Optimization through Automated Decision Support in District Cooling

Minimizing Electricity Use through Software-Based Start/Stop Control and Chiller Dispatch

Master's Thesis in Computer Science and Engineering

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Abstract

This thesis investigates how software-based decision support can improve operational efficiency in district cooling through automated start/stop control and chiller dispatch. The study was conducted as a design science case study at Göteborg Energi's district cooling network in Gothenburg, Sweden. The work addresses three main questions: identifying the main operational limitations in the current control strategy, designing a software-based artifact for improved dispatch decisions, and assessing which parts of the artifact are case-specific and which may be transferable to similar district cooling systems. The current operation was analyzed using historical operational data from 2025 together with input from domain experts. This analysis showed that the existing control strategy is only partly standardized in practice, since actual chiller dispatch varies under similar operating conditions and remains partly dependent on operator judgement. To address these limitations, a software-based artifact was developed consisting of empirical chiller performance models, a Mixed-Integer Non-Linear Programming (MINLP) optimization engine, and an interactive dashboard for visualization and fleet management. The artifact was evaluated through simulation using historical operating conditions from 2025 as a baseline. The results indicate that the proposed control strategy can improve operational efficiency while satisfying cooling demand and limiting daily start/stop events in accordance with the defined success criteria. The largest improvements were observed during the summer period when the electricity use was reduced by as much as 41.69%. The thesis thus contributes both a practical prototype and a design-oriented approach that may be adaptable to similar district cooling systems after local recalibration of the chiller models.

Keywords: Decision Support, Digital Twin, District Cooling Systems (DCS), Energy Efficiency Ratio (EER), Environmental Variable Modeling, Load Dispatch Optimization, Multivariate Linear Regression, Start/stop Scheduling.

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Jacob Clase & Samuel Lloyd, Gothenburg, June 2026

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1. Introduction

1.1 District Cooling

District cooling is a centralized cooling concept where chilled water is produced at central plants and distributed through a network to multiple buildings. Together with district heating, it forms part of integrated thermal energy systems in urban environments. Such systems enable interaction with other energy infrastructures and provide opportunities for improved overall energy efficiency, making district cooling a key component of future smart thermal grids (Lund et al., 2014).

1.1.1 Global Cooling Trends and Energy Use

The buildings and construction sector remains a primary driver of global energy demand, accounting for approximately 30–36% of global final energy use and 26% of energy-related emissions (GlobalABC, 2020; IEA, 2024). Within this sector, space cooling has emerged as the fastest-growing energy end-use in buildings, increasing at an average rate of 4% per year since 2000 (REN21, 2025). In 2022, electricity used for cooling accounted for approximately 20% of the total electricity use in buildings worldwide, a share that can rise to over 70% during peak demand periods on hot days in certain regions (IEA, 2023; UNEP, 2023). The global energy demand for space cooling is projected to triple by 2050 as rising temperatures and incomes increase access to air conditioning globally (UNEP, 2025).

As urban cooling demand increases, decentralized solutions in cities often result in high electricity use. District cooling addresses this challenge by enabling more energy-efficient and environmentally sustainable centralized cooling production (Buffa et al., 2019). However, literature emphasizes that the actual performance of district cooling systems depends not only on system design, but largely on operational control. Inefficient operating strategies can lead to significant energy efficiency losses even in technically well-designed systems, highlighting the importance of effective operational decision-making (Lund et al., 2018). To address these complexities, intelligent control systems can automate complex decisions and replace manual oversight with systematic, real-time control.

1.1.2 District Cooling in Sweden and the Evolving Global Market

In Sweden, the first district cooling system was commissioned in 1992 in Västerås, with the primary objective of replacing decentralized, local cooling chillers with a centralized cooling network (Abrahamsson & Nilsson, 2013). Since 1992 the district cooling has grown steadily and in 2023 Sweden (together with France) was the largest producer of district cooling in Europe with its 530 km district cooling net and spread across 40 different Swedish localities. That same year, Stockholm had the largest district cooling system in the world and both Gothenburg and Mölndal are planning to expand their district cooling to meet the rising demand (Renström & Haraldsson, 2023). Sweden has around 2500 delivery points where offices and commercial facilities account for for almost 40% of deliveries (Energiföretagen, 2025). The most common production techniques is cooling from heat pump followed by free cooling (Energiföretagen, 2025).

Climate change and increasing use of electrical equipment will together increase the temperature which makes the need for a cool indoor environment in both public and private facilities important even in northern countries such as Sweden (Palm & Gustafsson, 2018). Although Sweden is leading in district cooling production, the rapid expansion and increasing complexity of these networks have begun to challenge the traditional methods used to control them.

Globally, District Cooling Systems are increasingly recognized as a vital approach for delivering sustainable cooling, mitigating climate change, and reducing peak loads on power grids. However, the operational optimization of these expansive systems involves complex decision variables and constraints across multiple subsystems. Conventional control strategies often rely on local controllers that prioritize fixed set points over holistic, system-wide efficiency, causing significant energy losses when subsystems operate in isolation. Because the rigidity of fixed operational sequences is a primary barrier to energy-efficient operation, there is a documented global transition toward advanced, AI-driven and metaheuristic optimization frameworks designed to coordinate subsystems and minimize overall energy consumption (Reshi & Mursaleen, 2026).

1.2 Problem Description

District cooling systems operated by energy companies are inherently complex socio-technical systems (Hamstead et al., 2020). They typically consist of multiple production units with different characteristics and a diverse customer base with time-varying cooling demand (Liu et al., 2025). Despite this complexity, operational control in many cooling networks remains largely manual, relying on human intervention rather than systematic optimization and formalized decision support (Bian et al., 2025). This baseline configuration creates a general and recurring problem across energy companies offering district cooling, as operational decisions regarding unit scheduling, chiller start and stop sequences, storage utilization, and load balancing must be executed under continuous uncertainty and changing environmental conditions. Without integrated control and dispatch support, consistently operating these systems at or near optimal energy efficiency is difficult to achieve (Gang, Wang, Xiao, & Gao, 2016; Jangsten, 2020).

As district cooling systems expand in scale and infrastructure, this operational challenge is amplified. Long-term forecasts indicate significant growth in cooling demand within urban areas alongside increased thermal loads in commercial and public buildings. Scaling operations under these shifting baseline requirements exposes the limitations of experience-based control, leading to reduced process transparency, a high dependency on individual operator habits, and difficulties in maintaining consistent operational quality (Werner, 2017). A central issue with human-imposed control is that dispatch decisions are not always executed consistently with intended strategies or optimal operating conditions, introducing operational variability that affects overall system efficiency (Jelali, 2012). This industry challenge is clearly observable within the operational context of Göteborg Energi. Historical data reveals that cooling production efficiency varies under similar environmental conditions. This localized variance demonstrates that subjective human judgment cannot dynamically track the complex, non-linear efficiency curves of a multi-facility production fleet.

The underlying challenge is therefore the absence of a formalized, system-wide process and decision framework connecting production assets, storage capacity, network constraints, and control objectives. A prerequisite for addressing this issue is to identify, map, and structure operational processes and decision flows, enabling chillers and subsystems to be systematically integrated to form the basis for software-supported optimization and decision support (Conger, 2011). Taken together, these challenges reveal a distinct need for generic, transferable approaches that combine systematic process analysis with software-based optimization. Such frameworks must be broadly applicable across energy companies operating district cooling systems while remaining adaptable to local technical and organisational contexts (Lam et al., 2011).

1.3 Purpose of the Study

The purpose of this study is to investigate, design, and evaluate a software-based decision support artifact for the district cooling operations at Göteborg Energi in Gothenburg. This research involves mapping the current decision-making workflow, identifying operational constraints, and utilizing available data to specify the architecture of the artifact. This artifact is intended to recommend and automate operational dispatch decisions in a way that minimizes electrical power use while meeting fluctuating cooling demand. Based on a detailed process analysis, the developed artifact identifies which cooling chillers to operate and determines when to start or stop them to maximize electrical efficiency. These recommendations are based on key exogenous factors such as cooling demand, river water temperature, and outdoor temperature.

Another aspect of the study is to analyze the extent to which the developed artifact can be generalized and applied to other district cooling networks in Sweden. It is designed with a modular structure to explore how it might accommodate different facility configurations or the addition and removal of chillers. This investigation aims to distinguish between system specific components and those parts that are potentially transferable to other cooling networks with similar operational characteristics. The evaluation focuses quantitatively on the gains in electrical efficiency, determined by comparing the energy consumption of the proposed automated control strategy against the historical baseline of current manual operations. The final result provides a functional proof-of-concept and contributes to design knowledge within the district cooling sector.

1.4 Significance of the Study

This study is significant as it refines existing research on district cooling by focusing on combining software-based start/stop optimization with chiller-level operation. Previous research shows that district cooling systems have strong potential for high energy efficiency and reduced environmental impact when integrated with urban energy systems (Gang, Wang, Xiao, & Gao, 2016). The district cooling system in Gothenburg demonstrates this potential through the use of free cooling from the river (Göta Älv) and absorptions chillers driven by industrial waste heat. However, research also emphasizes that energy efficiency gains depend not only on system design but on optimized operational strategies and control (Werner, 2017). The current operation involves coordination between production units and manual operator intervention in the control and dispatch decisions, which can lead to suboptimal electricity use.

The significance of this study therefore lies not only in identifying operational inefficiencies in the current control strategy, but also in designing and evaluating a software-based artifact that addresses them. By developing empirical chiller models, an optimization-based dispatch engine, and a decision-support interface, the study contributes a transferable design approach for software-supported district cooling optimization, demonstrated through a functional proof-of-concept.

1.4.1 Research Questions

RQ1: What are the main operational limitations and inefficiencies in the current control strategy of Gothenburg's district cooling system, with respect to electrical power usage and chiller dispatch?

RQ2: How can a software-based tool be designed to automate start/stop decisions by utilizing exogenous environmental factors to predict optimal chiller efficiency, thereby minimizing electricity use while meeting varying cooling demand?

> **RQ2.1:** Which parts of the developed control and optimization tool are system-specific, and which parts are potentially transferable to other district cooling systems with similar operational characteristics?

2. Background

2.1 Historical Development of District Cooling in Gothenburg

Göteborg Energi started their district cooling system in 2002 when the cooling deliveries were around 30 GWh in Gothenburg. Today (2025) the demand is around 95 GWh and according to Göteborg Energi the demand is expected to grow to 160 GWh by 2040. At the same time, their strategic focus is to expand the centralized district cooling network while systematically reducing the use of decentralized, standalone cooling installations (Göteborg Energi AB, 2026).

2.2 Current System Overview

Today, there are 8 different facilities spread across Gothenburg. These facilities were fully integrated into one network in 2021, when the last facility, Lindholmen, was connected. The facilities are linked together through a nearly 50 km long pipeline that transports water between the production sites as well as to the customers. Cold water is delivered to the customers, who use it to cool their buildings or processes. The warmer return water is then transported back to the district cooling plants, where it is cooled down again.

The district cooling plants consist of absorption chillers driven by waste heat and compression chillers driven by electricity. Due to their ability to utilize waste heat, the absorption chillers are considered the most resource-efficient option, as they do not only rely on electricity that could be used for other purposes. In contrast, the compression chillers require electricity to produce cooling and are therefore less efficient from an energy system perspective. At the main facility, Rosenlund, it is also possible to use free cooling from the Göta Älv when the river water temperature is sufficiently low. During periods when the river water is not cold enough to fully cool the return water, it is possible to pre-cool the return flow using free cooling and then use the chillers to reach the required supply temperature. In addition, limited amounts of free cooling can be achieved using air cooling towers at the other facilities.

The temperature of the supply water is currently around 6°C and is heated by the customers to approximately 14°C - 16°C, which corresponds to the return temperature. This means that free cooling can be used when the river temperature is 5,5°C or below, allowing the return water to be cooled to approximately 6°C. As the river temperature increases, the capacity for free cooling gradually decreases, eventually making it necessary to rely solely on the cooling chillers. In practice, this implies that free cooling is available mainly during the winter period and is negligible during the summer.

In the academic literature, a distinction is commonly made between the Coefficient of Performance (COP) and the Energy Efficiency Ratio (EER). For cooling applications, the ratio between delivered cooling power and electrical input power is more precisely referred to as EER, whereas COP is traditionally defined using the heat rejected at the condenser divided by the electrical input power (W.-W. Wang et al., 2016). However, in Göteborg Energi's operational terminology, the term COP is used more broadly to denote cooling power divided by electrical power input. Since this study is based on Göteborg Energi's internal data, metrics, and operational practice, the terms COP, COSP, COPP, and CONP are retained throughout the thesis in accordance with the company's terminology.

The effectiveness of the chillers is measured as the total cooling power $P_{\text{cooling,unit}}$ delivered divided by the total power $P_{\text{elec,unit}}$ required to run the chillers. For a single chiller, this ratio is called COP, Coefficient of Performance. If the power needed for auxiliary equipment, such as pumps, fans, and cooling-tower components, is included, the metric is called COSP. If you instead divide the cooling power $P_{\text{cooling,plant}}$ delivered by an entire plant by the total power $P_{\text{elec,plant}}$ needed to operate that plant, you get COPP. Scaling one step further gives the COP of the entire network, which is called CONP. To evaluate chiller usage, this work focuses on COSP. It is the cooling power provided divided by the total power needed for a chiller to provide that cooling power, including auxiliary equipment.

$$COP = \frac{P_{\text{cooling,unit}}}{P_{\text{elec,unit}}}$$

$$COSP = \frac{P_{\text{cooling,unit}}}{P_{\text{elec,unit+aux}}}$$

$$COPP = \frac{P_{\text{cooling,plant}}}{P_{\text{elec,plant}}}$$

$$CONP = \frac{P_{\text{cooling,sys}}}{P_{\text{elec,sys}}}$$

The overall efficiency of the district cooling network, measured as CONP, can fluctuate significantly even when the total delivered cooling power, $P_{\text{cooling,sys}}$, remains constant. This network-level variation is largely driven by manual dispatch decisions, as human operators may select different combinations of chillers to satisfy the same demand. Simultaneously, efficiency variations occur at the individual chiller level. A specific chiller may deliver an identical cooling load, $P_{\text{cooling,unit}}$, but have a varying COSP due to fluctuating exogenous factors such as ambient temperature and humidity. Because this study aims to develop an optimized automated dispatch strategy, the focus is placed entirely on how chiller-specific environmental factors influence COSP, which ultimately dictates the optimal network configuration.

