downstream processes?
- Is there a storage function available?
- Can the process be regulated easily?

Selected examples of the process comparison and their results are shown in Table 18. The results show that there are similarities between the industrial processes and those in the project DSM_OPT. However, due to the dependencies between the processes, the similarities are not sufficient to be classified as similar. The comparison of the mode of operation (continuous or batch) shows that in energy-intensive industry, the majority of processes are operated continuously in full-load mode (Table 13 to Table 16). The processes are only turned on and off at the beginning and end of the production times. Some plants even have production times spanning several days, and processes are only turned off for maintenance reasons. Batch processes are turned on and off more often during the day, but this does not necessarily mean that these processes have a high flexibility potential (e.g., shifting the load over several hours). In industry, the dependence of the processes on each other is extremely important. This means that the KPIs for the characterization of the process can appear similar to those in the project DSM_OPT, but due to process dependencies, the process is not classified as similar.

Table 18: Result of the process comparison for selected processes

Industrial sector	Process	Operation mode	Process dependency	Storage function	Load shifting
Cement	Raw Mill	Batch	Low	Yes	Yes
Cement	Rotary Kiln	Continuous	High	No	No
Lime	Material Mill	Batch	Low	Yes	Yes
Refractory	Material Mill	Batch	Low	No	Yes
Chlorine	Electrolyzer	Continuous	High	No	Yes

4.6 Required Adaptions

Based on the insights gathered, the following conclusions can be drawn from a cross-industry comparison:

- Industrial sites differ significantly, even within the same industry sector.
- Flexibility potential analysis must be conducted on a case-by-case basis.
- A guideline for identifying flexibility potentials would be beneficial.
- Often, flexibility potentials span short periods, typically more minutes than hours.
- Resilient potentials are observed in up- or downstream processes with low process dependencies, such as material mills.
- There is also potential for aggregates that can be electrified.

These conclusions underscore the importance of tailored analyses and the development of specific guidelines to identify and harness flexibility potentials effectively across different industrial sites.

The comparison of the processes in the two use cases of DSM_OPT to the energy-intensive industry shows that there's a very small chance for a complete direct transfer. In addition to the high annual utilization of the processes (due to high capital expenditures), the dependence of individual processes on each other is the main difficulty in terms of flexibility and optimization in the energy-intensive industry. For the energy-intensive industry, approaches and methods have to be applied, which allow the overall system and process dependency to be well represented and considered. As the process comparison already demonstrates, only a few processes in the energy-intensive industry have flexibility concerning load shifting and peak shaving over several hours. This is due, among other things, to a (mostly) continuous mode of operation, a lack of capacity (configuration for full-load operation), and high process dependencies. Even short load shifts usually have high effects on the whole process chain.

5 Feature and Implementation Plan

To ensure the transfer of knowledge and the future application of insights gained from DSM_OPT, we developed a roadmap for the future development of DSM DSS toolboxes, which also includes a rough timeline to estimate the needed time for the overall development and implementation. This roadmap comprises the necessary steps to successfully implement a DSM DSS system at an industrial site. As industrial sites are heterogeneous, even within an industrial sector, this roadmap won't point out case-specific details but will give an overview of the necessary tasks to execute. The roadmap is displayed graphically in Figure 40 and will be described in the following subsections. In conclusion, we address the temporal factor: On the one hand, how much time should be scheduled for the individual tasks and, on the other, in what order they should be arranged to drive development forward as efficiently as possible. At this point, it should also be mentioned that the tasks cannot be considered decoupled from each other, as the development of a DSM DSS system is an extremely complex task. The arrows in Figure 40 are intended to illustrate which tasks build on each other and between which tasks feedback loops are necessary.

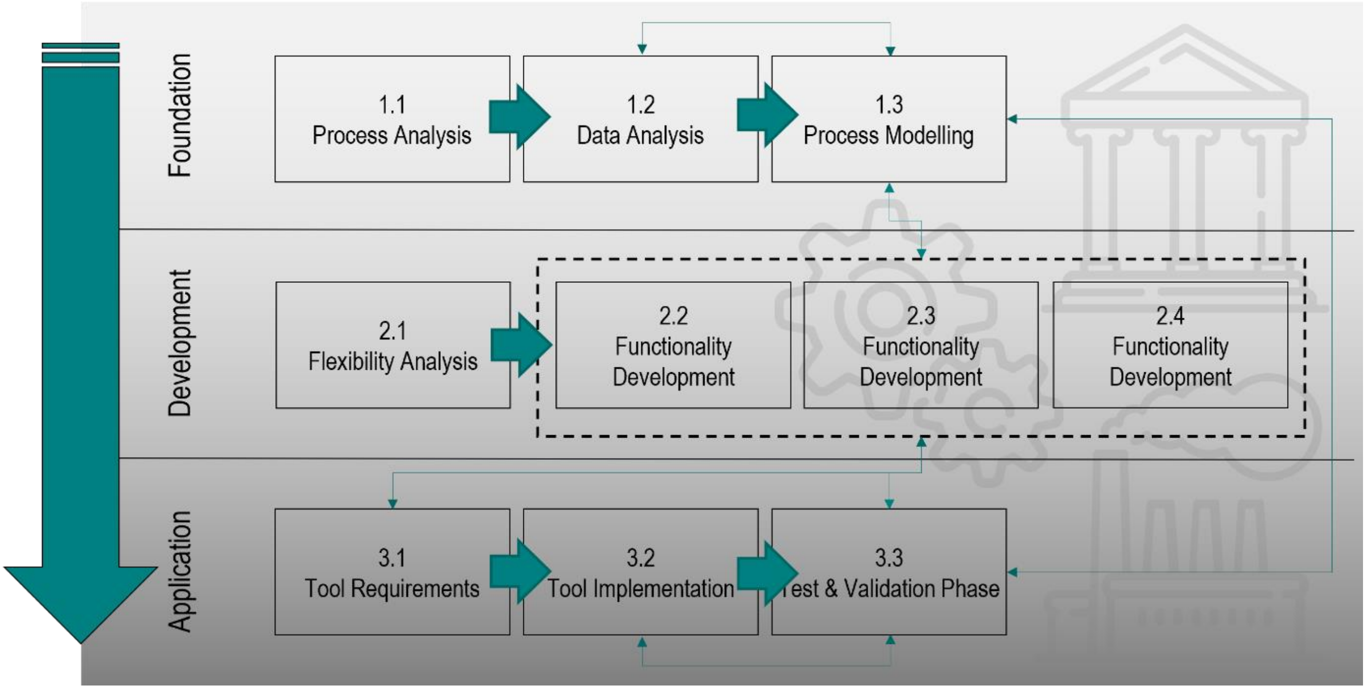


Figure 40: Roadmap for DSM DSS toolbox development at an industrial site

5.1 Foundation

The Foundation phase is critical for laying the groundwork of the DSM DSS system, encompassing three essential tasks: Process Analysis, Data Analysis, and Process Modelling. Process Analysis begins with a thorough examination of the existing production processes. This also includes data measurement and preparation, which may involve installing new data measurement systems if necessary. The goal here is to develop a comprehensive understanding of the production process, identifying key factors such as dependencies, bottlenecks, and storage capacities. The analysis also covers the nature of the processes—whether they are continuous or batch processes—and involves mapping out the general production workflow through flow diagrams. Additionally, this task requires an evaluation of the general energy requirements associated with the process, including considerations of shift models and their impact on production.

Following the general analysis, Data Analysis delves deeper into the temporal aspects of energy demand within the production process. This task focuses on understanding the temporal resolution of energy demands, identifying main energy consumers and energy peaks, and analyzing demand patterns. A key component of this analysis is the correlation analysis, which seeks to identify the influence of various process parameters on the energy demand (in detail on the aggregate level). This includes examining how factors like ambient temperature and product-specific requirements affect energy consumption. By understanding these dependencies, the analysis provides insights into how energy demand fluctuates and what factors drive these changes. Subsequently, it must be assessed which data is important for modeling and which is important for the operation of the forecasting model. Furthermore, it must be assessed which data is available in which form and whether it can also be retrieved automatically from another application.

The final task in the Foundation Phase is Process Modelling. In this task, the process is modeled using either first principles modeling, data-driven approaches, or a combination of both, depending on the needs of the project. Traditional modeling methods include thermodynamic or mathematics- and physics-based approaches, which rely on established scientific principles to simulate the process. On the other hand, data-driven modeling involves the use of machine learning techniques, which can provide more adaptive and potentially more accurate models based on large datasets. A critical decision in this task is determining the necessary level of detail required for the model, balancing the complexity of the model with the accuracy needed for effective decision-making. Together, these tasks in the Foundation phase establish a solid base for the subsequent phases, ensuring that the DSM DSS system is built on a comprehensive understanding of the production process, its energy demands, and the most appropriate modeling approach.

5.2 Development

The Development phase is where the foundational work transitions into actionable insights and tools that will drive the DSM DSS system. In the beginning the Flexibility Analysis focuses on identifying potential flexibility within the industrial system at various levels, including the overall system, specific process chains, and individual aggregates. The goal is to determine which processes or aggregates can be operated flexibly and to classify the type of flexibility available—whether it involves power regulation, time-shifting operations, or switching fuels. The analysis also considers the duration of this flexibility and its potential impact on other parts of the process. For example, operating an aggregate flexibly might influence the timing or efficiency of other linked processes. Understanding these dynamics is crucial for developing strategies that maximize energy efficiency while minimizing disruptions to production.