Göteborg Energi manages cooling production using a rule-of-thumb document that specifies a start up order for its chillers. Approximately 60 operators manage the system without standardized decision support, which results in significant operational variability. The primary control mechanism depends on temperature sensors at the supply water pipes. When temperatures exceed 6°C, the active chiller increases its load until reaching 100 percent capacity. If the supply temperature from a cooling plant exceeds 7°C, an alarm is triggered to alert the operators that additional cooling is needed and that an additional chiller may need to be started manually. Operators sometimes choose to start multiple units simultaneously to proactively cover expected demand rises over the following hours. This approach allows them to maintain the required temperature over a broader demand interval with fewer manual interventions even though it is less efficient than running a single chiller at its most efficient load. The predefined start up list is only overridden when specific constraints are present. These include limited waste heat for absorption chillers or chiller unavailability due to maintenance. In these instances, operators skip the affected units and proceed to the next available chiller on the list.

In 2029, Göteborg Energi plans to build an accumulator (ACK). The Accumulator (ACK) is a storage tank that can store chilled water with a capacity of 40 MW. It is intended to handle fluctuations in the network. It is planned to be charged during the night when demand is lowest.

3. Related Work

3.1 District Cooling Optimization Approaches

Powell et al. (2013) investigate the optimal operation of a district cooling system with thermal energy storage. The study evaluates performance by minimizing energy consumption and total cost. This is done using static optimization and dynamic optimization to determine how much chiller load should be produced over time. The factors considered in the study include load, temperature variables, and ambient conditions via wet-bulb temperature. This article is related to the present work because it addresses software-based operational optimization of cooling chillers in a district cooling system, with the goal of reducing electricity use. Although the study focuses on optimal chiller loading and thermal storage rather than explicit start/stop control, it is highly relevant since it optimizes chiller-level operation over time using measured system data. While Powell et al. (2013) focus on operational optimization of chiller loading and thermal storage, other studies address broader optimization problems in district cooling systems, including network design and system constraints.

Khir and Haouari (2015) examine how cooling production can be scheduled during off-peak hours and stored for later use through thermal energy storage. The article argues that the optimization of a district cooling system (DCS) requires a customized optimization model due to its specific system characteristics. In particular, pressure and temperature constraints are identified as important factors that are often overlooked in DCS optimization. The study develops a mathematical optimization model aimed at minimizing cost while maintaining system efficiency. The model considers parameters such as chiller capacity, storage tank size, as well as pipeline dimensions and lengths. Based on these factors, the optimal cooling production and storage schedule over time is determined. Wile Khir and Haouari (2015) successfully integrate physical infrastructure constraints into scheduling logic, their macro-level deterministic approach fails to capture the localized, non-linear variations in chiller performance caused by hourly ambient shifts. This thesis attempts to address this limitation through empirical, data-driven modeling of the chillers.

In addition to optimization model development, review studies provide a broader overview of how district cooling optimization has been approached in planning, design, and operation. Gang, Wang, Xiao, and Gao (2016) review research on the optimization of district cooling systems (DCS) in terms of planning, design, and operation. It concludes that the operation and control of a DCS are more complex compared to traditional cooling systems. The authors emphasize that accurate cooling load prediction is essential for system control, particularly when thermal energy storage is used. Furthermore, previous research on operational optimization has applied both linear programming and, in more recent studies, nonlinear programming methods. Key strategies identified to reduce energy consumption include: (1) reducing pipeline resistance, (2) increasing the thermal capacity of the fluid in the chilled water network, and (3) limiting pipe distances while enlarging the temperature difference between supply and return chilled water. The article further argues that research on global system-level control of DCS remains insufficient. It also states that "operation optimization considering the dynamic response of DCS and the interaction between users and operators needs to be studied" (Gang, Wang, Xiao, & Gao, 2016). This thesis attempts to address this gap by first evaluating the empirical limitations of manual control. Based on these diagnostic insights, a Mixed-Integer Nonlinear Programming (MINLP) approach is utilized to map real-time exogenous variables to automated dispatch logic. This artifact is designed to replace subjective operator judgment with optimized actions, aiming to mitigate system-level inefficiencies.

3.2 Operational Challenges in District Cooling Systems

Jangsten et al. (2020) address performance challenges related to a low temperature difference between supply and return water, commonly referred to as low ΔT. The article describes this as a widespread issue in district cooling systems and notes that it has been documented since the 1980's under the term "low ΔT syndrome." A low ΔT leads to increased flow rates and consequently unnecessary electricity consumption for pumping. The issue is therefore strongly related to the present work, although the study does not focus on the cooling chillers themselves. The study proposes several measures to increase the ΔT in order to reduce electricity consumption and therefore serves as a valuable complement to the present work when optimizing energy efficiency. A more detailed description of the studied system is provided in the related thesis by Jangsten, 2020.

3.3 Human Factors in Operational Decision-Making

Muhammad (2021) investigates how human operation can affect a system's performance, and notes that performance can be influenced by human factors such as workload. The paper argues that the performance of the operator directly influences the overall system performance. It also describes that operator and work related factors, such as fatigue, sleep schedule, task type, and shift related factors, can affect mission objectives and performance in human in the loop systems. This supports the decision to develop an automatic software-based start/stop control system to reduce the influence of human factors when determining which chillers should be on or off.

3.4 Software-Based Start/Stop Control in Related Systems

While previous studies have addressed software-based operational optimization of district cooling systems, we have not identified prior work that specifically focuses on software-based start/stop control optimization for chiller-level operation in district cooling systems. However, there is related research on minimizing electricity use in HVAC (Heating, Ventilation and Air Conditioning) systems. H. Wang et al. (2023) studied how to reduce energy consumption through periodic start/stop control while still meeting indoor environmental requirements. This study was also based on operational data. Although the study is not based on district cooling, it is relevant to the present work because it demonstrates that software-based start/stop control can reduce energy use in a real operational environment.

3.5 Identification of Related Research

To position this study in relation to existing research, a structured search of the literature was conducted with the aim of identifying previous work on similar problems. The search focused particularly on software-based approaches for start/stop optimization to reduce electricity use, prior research on district cooling optimization, and studies addressing how manual human involvement may influence system performance.

Google Scholar was used as the primary search engine for identifying relevant publications. Scopus, IEEE Xplore, and ScienceDirect were mainly used to retrieve full-text articles when available, although additional sources were consulted when highly cited publications were not accessible through these databases. Both domain-based keyword searches and author-tracking were applied. The following search keywords were used: District cooling optimization, Maria Jangsten, Bottlenecks district cooling, Operator intervention OR manual override OR human-in-the-loop, Start/stop optimization district cooling AND software, Optimal chiller AND district cooling. The screening process was iterative. First, relevant titles were identified from the initial search results. Second, abstracts were reviewed to assess the relevance of each study. The remaining articles were then screened further through their figures, section headings, and overall scope. Finally, the most relevant articles were read in full and included only if they were still considered relevant.

To identify the most relevant articles, keywords such as operational optimization, energy consumption, real-time control, start/stop scheduling, energy minimization, and electricity use were used. The most relevant articles were those that included these terms in the context of district cooling, cooling plants, or other relevant industrial energy systems. Articles were excluded if they focused only on software source-code optimization, were purely theoretical without evaluation, or addressed only component-level analysis without considering system-level operational decisions.

3.6 Research Gap

Overall, previous research has addressed district cooling optimization, operational performance challenges, and software-based control in related HVAC applications. Based on the conducted literature review, we have not identified prior work that combines software-based start/stop optimization with chiller-level operation in district cooling systems in the same way as the present study. To the best of our knowledge, the reviewed literature also does not include prior studies that combine city-scale, chiller-level start/stop and dispatch optimization with an explicit representation of river water as an operational cooling source (e.g. for free cooling and pre-cooling) in the decision logic.

4. Methods

4.1 Research Approach

In this study, Design Science Research (DSR) is used because the work addresses a practical problem that the study aims to solve. The problem is addressed by designing and evaluating an artifact, rather than solely answering research questions. In this thesis, the artifact is a software-based decision support tool designed to automate start/stop and dispatch decisions for district cooling production units. Wieringa (2010) distinguishes between practical problems (e.g., stakeholders' goals and the current situation) and knowledge questions. In Design Science Research, the starting point is ultimately a practical problem that the artifact is intended to improve. Baskerville et al. (2009) state that the problems addressed in Design Science Research are often socio-technical in nature, which makes them more difficult to evaluate than purely technical problems.

Design Science Research (DSR) serves as the overall research approach of this study, since the work aims to address a practical problem through the design and evaluation of an artifact. To structure this process more explicitly, the study applies the Design Science Research Methodology (DSRM) proposed by Hevner and Chatterjee, 2010, which provides the stepwise framework used to organize the research process.

This methodology is also suitable because it requires stakeholders' goals to be operationalized into measurable evaluation criteria, and the artifact to be validated and/or evaluated against those criteria. Wieringa (2010) notes that treating a design problem as purely empirical research risks neglecting key design-science concerns, such as practical problem identification, stakeholder-motivated evaluation criteria, and trade-off and sensitivity analysis. In addition, Baskerville et al. (2009) emphasize an iterative design–build–evaluate process that is repeated until the specific requirements are met.

Finally, Wieringa (2010) describes how empirical methods in design science can be used either for validation before an artifact is implemented in practice or for evaluation after implementation. He also notes that design knowledge often has middle range generalizability, meaning that it is neither fully case specific nor fully universal. This aligns with an approach where a solution is developed for a specific case while also analyzing which parts may be transferable to other contexts.

This study follows the Design Science Research Methodology (DSRM) described by Hevner and Chatterjee (2010). The methodology structures the research process into six steps: (1) problem identification and motivation, (2) definition of the objectives for a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication.

DSRM was chosen because it provides a clear and commonly understood structure for organizing a design science thesis, ensuring that the work progresses logically from problem identification and solution objectives to artifact development, demonstration, and evaluation, and that these elements are reported in a consistent way (Hevner & Chatterjee, 2010). Using this framework makes it easier to present the study's contribution as a design artifact and to connect the evaluation directly to the stated objectives, rather than describing the work as a set of disconnected activities. It therefore supports a transparent research process and a clear presentation of objectives, methods, and outcomes within a recognized structure.

4.2 Problem Identification and Motivation

The first phase of the DSRM process involves defining the specific research problem and justifying the value of a solution. In this thesis, the problem identification was informed by both prior research and practical insights from the case context. While the synthesis of prior research is presented in Chapter 3 and serves to establish the academic motivation for the study, this section focuses on the practical operational challenges identified at Göteborg Energi and how these shaped the problem formulation. This phase primarily addresses RQ1 by identifying the practical operational challenges that motivate the study.

4.2.1 Qualitative Insights from Domain Experts

To understand the system, informal conversations were used. This approach was chosen because informal conversations can facilitate ease of communication and provide more naturalistic insights into everyday operational reasoning (Swain & King, 2022). These conversations were primarily conducted with a process engineer and a business manager. In addition, working mainly from Göteborg Energi's headquarters enabled input from several other employees, and this information could be validated by the business manager. However, a recognized methodological limitation of such conversational approaches is that they do not ensure uniform questioning or standardized interpretation. Consequently, the qualitative insights obtained through this process may be subject to variations in how specific operational issues were contextualized, discussed, and understood (Conrad & Schober, 1999).

Throughout the project, informal conversations were conducted continuously as part of recurring weekly meetings with representatives from Göteborg Energi. These conversations primarily involved a process engineer and a business manager and typically lasted between 30 and 60 minutes. Notes were taken in some of the meetings to document operational explanations and system-related clarifications. Additional clarifications were also obtained through digital communication channels, mainly Microsoft Teams, when needed. The conversations were used primarily to improve the understanding of the district cooling system, current operational workflows, and practical system constraints. They also supported the interpretation of operational data, the clarification of assumptions used in the study, and the identification of requirements relevant to the design of the proposed artifact. Throughout the process, these recurring discussions also served to continuously assess whether the ongoing work was aligned with the practical conditions and operational understanding at Göteborg Energi.

Today, the system is operated by human operators who follow a rule-of-thumb document specifying a start-up order for the chillers. The system does not provide instructions on when to start and stop production units, nor does it clearly indicate the optimal timing. As a result, units may be started too early or too frequently, and may operate at suboptimal efficiency. Based on these conversations, the current approach is not described as being based on statistical analysis. Instead, operators primarily aim to ensure that the supply water temperature is maintained.

4.3 Definition of Objectives for a Solution

In accordance with the DSRM framework, the objectives of the proposed solution must be explicitly defined. This involves establishing the operational boundaries of the specific case study and defining the quantitative success criteria used to evaluate the final artifact. Building on the findings related to RQ1, this phase defines the objectives that the proposed artifact must fulfill in order to address RQ2.

4.3.1 Case Study and System Boundaries

The case studied in this work is the district cooling system in Gothenburg. The system is operated by Göteborg Energi, which is interested in a decision support tool for optimizing start/stop decisions in order to reduce electricity use for different types of cooling production units. The study investigates whether an automated approach, evaluated through a prototype, can reduce electricity use and thereby indicate the potential of software-supported start/stop operation of the production units. More specifically, the prototype evaluates relevant parameters to simulate which chillers should be started or stopped over time, how many units should be running, and how the cooling load could be distributed among the running units. The production units considered in this study include compressor chillers, absorption chillers, and free cooling, and there are also plans to build a large thermal energy storage tank for chilled water by 2029. The study focuses on start/stop decisions and does not include system design decisions such as pipeline dimensions or plant locations. Instead, it focuses on the current system without recommending new system designs. The study also assumes that the supply and return water temperatures are well controlled. The analyzed data consists of hourly measurements from 2025. The goal is to improve CONP (and thereby reduce electricity consumption) compared with previous years, and to be better prepared for a future increase in district cooling demand.

4.3.2 Success Criteria and Metrics

The success of the proposed automated decision support approach is evaluated by comparing the simulated operation against the historical operation during 2025. The primary success criterion is an improved system performance, measured as a higher CONP, which corresponds to reduced electricity use for the same cooling delivery. Performance is reported as a relative improvement compared with the historical 2025 operation. The evaluation is performed on a daily basis across 2025 to assess whether the simulated operation consistently performs better than the observed operation.

$$\mathrm{CONP}_{\mathrm{sim}}(2025) > \mathrm{CONP}_{\mathrm{hist}}(2025)$$

In order for the success criterion to be considered achieved, the following baseline requirements must also be satisfied:

- Cooling demand is fully met for each evaluated timestep.
- The number of daily start/stop events per unit does not exceed 2.

4.4 Design and Development

The third step of the DSRM framework involves creating the artifact and determining its architecture. For this study, the artifact is a software-based optimization tool built upon historical operational data, rule-based control logic, and a formal MINLP mathematical formulation. This phase primarily addresses RQ2 through the design and development of the artifact. Furthermore, by explicitly defining the case-specific constraints of the Gothenburg network in this section, we lay the groundwork for RQ2.1. This documentation enables the analysis in Chapter 7, which evaluates which components of the artifact are unique to this system and which are scalable to other district cooling networks.

4.4.1 Quantitative Operational Data Extraction

The quantitative data used in this study primarily includes COP, COSP, and CONP as performance metrics (result variables). The exogenous variables considered to affect these metrics include outdoor temperature, river temperature, air humidity, wet-bulb temperature, and cooling demand (MW). The dataset was obtained from Göteborg Energi upon request, is owned by Göteborg Energi, and covers the district cooling system in Gothenburg. COP, COSP, and CONP are derived from Göteborg Energi's internal metering installed on each chiller, where electricity use is measured for the chiller only, for the chiller plus auxiliary equipment, and for the entire plant. Cooling output (i.e., the measured cooling production) is also measured, enabling calculation of the performance metrics. This study analyzes hourly data from 2025, but some observations are excluded due to incorrect data (see: Data Preprocessing and Cleaning). All explanatory variables except cooling demand are obtained from

SMHI or calculated based on SMHI data (wet-bulb temperature), while cooling demand is provided by Göteborg Energi.

4.4.2 Data Preprocessing and Cleaning

The raw operational data from Göteborg Energi and the meteorological data from SMHI were both extracted in a unified hourly format. A fundamental principle of the data cleaning process was to avoid generating synthetic data points that could skew the thermodynamic baseline. Consequently, missing observations were generally excluded from the dataset rather than imputed. A necessary exception was made for the river water temperature readings at the Rosenlund facility. When cooling production halts at this specific plant, the stagnant water causes the local temperature sensors to record inaccurate environmental readings, sometimes persisting for intervals exceeding two weeks. Because river temperature is governed by high thermal inertia and exhibits highly predictable, slow-changing temporal gradients (Monteith & Unsworth, 2013, Chap. 3), linear interpolation was applied to bridge these specific gaps. This approach preserved the continuity of the environmental state vector without introducing high-frequency noise or synthetic anomalies into the dataset.

Outlier detection and removal were strictly governed by qualitative domain knowledge provided by process engineers at Göteborg Energi. Several physical and mechanical sensor limitations required data exclusion to ensure the validity of the subsequent models. First, operational data recorded when a chiller was running at less than 30% of its nominal capacity was removed, as internal sensor accuracy degrades significantly at these extreme low-load conditions. Second, observations from specific chillers with documented sensor defects were either entirely excluded or filtered to remove exceptionally high, physically improbable COSP values exceeding 10.0. Furthermore, it was identified that the internal logging system artificially caps recorded COSP values at 30.0. While the machinery can theoretically achieve higher efficiencies under optimal conditions, these artificially capped values were retained in the dataset but are explicitly acknowledged as a boundary limitation in the final evaluation of the model's predictive accuracy.

Finally, to accurately model the thermodynamic efficiency of the cooling towers and heat exchangers, the wet-bulb temperature was calculated as a derived feature using Stull formula. Let T denote the ambient air temperature in degrees Celsius and RH denote the relative humidity as a percentage. The wet-bulb temperature, T_{wb}, was mathematically derived for every hourly observation as follows:

$$
\begin{aligned}
T_{wb} = T &\cdot \arctan(0.151977 \cdot (RH + 8.313659)^{0.5}) \\
&+ \arctan(T + RH) \\
&- \arctan(RH - 1.676331) \\
&+ 0.00391838 \cdot RH^{1.5} \cdot \arctan(0.023101 \cdot RH) \\
&- 4.686035
\end{aligned}
\tag{4.1}
$$

4.4.3 chiller Performance Modeling and Parameter Fitting

Empirical mathematical models were developed to represent the thermodynamic efficiency of each individual chiller. These models are utilized to estimate the power consumption of a chiller under varying environmental conditions and cooling loads. This provides the mathematical foundation for the optimization objective. Data-driven parameter fitting was performed using regression analysis. For each chiller, historical operational data was utilized to fit performance curves that map the dependent variable, electricity consumption, to key exogenous variables, specifically the required cooling load, wet-bulb temperature, and river water temperature. The accuracy and predictive reliability of these resulting polynomial curves were evaluated using the coefficient of determination (R^2).

4.4.4 Control Logic and Decision Concepts

The proposed software-based artifact is designed to evaluate a conceptual transition of operational decision-making from human intervention to a deterministic, efficiency-oriented algorithm. For the purposes of the model, the control logic treats the 50 km interconnected pipeline and its 8 facilities as a single contiguous thermal grid. The algorithm's decisions are computed strictly to maximize the overall Coefficient of Network Performance (CONP) while satisfying fluctuating cooling demands.

A primary priority within the dispatch logic is the maximization of free cooling from the Göta Älv river. Because free cooling operates independently of the mechanical chiller dispatch, it is treated as a deterministic exogenous parameter rather than an optimized variable. For every discrete hourly interval t, the simulation algorithm imports the exact historical free cooling production recorded during the 2025 operational baseline. Mechanical cooling units are only permitted to start when the cooling demand exceeds the physical capacity of the free cooling. When mechanical cooling is required, the algorithm ranks all available chillers based on their real-time predicted Coefficient of System Performance (COSP), which accounts for all electricity needed to power, pump, and sustain the machinery.

A fundamental operational constraint of the district cooling network is that the cooling demand must be satisfied at all times to prevent supply temperature degradation, excessive network flow rates, and subsequent breaches of customer service agreements. To manage this while maximizing CONP, the algorithm continuously evaluates the marginal electrical cost of the required cooling. When demand fluctuates, the algorithm evaluates whether it is more efficient to adjust the intensity of the currently active fleet or to initiate an additional chiller. While starting a new chiller to cover a minor load increase might result in a temporary simulated degradation of CONP, this action is treated as a necessary operational constraint if the modeled active fleet reaches 100% capacity. In such instances, the hard constraint to cover the system demand overrides efficiency optimizations within the simulation, and an additional chiller is started.

4.4.5 Optimization Formulation and Constraints

The operational control of the district cooling network is formulated as a Mixed-Integer Non-Linear Programming (MINLP) problem. The application of MINLP is an established approach in district cooling optimization, as it accommodates both the discrete binary decisions required for chiller sequencing and the non-linear thermodynamic behavior of chiller efficiency under varying loads (Powell et al., 2013). Because the thermal energy storage is excluded from this baseline formulation, the system does not require a predictive dynamic time horizon. Instead, the problem is treated as a sequence of real-time static optimizations evaluated at discrete time intervals, t. The objective is to determine the optimal active set of cooling chillers and their respective thermal loads to minimize the total electrical power consumption of the network, thereby maximizing the overall Coefficient of Network Performance (CONP).

To formulate this mathematically, two distinct types of decision variables are required. For each mechanical cooling unit i in the set of all available chillers N, a continuous decision variable, $Q_{i,t}$, represents the thermal cooling load assigned to that chiller at time t, measured in megawatts. To accommodate the non-linear operational limits of the equipment, a binary decision variable, $\delta_{i,t} \in \{0, 1\}$, is introduced. This binary variable dictates the operational state of the chiller, where $\delta_{i,t} = 1$ if chiller i is active at time t, and $\delta_{i,t} = 0$ if it is offline.

The objective function of the algorithm is to minimize the total electrical power consumption of the active mechanical fleet while penalizing excessive chiller cycling. The power consumption of an individual chiller i, denoted as P_i, is a non-linear function of its assigned cooling load $Q_{i,t}$ and an environmental state vector E_t, which encompasses all external variables that impact chiller efficiency. A recognized vulnerability in discrete dynamic chiller optimization is excessive switching that induces mechanical wear and transient electrical inefficiencies (Powell et al., 2013). To deter this behavior, a start-up penalty variable, S_i, is applied when a chiller transitions from an offline state in the previous time step, $\delta_{i,t-1}$, to an active state. The objective function evaluated at any given time step t is expressed as:

$$\text{Minimize} \quad Z_t = \sum_{i=1}^{N} \Big(P_i(Q_{i,t}, E_t) \cdot \delta_{i,t} + S_i \cdot \max(0, \delta_{i,t} - \delta_{i,t-1}) \Big) \tag{4.2}$$

Subject to this objective, the algorithm must satisfy the physical and thermodynamic boundaries of the district cooling infrastructure. The primary constraint dictates that the aggregate cooling load generated by the active fleet, in addition to any available free cooling from the river, $Q_{free,t}$, must equal the total system demand, D_t, at all times. This demand constraint is defined as:

$$Q_{free,t} + \sum_{i=1}^{N} Q_{i,t} \cdot \delta_{i,t} = D_t \tag{4.3}$$

Furthermore, the continuous variable $Q_{i,t}$ is strictly bounded by the physical capacity of the machinery. If a chiller is designated as active, its assigned load must fall between its minimum stable operational limit, $Q_{min,i}$, and its maximum nominal capacity, $Q_{max,i}$. This boundary constraint is expressed as:

$$Q_{min,i} \cdot \delta_{i,t} \leq Q_{i,t} \leq Q_{max,i} \cdot \delta_{i,t} \quad \forall i \in N \tag{4.4}$$

Finally, the dispatch logic must account for the thermodynamic constraints of the absorption chillers. Let $A \subset N$ denote the subset of mechanical units that are absorption chillers. Due to the lack of data regarding the availability of industrial waste heat throughout the evaluated year, a simplified deterministic heuristic was established in consultation with a process engineer. First, thermal waste heat is assumed to be available to the cooling network strictly when the average daily air temperature is 12°C or higher. Second, during these periods of availability, it is assumed that the district heating supply temperature is consistently sufficient to allow all active absorption chillers to operate up to their nominal maximum cooling capacities. This 12°C threshold is a simplified modeling approximation rather than a real-world certainty. Shifting this parameter to 10°C or 14°C would merely alter the simulation's estimations, risking either an overestimation or underestimation of waste heat. It functions strictly as a balanced approximation for evaluating the prototype. While it is acknowledged that physical waste heat availability is not strictly binary, this temperature-based threshold was necessary to avoid introducing synthetic data. Let $H_i(Q_{i,t}, E_t)$ represent the thermal energy required by an absorption chiller to produce its assigned cooling load under the current environmental state. The total thermal energy consumed by the active absorption fleet must not exceed the maximum available waste heat, $W_{\text{avail},t}$, at time t. This resource constraint is defined as:

$$\sum_{i \in A} H_i(Q_{i,t}, E_t) \cdot \delta_{i,t} \leq W_{\text{avail},t} \tag{4.5}$$

4.5 Demonstration

The fourth stage of the DSRM process involves demonstrating the utility of the developed artifact in solving one or more instances of the identified problem. In this study, the effectiveness of the automated decision support tool is demonstrated through a complete time-series simulation utilizing the full 365-day historical dataset from the Gothenburg district cooling network for the year 2025. This step demonstrates the artifact's ability to address RQ2 under historical operating conditions.

4.5.1 Simulation Environment

To demonstrate the utility of the MINLP optimization algorithm, the simulation was implemented in Python utilizing the GEKKO optimization suite. The decision support tool was sequentially subjected to the exact exogenous conditions experienced by the physical system historically.

The simulation steps through the 2025 dataset in discrete 60-minute intervals (t). At each step, the algorithm is fed the recorded cooling demand, ambient wet-bulb temperature, and river water temperature. To accurately handle the start/stop constraints without foresight of future demand, the model functions sequentially. The binary operational state of each chiller at time t is explicitly constrained by its state at $t-1$. Constrained by these external variables and the physical boundaries of the machinery, the GEKKO solver computes the optimal active fleet configuration and proportional load distribution for that specific 60-minute window, mirroring the conditions of real-time operational dispatch.