This task involves the design and implementation of specific DSM measures tailored to the industrial setting. These measures are informed by the earlier data analysis, process modeling, and flexibility analysis. Potential functionalities include improving energy efficiency (a permanent measure), optimizing the timing of energy use (mid-term), and participating in market demand response (mid- to short-term). Some key functionalities are mentioned here: energy monitoring to detect real-time issues related to elevated energy demand, an interactive "what-if" tool for simulating different energy demand scenarios, and tools for enhancing energy efficiency through improved production scheduling. Additionally, functionalities can be designed for optimal scheduling that accounts for time-dependent, volatile energy prices and unit commitment strategies such as fuel switching. Other possibilities include providing recommendations on how to purchase energy cost-effectively to meet demand. These functionalities can be applied to individual aggregates or entire process chains. Moreover, the potential exists to evolve these functionalities into a digital twin, enabling not just decision support but also direct control of the processes.

5.3 Application

This task outlines the specific data and IT infrastructure needed for the tool’s implementation. It covers the type and format of data required, the necessary temporal resolution, and the existing IT infrastructure at the industrial site. Key considerations include how the data are stored, how the tool will access these data, the type of database to be used, and whether existing interfaces are adequate or new ones need to be developed. Additionally, the input data requirements for different functionalities are assessed alongside the hardware needs at the industrial site to run the tool effectively. Moreover, for an automated operation of the tool, it must also be capable of recognizing downtimes, such as weekends and holidays, to ensure accurate scheduling and functionality.

Task 3.2 focuses on establishing how the development team will access the industrial site's systems during the implementation phase. This could involve setting up VPN access or determining whether a physical on-site presence is necessary. The implementation phase ensures that the tool is fully integrated into the industrial environment, enabling its functionalities to operate as designed.

Task 3.3 is characterized by multiple feedback loops designed to iteratively refine and enhance the tool's overall performance. During this phase, the tool's functionalities are rigorously tested in real-world conditions, with continuous feedback informing improvements. This iterative approach ensures that the DSM DSS system is not only functional but also optimized for the specific needs and constraints of the industrial setting.

5.4 Timing and Duration

The development of the DSM DSS system is structured around six key milestones, each representing a critical phase in the progression of the project. The timing of each work task within the three main project phases (foundation, development, and application) is flexible and highly dependent on the specific use case, considering factors such as the complexity of the developed DSM DSS system, the scope of DSM functionalities, the interaction with the production process, the status of the existing digital infrastructure, and data availability and accessibility. Consequently, we have specified a period for each task rather than a fixed duration (Figure 41).

The process begins with phase 1, which focuses on the foundation of the system. Here, the Process Analysis (Task 1.1) spans 4 to 6 months, ensuring that a thorough understanding of the existing processes is achieved. Following this, the Data Analysis (Task 1.2), lasting 2 to 4 months, is conducted to gather and prepare the necessary data. These two tasks are prerequisites for the Process Modelling (Task 1.3), which takes between 10 to 14 months. It's essential to complete the process and data analyses before starting the Flexibility Analysis (Task 2.1) in phase 2, which also takes 4 to 6 months. This sequence ensures that all necessary data is available for the flexibility assessment.

Phase 2, the development phase, begins in parallel with the Process Modelling (Task 1.3). This overlap is strategic, allowing for any findings from the flexibility analysis to be integrated into the ongoing process modeling. Once the flexibility analysis is underway, phase 3 (Application) can also commence to determine the specific requirements for the tools that will support the DSM functionalities. As Process Modelling (Task 1.3) progresses and a shared understanding of the process models is established, the development of DSM functionalities begins. Tasks 2.2 to 2.4 involve the Functionality Development of these features, with each functionality requiring 4 to 6 months, depending on its complexity. These functionalities may include energy monitoring, what-if analysis tools, or operation optimization approaches. Importantly, the Tool

Requirements (Task 3.1) phase extends over 6 to 12 months, and it evolves in tandem with the development of functionalities to ensure a seamless implementation.

Finally, Phase 3 culminates with the Tool Implementation (Task 3.2), taking 3 to 4 months, followed by a Test & Validation Phase (Task 3.3) that spans a minimum of 6 months. This comprehensive testing phase is critical to validate the entire DSM DSS system and ensure that it meets all specified requirements.