4.5.2 Baseline Definition

A critical component of demonstrating the artifact's effectiveness is establishing a comparative baseline. The baseline for this study is defined as the actual, human-operated dispatch decisions recorded during the full 2025 operational year, sampled at identical 60-minute intervals.

Because the proposed optimization artifact only dispatches specific cooling chillers rather than the entire pumping network, utilizing the standard, system-wide CONP would dilute the comparative results. Therefore, a Modified Coefficient of Network Performance (CONP_{mod}) is established for this demonstration. This modified baseline isolates the actual Coefficient of System Performance (COSP) of the specific chillers targeted by the algorithm, excluding the electricity consumption of unoptimized ancillary pumps. By isolating these variables, the simulation indicates how the deterministic GEKKO model responds to identical cooling loads compared to the manual, rule-of-thumb approach utilized by the control room operators.

4.6 Evaluation

The fifth stage of the DSRM framework involves observing and measuring how well the artifact supports a solution to the problem. This is achieved by comparing the objectives defined in Section 4.3 against the observed results from the demonstration phase. This section outlines the methodological strategy used to evaluate the artifact's performance and acknowledges the validity and limitations of the research design. This step evaluates how well the artifact meets the objectives defined for RQ2.

4.6.1 Evaluation Strategy

The primary success criterion for the proposed automated decision support approach is a quantifiable improvement in the active fleet's efficiency. The evaluation strategy utilizes a comparative time-series analysis between the simulated MINLP operation and the historical 2025 baseline over the full 365-day period.

To evaluate the performance of the artifact, the Modified Coefficient of Network Performance (CONP_{mod}) is aggregated and analyzed. For the artifact to meet the defined success criterion on any given day, the simulated result must give a mathematically higher performance metric than the historical baseline: $\text{CONP}_{\text{mod, sim}} > \text{CONP}_{\text{mod, hist}}$. Furthermore, the evaluation incorporates strict penalty checks to ensure operational feasibility.

4.6.2 Research Validity and Limitations

To ensure the validity of the evaluation, the simulation utilized the exact same historical exogenous variables experienced by the human operators. However, several limitations must be acknowledged when interpreting the results. First, the evaluation relies on mathematical component models that assume the chillers operate strictly according to their derived thermodynamic efficiency curves.

Second, the historical dataset contains real-world operational noise, including known sensor inaccuracies and general measurement errors. While preprocessing mitigates extreme outliers, this introduces a degree of uncertainty when comparing simulated optimization against actual operations. Furthermore, data availability varies heavily across the chillers. Frequently used chillers have over 3,000 data points, while rarely used ones have as few as 45, making the efficiency models for these lesser-used chillers much less reliable.

Third, as identified during the data preprocessing phase, the internal logging system at Göteborg Energi artificially caps recorded COSP values at 30.0. While retained in the baseline dataset, this artificial ceiling may slightly skew the historical baseline's thermodynamic representation. Finally, the evaluation focuses strictly on the current operational configuration and does not dynamically model the thermal accumulator (ACK) planned for deployment in 2029, which will fundamentally alter future start/stop constraints and load-shifting capabilities.

Lastly, a limitation of the proposed optimization model is the abstraction of intra-plant hydraulics. The MINLP formulation simplifies piping constraints and internal control logic of individual cooling plants, treating each chiller as an independent unit within a unified thermal network. This abstraction was chosen to ensure the software artifact remains highly generalizable, allowing the model to demonstrate the theoretical potential of system-wide thermodynamic optimization across diverse district cooling architectures. Consequently, certain theoretical load distributions dictated by the generated dispatch schedule may prove physically infeasible in practice.

Ethical Considerations

Ethical considerations in this study primarily concerned the handling of operational data and contextual information obtained through collaboration with Göteborg Energi. Informal conversations were used only to support system understanding and are therefore not reported at the individual level, but only through professional roles. No personal data from employees were analyzed or presented in the thesis. The operational data provided by Göteborg Energi were used exclusively for the purposes of this study and were handled with attention to confidentiality and data minimization. Results are presented in aggregated form, and the study was conducted with consideration for principles of research integrity, reliability, honesty, respect, accountability, and responsible data handling, in line with the European Code of Conduct for Research Integrity (ALLEA, 2023).

4.7 Communication

The sixth and final stage of the DSRM framework involves communicating the specific problem, the developed artifact, its utility, and its contribution to academic research. Because this research bridges theoretical computer science and applied industrial engineering, the communication strategy is dual-pronged, targeting both the academic community and the industrial stakeholders at Göteborg Energi.

Within the academic context, this research is communicated through the publication and formal defense of this master's thesis at the Department of Computer Science and Engineering at Chalmers University of Technology. The thesis documents the transition from a manual, rule-based dispatch heuristic to an automated, MINLP-driven decision support system, thereby contributing empirical findings to the broader academic discourse on smart thermal grid optimization and district cooling digitalization.

Within the industrial context, the practical utility and operational implications of the IT artifact are communicated directly to the process engineers, management, and control room operators at Göteborg Energi. This is achieved through formal presentations and the handover of the quantitative results. By communicating these findings, the theoretical energy savings identified via the Modified Coefficient of Network Performance (CONP_{mod}) can be evaluated by the stakeholders for future integration into the live production environment.

5. Results

5.1 Operational Limitations and Inefficiencies in the Current Control Strategy

To manage chiller start/stop decisions, operators follow a predefined start-up list developed by a process engineer at Göteborg Energi. The list is based on which chillers typically provide the best COSP. This is used together with a system called Optima, which generates an operational plan and informs the operator about the availability of waste heat. According to the informal conversations, different operators use different approaches to manage the operation. Some rely on Optima, while others only follow the start-up list.

As shown in Figures 5.1 and 5.2, both river temperature and wet-bulb temperature are correlated with chiller efficiency. The figures show higher COSP values at lower river and wet-bulb temperatures. Similar temperature dependencies were observed for several production units, motivating the inclusion of river and wet-bulb temperature as explanatory variables in the analysis.

Figure 5.3 shows a substantial spread in CONP across a wider range of river and wet-bulb temperatures. In Figure 5.3, the wet-bulb temperature ranges from 10°C to 18°C and the river temperature ranges from 14°C to 20°C.

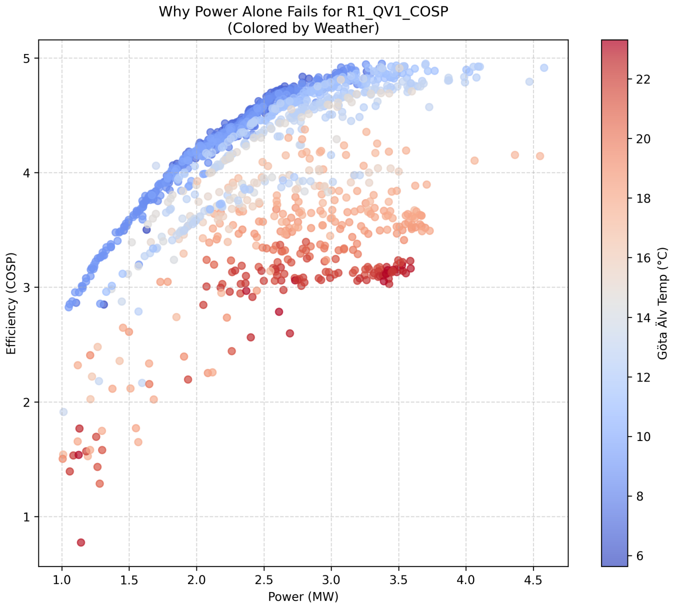


Figure 5.1: COSP as a function of electrical power for unit R1 QV1 (compressor chiller), colored by Göta Älv river temperature (2025 hourly data).

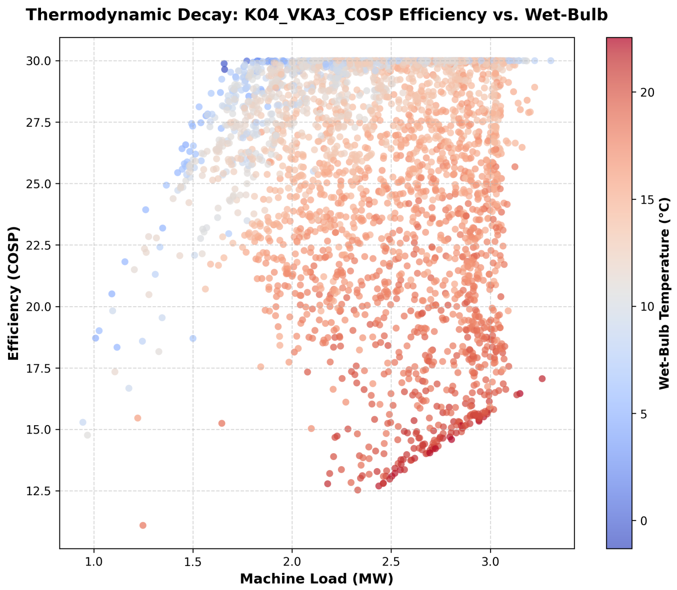


Figure 5.2: COSP as a function of chiller load for unit K04 VKA3, colored by wet-bulb temperature (2025 hourly data).

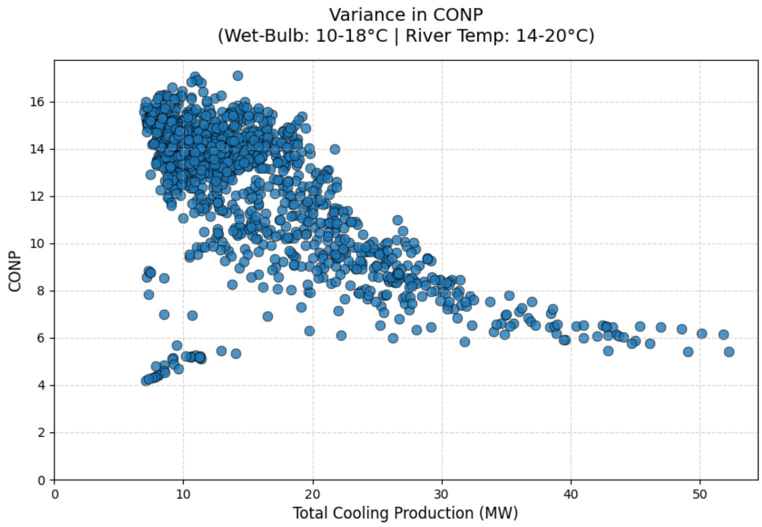


Figure 5.3: CONP versus cooling production for hourly data in 2025 (broad temperature ranges).

To reduce the influence of weather conditions, the data was then restricted to a narrower interval. Figure 5.4 shows that even when river temperature and wet-bulb temperature are within a narrow range (river: 15°C - 17°C and wet-bulb: 12°C - 16°C), CONP varies substantially across the system. Since the figure is restricted to a narrow wet-bulb and river temperature interval, the influence of weather conditions is partly controlled for. As illustrated in the figure, CONP can differ by approximately 4 units even at similar cooling production levels.

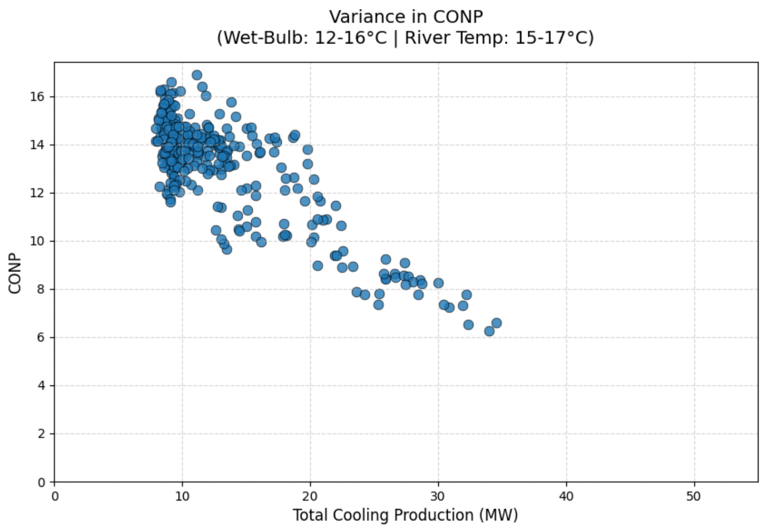


Figure 5.4: CONP versus cooling production for hourly data in 2025 (narrow temperature ranges).

To investigate this further, the start/stop sequence is illustrated in Figure 5.5. As shown, the order in which the chillers are started differs between these days, even though the operating conditions are similar.

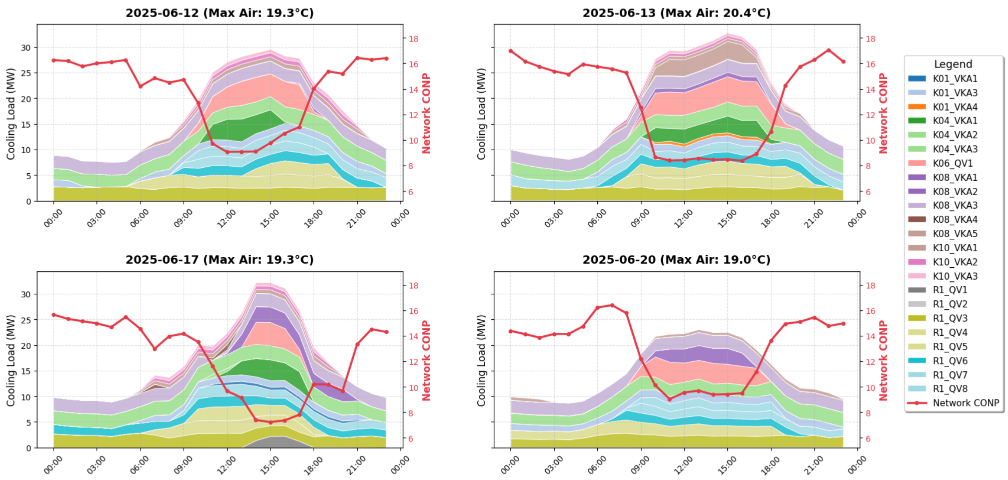


Figure 5.5: Daily chiller dispatch and network efficiency (CONP) for selected days with similar maximum outdoor temperature. Stacked areas show cooling production by unit, and the red line shows CONP.

Figure 5.6 illustrates the current rule-based start-up order. However, Figure 5.5 suggests that the observed chiller dispatch does not always follow this ranking in practice. For example, on 2025-06-17, K04–VKA1 appears to have been started before K06–QV1, although Figure 5.6 places K06–QV1 at the highest rank among the compression chillers.

Absorption chillers

Rank 1 (A:R1)
VKA3 – Lindholmen K08
VKA3 – Gullbergsvass K04

Rank 2 (A:R2)
VKA3 – Odinsplatsen K01
VKA1 – Sv. Mässan K10
VKA2 – Sv. Mässan K10
VKA3 – Sv. Mässan K10
QV3 – Rosenlund FK1
QV4 – Rosenlund FK1
QV5 – Rosenlund FK1
QV6 – Rosenlund FK1
QV7 – Rosenlund FK1
QV8 – Rosenlund FK1

Compression chillers

Rank 1 (C:R1)
QV1 – Ceres K06

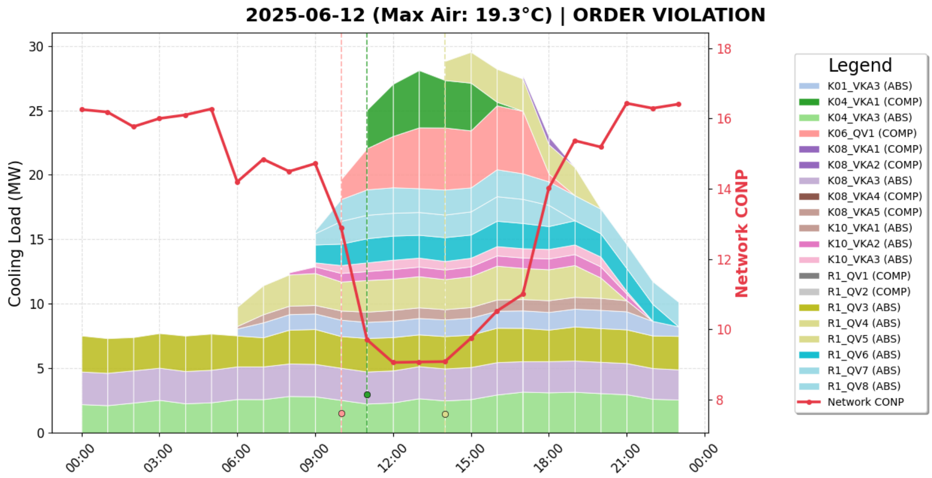
Rank 2 (C:R2)
VKA5 – Lindholmen K08
VKA1 – Gullbergsvass K04
VKA1 – Lindholmen K08
VKA4 – Lindholmen K08
VKA4 – Gullbergsvass K04
QV1 – Rosenlund FK1
QV2 – Rosenlund FK1
VKA4 – Odinsplatsen K01
VKA1 – Odinsplatsen K01

Rank 3 (C:R3)
VKA1 – Arkaden K03
VKA2 – Arkaden K03
VKA2 – Gullbergsvass K04
VKA2 – Lindholmen K08
VKA4 – Sv. Mässan K10

Reserve (C:RR)
QV1 – Sahlgrenska K05
QV2 – Sahlgrenska K05
KA1 – Sahlgrenska K05

Figure 5.6: Start-up order during 2025 for absorption and compression chillers used in the existing rule-based operation.

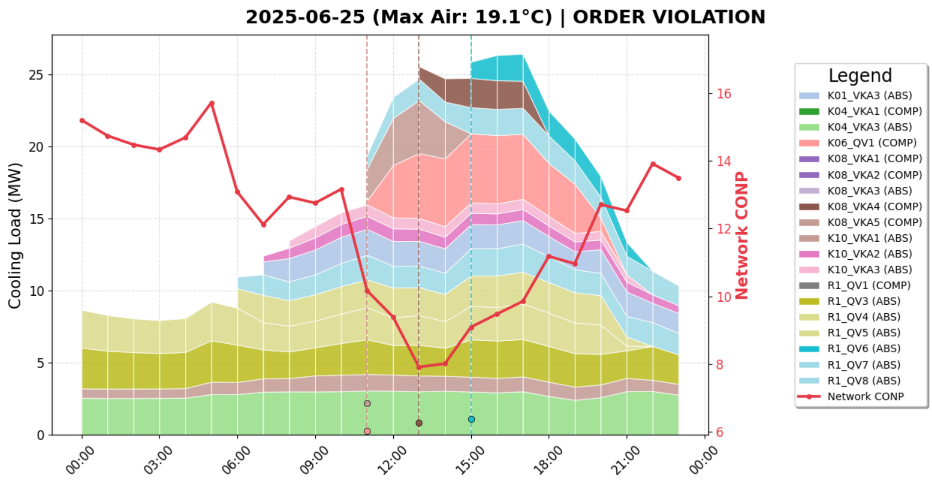
Figure 5.7 to Figure 5.10 show four different days on which the maximum air temperature ranged from 19.1 to 19.8°C and the cooling demand reached similar peak levels. This interval was selected because days with low outdoor temperatures typically involve little need for district cooling, while on very hot days most chillers are already active, making differences in the start-up sequence less useful for comparing dispatch behavior under similar operating conditions. The figure is intended to illustrate how the observed start-up sequence appears to differ from the predefined ranking shown in Figure 5.6. To make the sequence of chiller starts easier to interpret, the most recently started chiller is shown at the top of the stacked areas. Vertical dashed lines mark the time points at which the chillers listed in the violation box were started, thereby making it easier to identify when the observed start-up order appears to deviate from the predefined ranking.



Order Violation 2025-06-12

1. 10:00 K06_QV1 (C:R1) before 14:00 R1_QV5 (A:R2)
2. 11:00 K04_VKA1 (C:R2) before 14:00 R1_QV5 (A:R2)

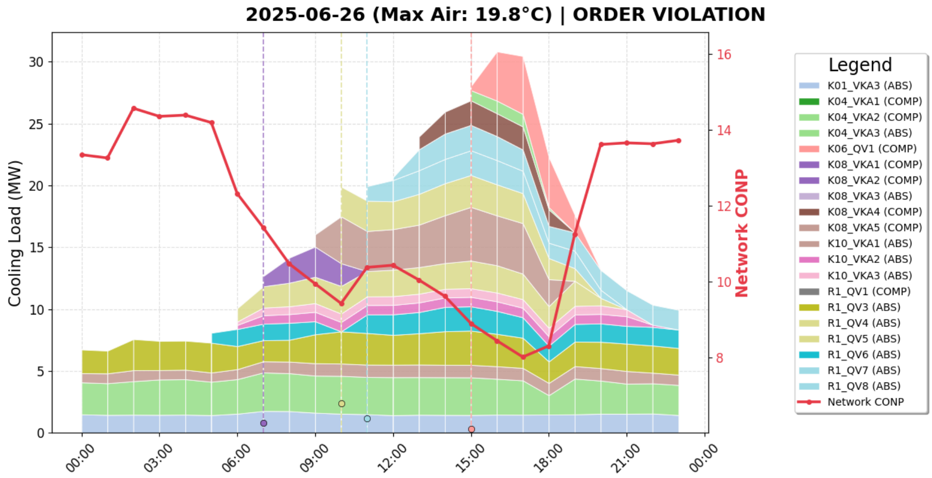
Figure 5.7: Daily chiller dispatch for 2025-06-12.



Order Violation 2025-06-25

1. 11:00 K06_QV1 (C:R1) before 15:00 R1_QV6 (A:R2)
2. 11:00 K08_VKA5 (C:R2) before 15:00 R1_QV6 (A:R2)
3. 13:00 K08_VKA4 (C:R2) before 15:00 R1_QV6 (A:R2)

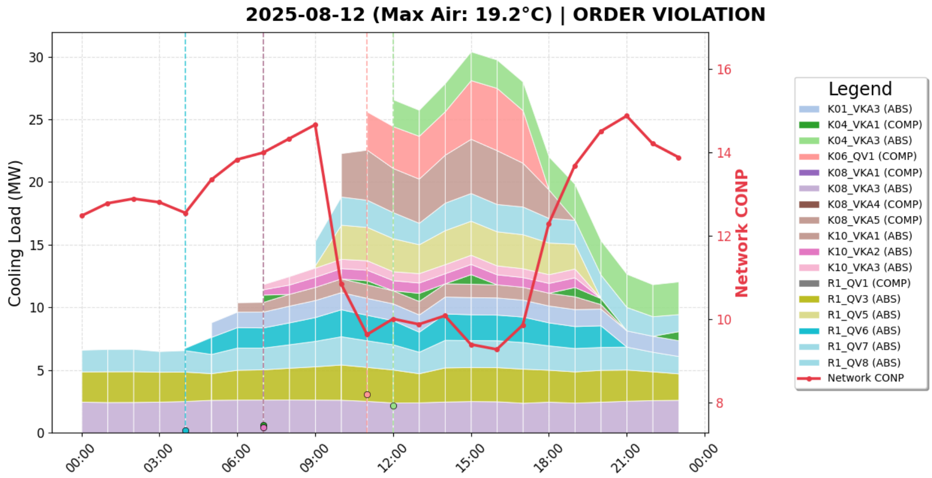
Figure 5.8: Daily chiller dispatch for 2025-06-25.



Order Violation 2025-06-26

1. 07:00 K08_VKA1 (C:R2) before 10:00 R1_QV5 (A:R2)
2. 07:00 K08_VKA1 (C:R2) before 11:00 R1_QV7 (A:R2)
3. 07:00 K08_VKA1 (C:R2) before 12:00 R1_QV8 (A:R2)
4. 09:00 K08_VKA5 (C:R2) before 10:00 R1_QV5 (A:R2)
5. 09:00 K08_VKA5 (C:R2) before 11:00 R1_QV7 (A:R2)
6. 09:00 K08_VKA5 (C:R2) before 12:00 R1_QV8 (A:R2)
7. 07:00 K08_VKA1 (C:R2) before 15:00 K06_QV1 (C:R1)
8. 09:00 K08_VKA5 (C:R2) before 15:00 K06_QV1 (C:R1)
9. 13:00 K08_VKA4 (C:R2) before 15:00 K06_QV1 (C:R1)
10. 15:00 K04_VKA2 (C:R3) before 15:00 K06_QV1 (C:R1)

Figure 5.9: Daily chiller dispatch for 2025-06-26.



Order Violation 2025-08-12

1. 07:00 K04_VKA1 (C:R2) before 07:00 K10_VKA2 (A:R2)
2. 07:00 K04_VKA1 (C:R2) before 07:00 K10_VKA3 (A:R2)
3. 07:00 K04_VKA1 (C:R2) before 09:00 R1_QV5 (A:R2)
4. 07:00 K04_VKA1 (C:R2) before 09:00 R1_QV7 (A:R2)
5. 07:00 K04_VKA1 (C:R2) before 12:00 K04_VKA3 (A:R1)
6. 10:00 K08_VKA5 (C:R2) before 12:00 K04_VKA3 (A:R1)
7. 11:00 K06_QV1 (C:R1) before 12:00 K04_VKA3 (A:R1)
8. 04:00 R1_QV6 (A:R2) before 12:00 K04_VKA3 (A:R1)
9. 05:00 K01_VKA3 (A:R2) before 12:00 K04_VKA3 (A:R1)
10. 06:00 K10_VKA1 (A:R2) before 12:00 K04_VKA3 (A:R1)
11. 07:00 K10_VKA2 (A:R2) before 12:00 K04_VKA3 (A:R1)
12. 07:00 K10_VKA3 (A:R2) before 12:00 K04_VKA3 (A:R1)
13. 09:00 R1_QV5 (A:R2) before 12:00 K04_VKA3 (A:R1)
14. 09:00 R1_QV7 (A:R2) before 12:00 K04_VKA3 (A:R1)
15. 07:00 K04_VKA1 (C:R2) before 11:00 K06_QV1 (C:R1)
16. 10:00 K08_VKA5 (C:R2) before 11:00 K06_QV1 (C:R1)

Figure 5.10: Daily chiller dispatch for 2025-08-12.

Taken together, the results show three main findings regarding the current control strategy. First, chiller efficiency varies with exogenous conditions such as river temperature and wet-bulb temperature. Second, network efficiency still varies substantially even under relatively similar external conditions. Third, the observed chiller dispatch does not always follow the predefined start-up ranking. Although some of these deviations may in practice reflect operational constraints not captured in the available data, the overall pattern still indicates that the current control strategy is not applied fully consistently in operation.

5.2 Design of the Software-Based Decision Support and Control Tool

To address the operational variability and inefficiencies identified in the current control strategy, this section details the design of the software-based decision support tool. The development of this artifact directly answers RQ2 and follows a systematic progression to demonstrate exactly how exogenous environmental factors can be utilized to automate chiller start and stop decisions. The system architecture is presented in three sequential parts. Section 5.2.1 evaluates the empirical performance models used to predict optimal chiller efficiency. Section 5.2.2 outlines the implementation of the mathematical optimization engine designed to minimize electricity use while meeting fluctuating cooling demand. Finally, section 5.2.3 presents the interactive user interface and fleet management module that encapsulate the underlying algorithms into a practical operational tool.