In summary, the overall project spans a period from approximately 2.5 to 3.5 years, depending on the scope, data availability, and complexity of the integrated DSM DSS system. The timeline is structured to allow for flexibility and adaptation as the project progresses, with a clear emphasis on parallel processing and iterative development to achieve a robust and well-integrated DSM DSS system.

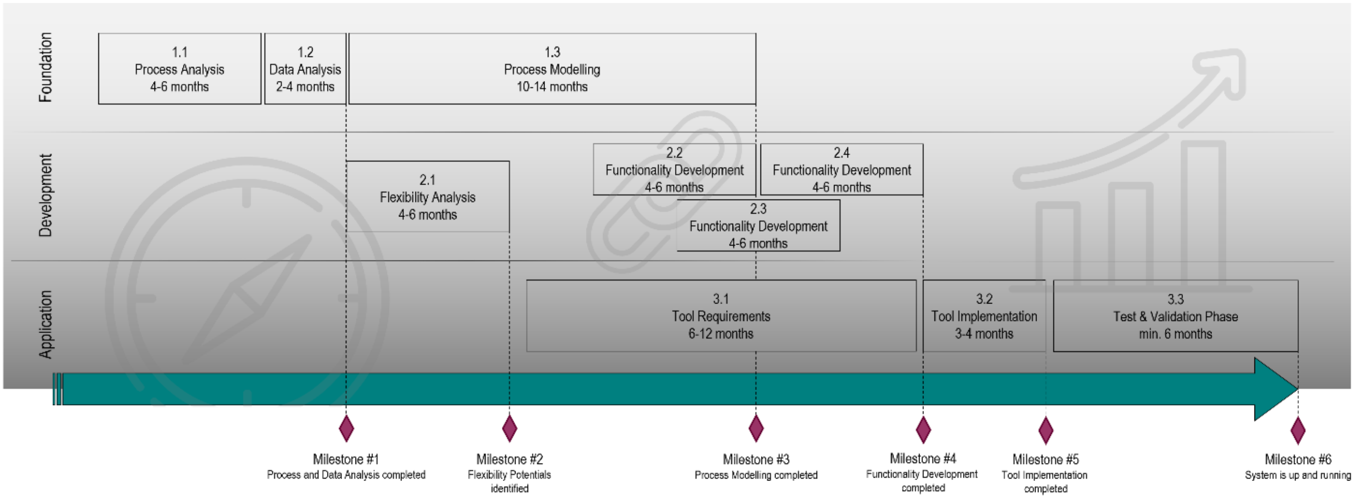


Figure 41: Timetable for DSM DSS-system project

6 Conclusion and Outlook

Based on the work done in the project DSM_OPT, the following general conclusions can be drawn:

- Optimized Forecasting and Scheduling
  Advanced forecasting models and improved day-ahead (or longer-term) planning can significantly reduce electricity procurement costs and energy balancing needs for industrial consumers. This also alleviates grid stress and enhances overall energy efficiency. However, forecast accuracy declines over longer horizons, necessitating adaptive strategies such as rolling horizon approaches and real-time feedback loops (e.g., digital twins) to maintain alignment with actual operations.
- Industrial Flexibility and CO_2 Reduction
  DSM and optimized scheduling contribute to energy efficiency and CO_2 reduction. Improved scheduling helps avoid excess energy provision, leading to lower CO_2 emissions. Process automation and enhanced data connectivity increase predictability, making demand response strategies more effective.
- Economic and Technical Feasibility
  Optimized production scheduling enables cost savings and industrial flexibility without disrupting production continuity. By leveraging electricity price fluctuations, industries can achieve implicit

demand response. Optimization models are computationally feasible and provide realistic decision support, particularly when compared to manual scheduling efforts.

- Challenges and Future Potential
  Successful DSM implementation requires addressing operational, digitalization, and market challenges. A key barrier is the lack of mid-term electricity price forecasts, which limits the monetization of industrial flexibilities. This highlights the need for improved market structures, dedicated flexibility markets, and advanced forecasting tools. Digitalization investments and the integration of interactive scheduling tools can bridge the gap between theoretical optimization and practical application, supporting the transition to a more flexible and energy-efficient industry.
- Industry-Specific Considerations
  The application of DSM in industries with lower automation levels, such as bakeries, presents unique challenges despite its potential for energy savings. Manual labor, human expertise, and seasonal product variability create additional complexity. Traditional production methods, product-specific constraints (e.g., proofing times), and the prioritization of quality over high production volumes further limit the straightforward application of advanced DSM techniques.
  Expanding DSM adoption in such industries requires overcoming scalability issues, providing user-friendly interfaces, and fostering awareness of energy efficiency among staff. Additionally, external factors such as electricity market advancements, incentives for electrification, and investments in automation technologies will play a critical role in unlocking DSM's full potential.

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