5.2.1 Evaluation of Chiller Performance Models

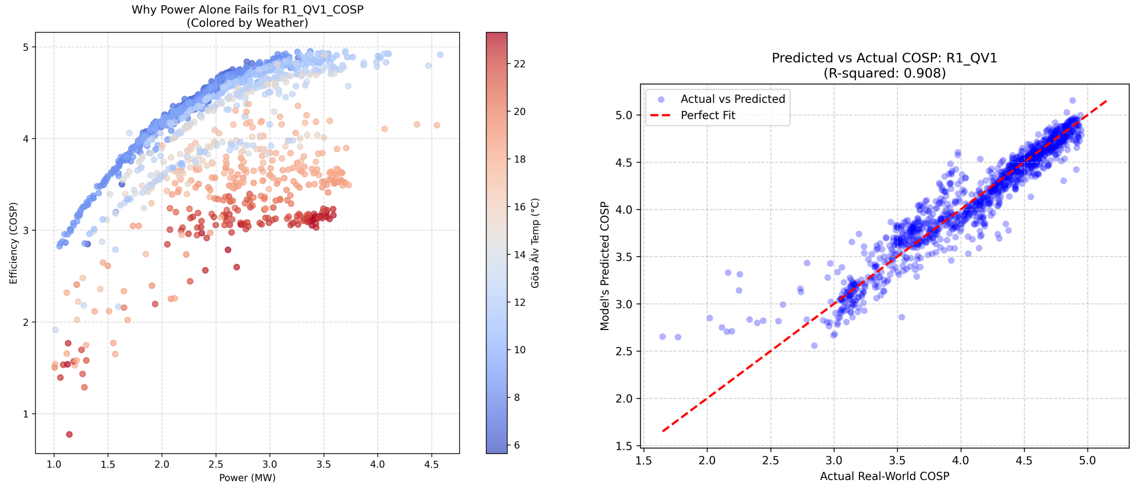
This subsection evaluates the empirical polynomial equations developed to predict the efficiency of each unit under varying environmental conditions and loads. First, the predictive accuracy of these models is visually validated to demonstrate how well they capture both stable and infrequent operating behaviors. Following this validation, selected mathematical equations are presented to illustrate the statistical fit and the specific variables driving the efficiency calculations across the fleet.

Visual Validation of Model Predictive Accuracy

The cooling chillers operate across diverse facility configurations and range from continuous baseload provision to intermittent peak-shaving operations. Consequently, their operational datasets vary in both volume and predictive stability.

This variance is illustrated by examining the predictive performance of two contrasting compression chillers: the highly stable baseload unit R1_QV1 and the infrequently operated unit K08_VKA1.

Figure 5.11 shows that the model for R1_QV1 demonstrates high predictive accuracy, achieving a coefficient of determination (R^2) of 0.908. This model was trained on 1,162 complete hourly observation rows. Figure 5.11a shows how the chiller's COSP varies with temperature, forming distinct clusters of operating behavior. Because the unit operates frequently and for sustained durations, the recorded data primarily captures the chiller during stable, steady-state operation. This allows the multivariate regression to robustly map the relationship between cooling load, external temperature, and efficiency. As a result, the predicted COSP clusters tightly along the identity line in figure 5.11b.

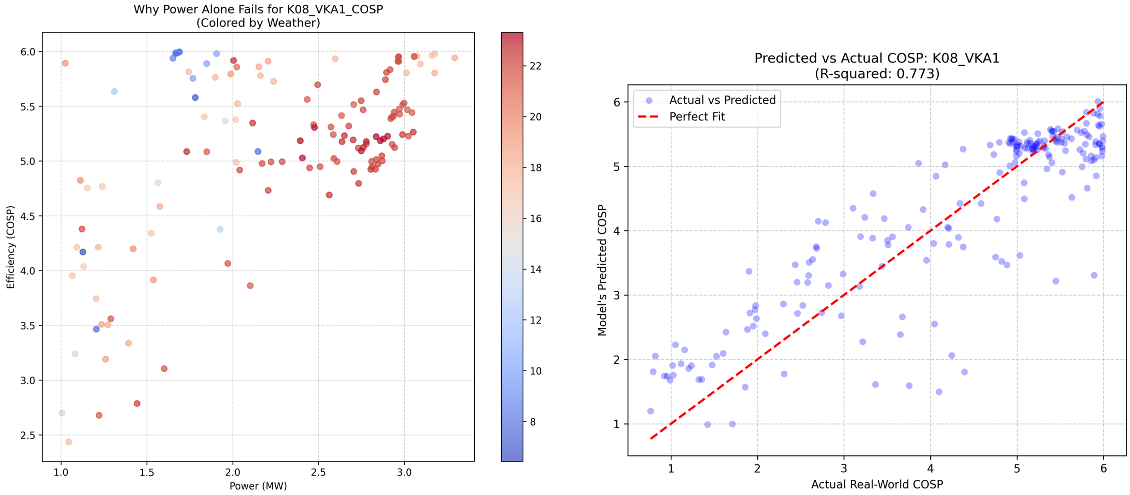


(a) Observed variance under varying loads and temperatures.

(b) Predicted versus actual COSP ($R^2 = 0.908$).

Figure 5.11: Empirical performance analysis of compression chiller R1_QV1. The left panel plots the observed COSP under varying loads and external conditions. The right panel compares the model's predicted COSP against measured values.

In contrast, Figure 5.12 illustrates the limitations when modeling infrequently utilized chillers. The regression model for K08_VKA1 yields a lower R^2 of 0.773. The diagnostics reveal that this specific chiller registered only 127 valid operational hours throughout the evaluated year. Figure 5.12a displays a high degree of scatter in the performance data, which the exogenous parameters cannot fully account for. While the resulting regression curve remains the best mathematical fit for the available data, the broader prediction interval highlights the difficulty in accurately predicting the efficiency of this specific chiller. A summary of the valid operational data points (hourly observations) per chiller is presented in Appendix B.



(a) Observed variance under varying loads and temperatures.

(b) Predicted versus actual COSP ($R^2 = 0.773$).

Figure 5.12: Empirical performance analysis of compression chiller K08_VKA1. The left panel plots the observed COSP under varying loads and air temperatures. The right panel compares the model's predicted COSP against measured values.

Selected Chiller-Level COSP Equations

Before presenting the explicit mathematical equations, it is necessary to define the nomenclature used for the regression variables. The expected efficiency of each chiller is modeled as a polynomial function of its assigned load and various exogenous environmental factors. The variables driving these equations are defined in the box below.

P	The assigned cooling load or part-load ratio of the unit
WB	The external wet-bulb temperature
AH	The ambient absolute humidity
A	The external air temperatur
$\mathbf{A}_{\text{roll}}$	The rolling average of the ambient air temperature
$\mathbf{T}_{\text{river}}$	The water temperature of the Göta Älv river

Interaction terms in the equations represent the multiplied product of their respective individual variables.

To illustrate the variation in model fit across units, four representative chiller-level regression equations are shown below, sorted by coefficient of determination (R^2): the three best-performing models and the worst-performing model. The full set of chiller-level regression equations is presented in Appendix A.1.

`K08_VKA3` $R^2 = 0.934$, Avg. error = 4.86%

$$\text{COSP} = -20.3862 + 41.0961P - 8.6185P^2 + 1.5618WB - 0.0945WB^2 - 0.3234A_{\text{roll}}$$

Maximum cooling capacity: 3.1 MW

`K03_VKA2` $R^2 = 0.922$, Avg. error = 1.87%

$$\text{COSP} = 0.1963 + 4.1044P - 0.8448P^2 - 0.004WB^2 + 0.0139PWB + 0.0002AH$$

Maximum cooling capacity: 2.9 MW

`R1_QV1` $R^2 = 0.905$, Avg. error = 3.21%

$$\text{COSP} = 1.4772 + 3.1332P - 0.297P^2 - 0.0689R - 0.0446RP - 4.5098\frac{P}{R}$$

Maximum cooling capacity: 5.0 MW

⋮

`K10_VKA2` $R^2 = 0.356$, Avg. error = 13.52%

$$\text{COSP} = 17.3474 - 1.3786P - 0.0479WB^2 + 0.8454A + 0.0063AH - 0.6695A_{\text{roll}}$$

Maximum cooling capacity: 1.2 MW

5.2.2 Implementation of the MINLP Optimization Engine

The operational control logic formulated in the methodology was successfully translated into a Python-based software artifact utilizing the GEKKO Optimization Suite. The implemented engine acts as the central decision layer, as illustrated in the architectural flowchart in Figure 5.13. It integrates exogenous environmental conditions with empirical thermodynamic models to compute the most efficient chiller dispatch schedule.

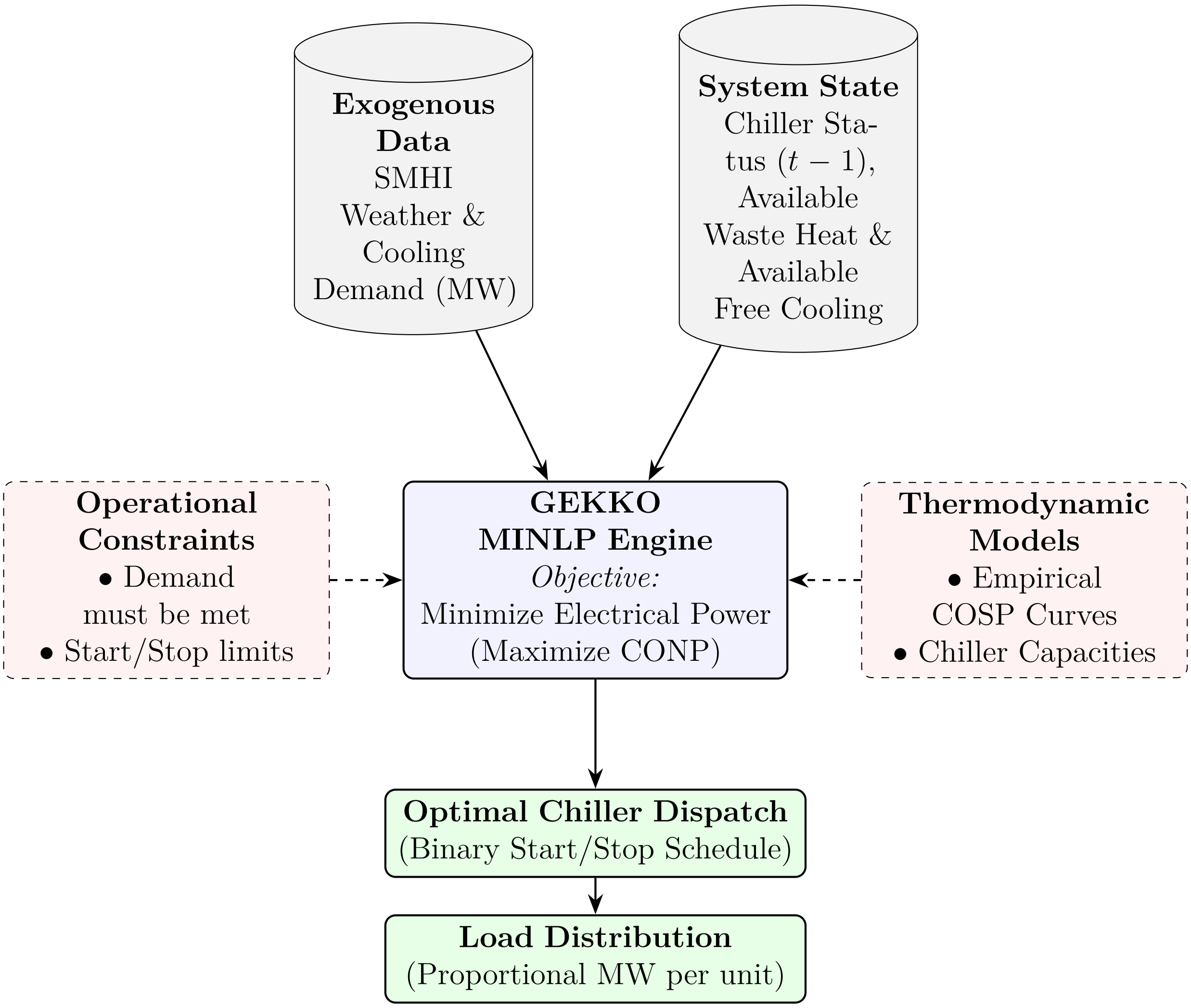


Figure 5.13: Data flow and decision architecture of the MINLP optimization engine.

The optimization model was configured to evaluate the fleet dispatch sequentially across the 2025 operational dataset. A standard non-leap year contains 8,760 hourly time steps. However, 24 hours were excluded during the data cleaning phase due to missing values, such as river temperature. As a result, the simulation was executed across the remaining 8,736 valid hours.

To process the MINLP formulation, the engine was set to use the APOPT solver. To mimic the time constraints of a live control room, strict computational boundaries were applied to the solver. Specifically, these boundaries were a maximum of 500 iterations and a time limit of 30 seconds per hourly step.

During the simulation, the optimization engine showed high computational stability. Out of the 8,736 evaluated hours, the APOPT solver successfully found a start and stop sequence, along with a load distribution schedule, for 8,694 hours. The remaining 42 hours, which represent roughly 0.48% of the simulated period, failed to converge within the 30-second limit. These failed intervals mostly occurred during periods of extreme peak demand where the fleet had very little operational flexibility. To ensure a fair and accurate comparison, these 42 non-converged hours were removed from the historical baseline evaluation. These non-converged intervals are detailed across specific operational scopes in Table 5.2.

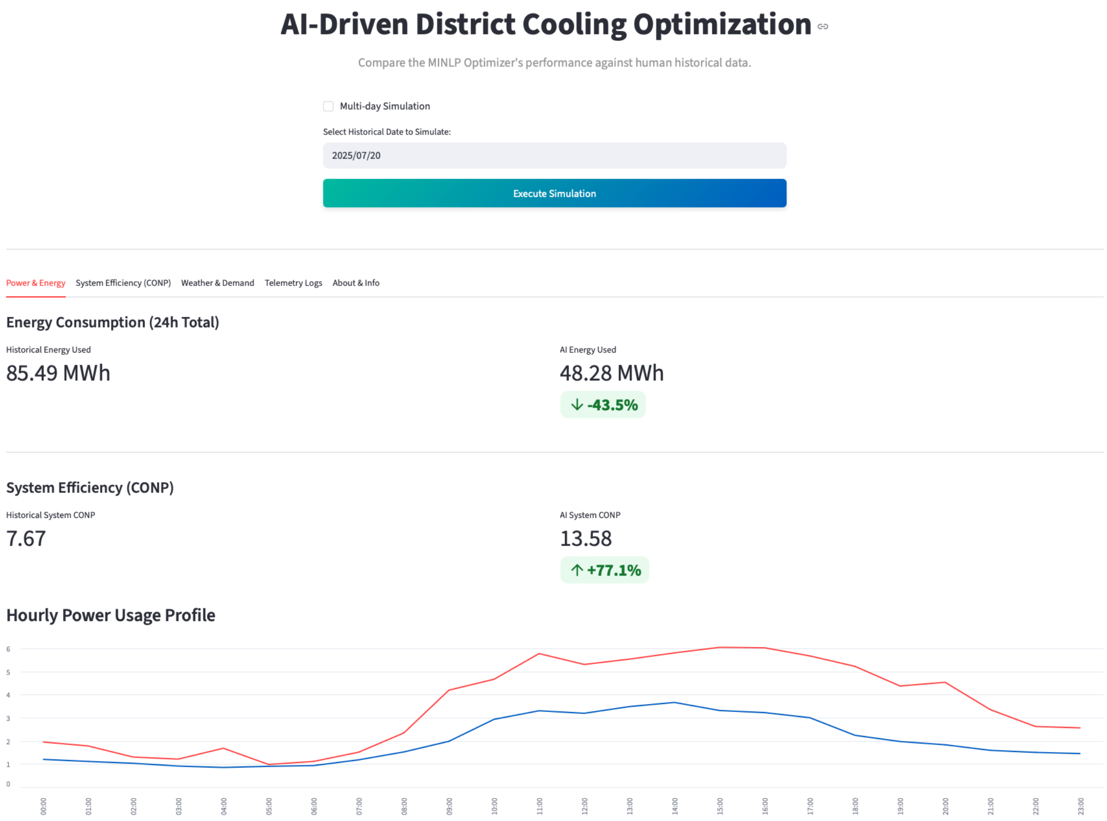
5.2.3 User Interface and Interactive Fleet Management

In accordance with the design science research methodology, the final step of the development process is to encapsulate the optimization engine into a practical design artifact. This artifact is a graphical user interface. The interface makes the optimization model accessible and serves as a generalized decision support tool for district cooling analysis. The architecture is divided into two primary environments. These are the simulation dashboard and the fleet configuration module.

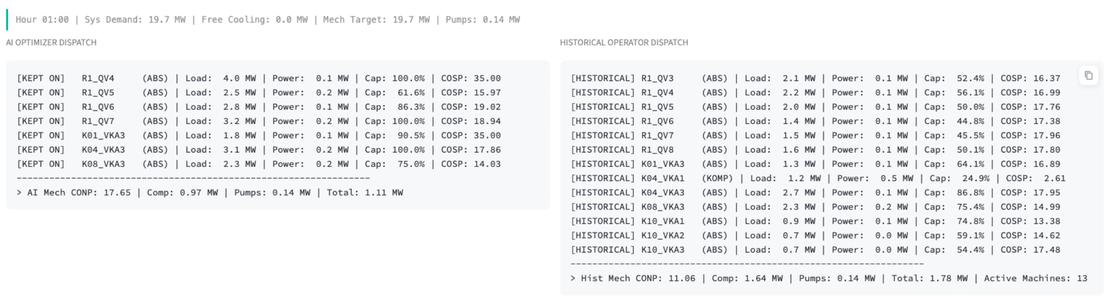
Simulation and System Explainability

The simulation dashboard is the primary evaluation environment. Here users can run a 24-hour simulation to compare the automated dispatch strategy against historical human operation. As illustrated in Figure 5.14a, the interface computes and visualizes aggregate thermodynamic metrics to compare total energy consumption and the system coefficient of network performance.

Because this tool represents the first step of an automated decision support for the Gothenburg district cooling network, it is necessary to show exactly how the chillers should be controlled. The simulation tab therefore features a detailed telemetry module as seen in Figure 5.14b. These logs provide the proposed start and stop schedule for every hour of the simulated period. They display the exact mathematical output from the solver and tell the operator which chiller to activate, how much cooling load to assign to each unit, and the expected efficiency.



(a) Simulation dashboard comparing historical and simulated system efficiency.



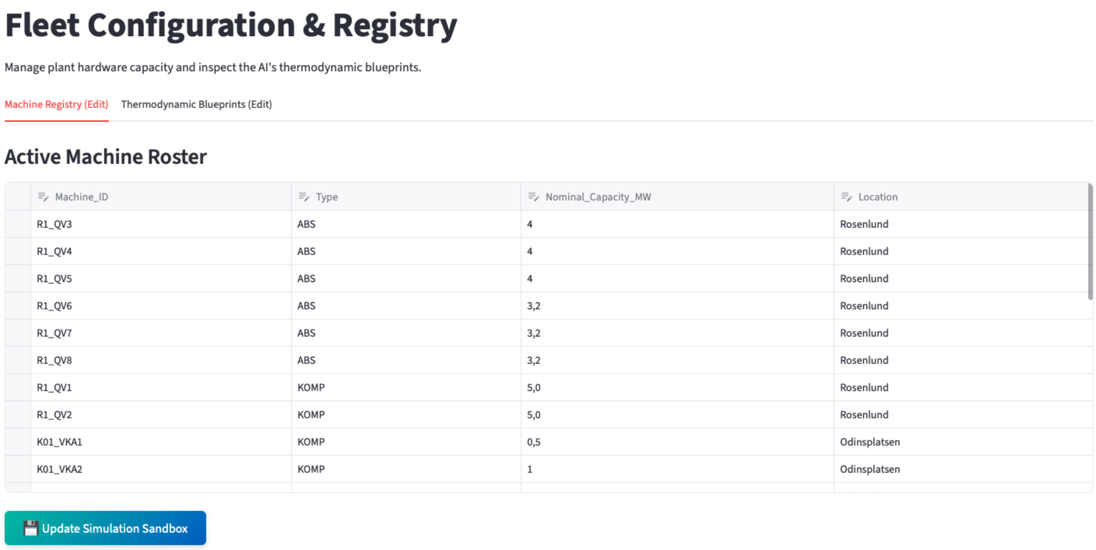
(b) Hourly telemetry logs showing the proposed start and stop schedule.

Figure 5.14: The simulation module and the hourly dispatch logs.

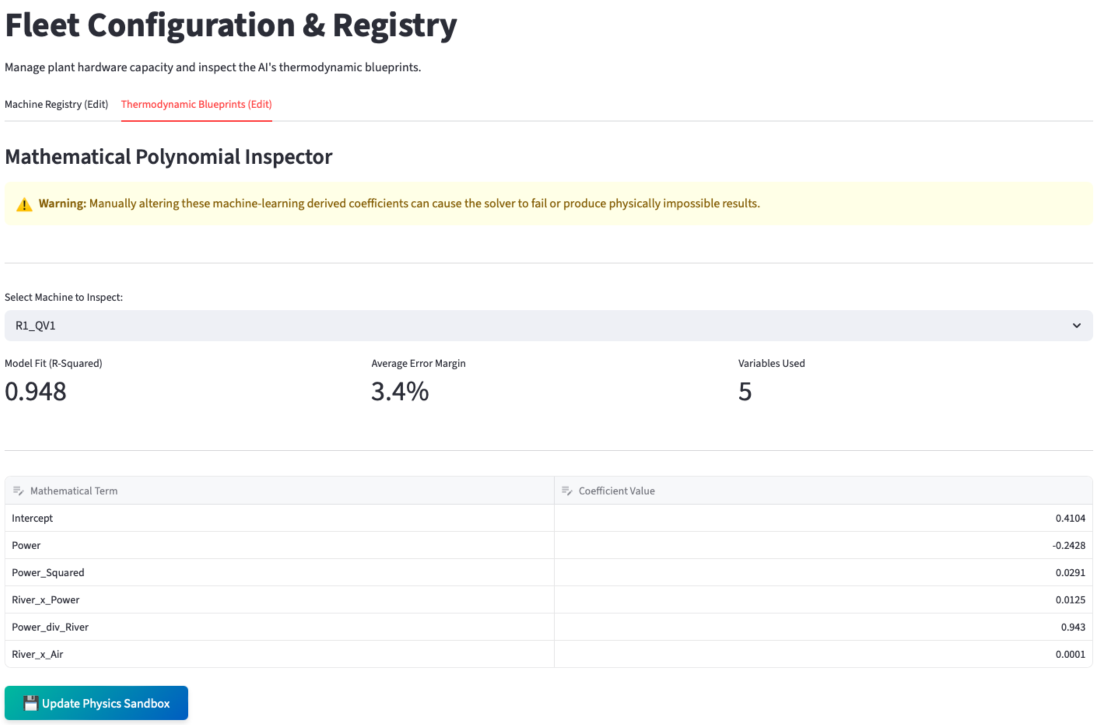
Modular Fleet Configuration

District cooling networks change over time as machinery requires maintenance and thermodynamic efficiency degrades. To guarantee that the design artifact remains robust, the tool incorporates a modular fleet configuration environment. This design choice ensures the application serves as a general tool rather than a hardcoded script.

Through the active chiller roster shown in Figure 5.15a, users can dynamically alter the operational constraints passed to the optimization engine. This allows operators to add new chillers, remove unavailable units, or adjust physical capacities without modifying the underlying code. Furthermore, the mathematical polynomial inspector in Figure 5.15b exposes the empirical regression equations that drive the optimization objective. This modular architecture allows the tool to be updated with new machine learning models, ensuring the decision support system can evolve alongside the physical plant.



(a) Active machine roster for adjusting hardware availability and capacity.



(b) Polynomial inspector for viewing and updating machine performance models.

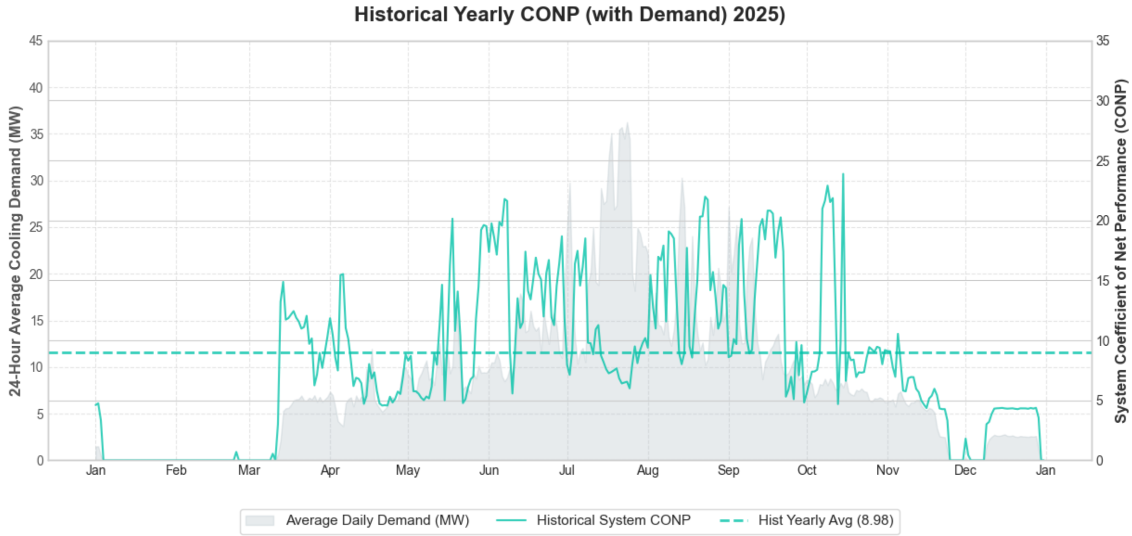
Figure 5.15: The fleet configuration module for updating system parameters.

5.3 Evaluation of the Proposed Control Strategy

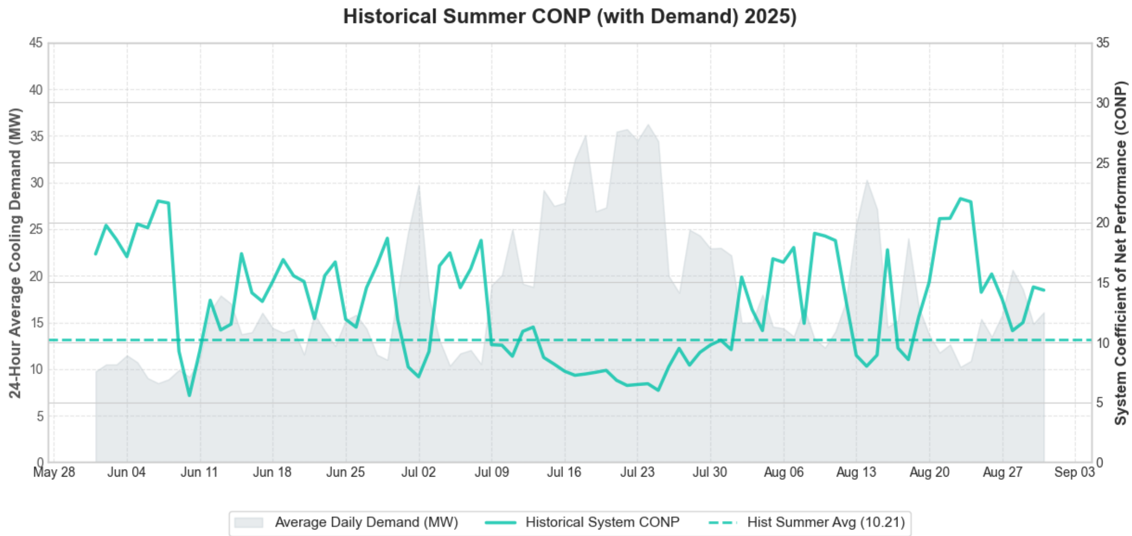
This section evaluates the effectiveness of the proposed software-based, automated decision support by comparing its simulated performance against the actual manual operation recorded during 2025. The evaluation is structured into three main parts. First, the historical dispatch and performance of the chillers are analyzed over the full year, followed by a specific focus on the summer period and three representative summer days to establish a detailed operational baseline. Second, the performance of the simulated, AI-driven dispatch strategy is presented and directly compared against this historical baseline across the exact same temporal scopes: annually, throughout the summer, and during the three specific days. Finally, the practical impact of the proposed control strategy is quantified, utilizing a comparative table to present the total electrical energy that could be saved by the simulated operation and its corresponding operational implications.

5.3.1 Historical Operational Baseline

Figure 5.16a shows the historical CONP and cooling demand during 2025. Because the modified CONP used in this study is based on the operation of active cooling chillers, gaps appear during parts of the winter period when cooling production is provided entirely by free cooling. When chillers are occasionally started during winter, they are often compression chillers due to limited waste heat availability, which contributes to the relatively low observed CONP values. Although the full-year evaluation remains the primary basis for assessment, the summer period is highlighted as the most operationally informative part of the year, since the chillers are then active more continuously, as illustrated in Figure 5.16b. As shown in the figures, higher cooling demand is generally associated with lower CONP, while lower demand tends to correspond to higher CONP.



(a) Historical CONP in 2025, including cooling demand.

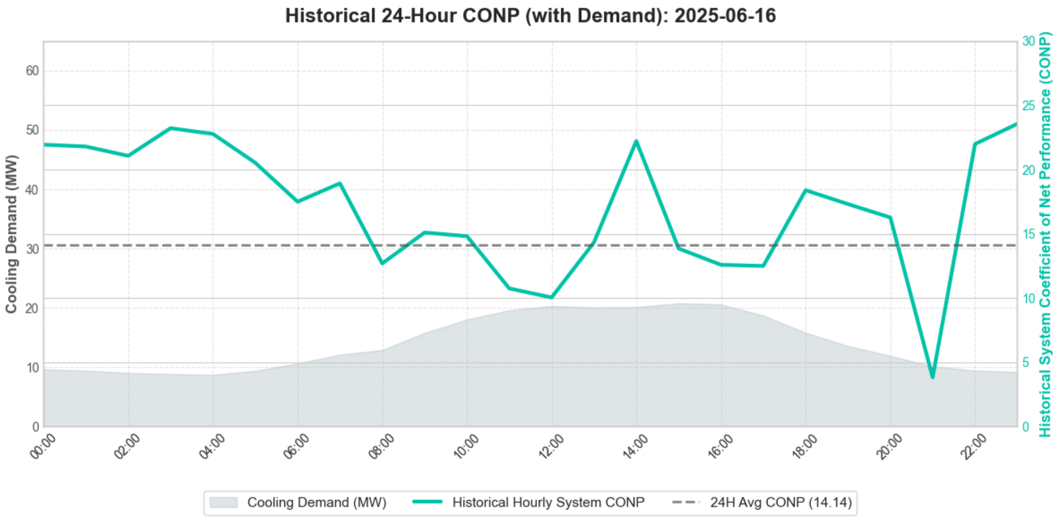


(b) Historical summer CONP in 2025, including cooling demand.

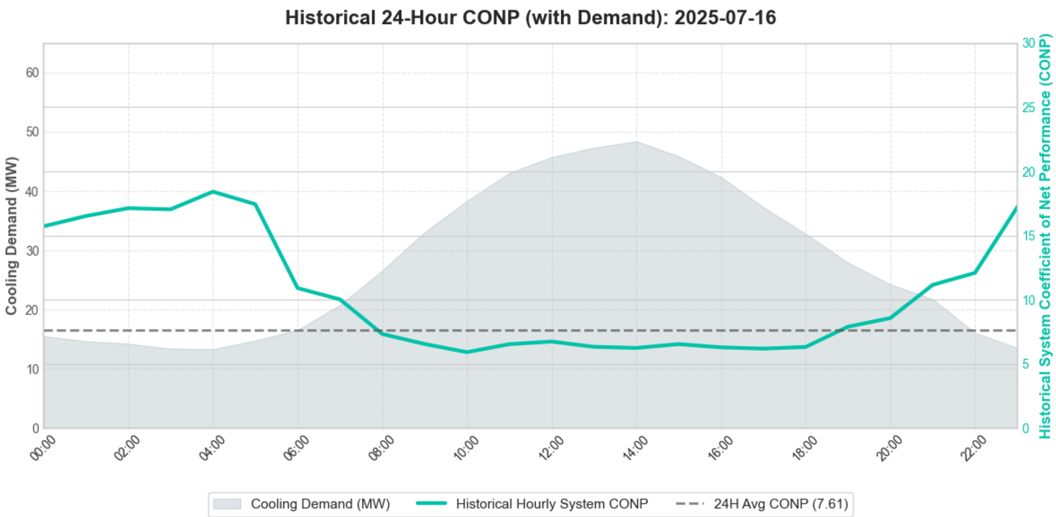
Figure 5.16: Historical comparison of CONP in 2025.

Figure 5.17 shows three selected summer days from the historical operation. One day from the middle of each summer month was chosen to illustrate the historical chiller dispatch. Figure 5.20 shows the corresponding simulated chiller operation for the same days.

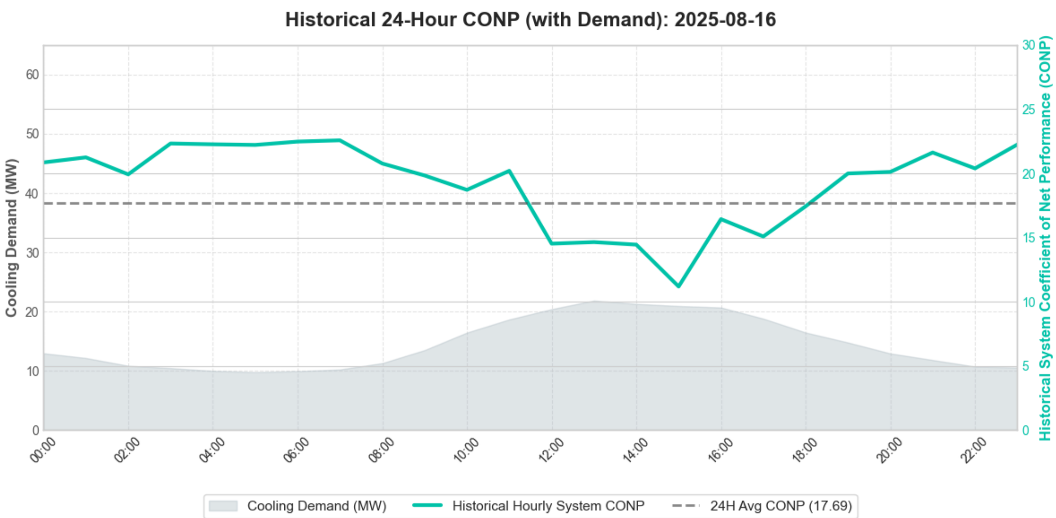
The three graphs in Figure 5.17 provide a representative comparison, as they reflect different cooling demand levels and different CONP profiles. This makes them suitable for illustrating how the software-based tool performs under varying operating conditions.



(a) 2025-06-16



(b) 2025-07-16



(c) 2025-08-16

Figure 5.17: Historical daily operation for selected days.

5.3.2 Simulated Operational Performance

Figure 5.18 shows both the simulated and historical CONP during 2025. In the simulation, waste heat is assumed to be available when the average daily outdoor temperature exceeds 12°C. When the average daily temperature is below this threshold, waste heat is assumed to be unavailable, and the system is therefore required to rely solely on compression chillers. The simulation also assumes an optimal district heating temperature for the waste heat, allowing the absorption chillers to operate at their maximum capacity whenever waste heat is available.

As illustrated in Figure 5.18, the simulated operation increases the annual average CONP from the historical baseline of 8.98 to 10.66. This corresponds to an overall system efficiency improvement of nearly 19%. Furthermore, the data reveals markedly higher performance peaks for both the historical and simulated operations during the spring and autumn months.

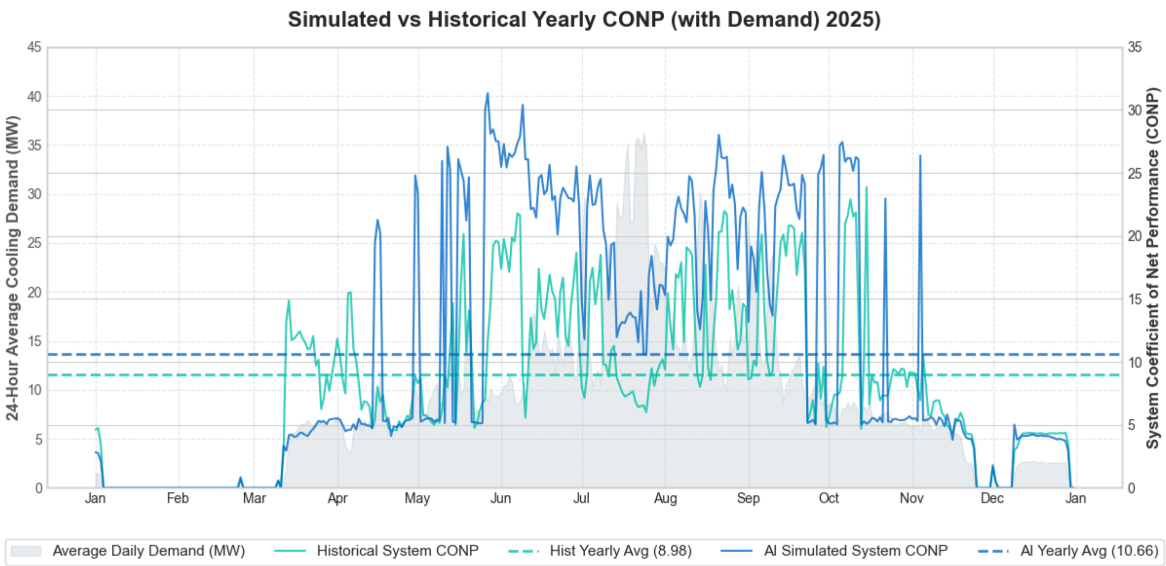


Figure 5.18: Simulated CONP in 2025, including cooling demand

Figure 5.19 shows the simulated summer period during 2025. As shown, the average CONP is higher than in the historical summer graph. More specifically, the average CONP increases by almost 72%, from 10.21 to 17.51. The simulated operation also results in a more stable CONP profile, with noticeable drops occurring mainly during periods of very high cooling demand when all chillers are active.

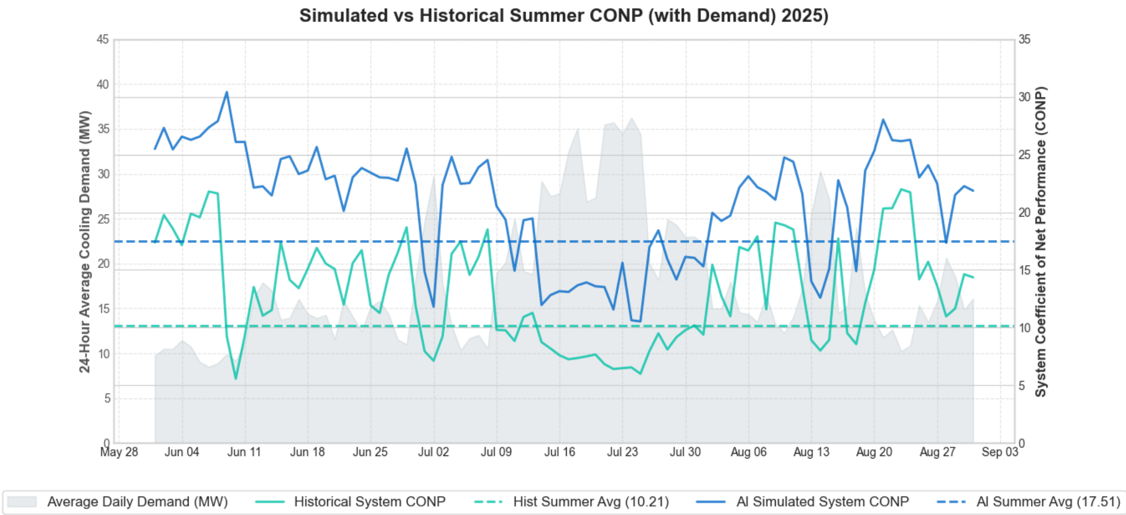
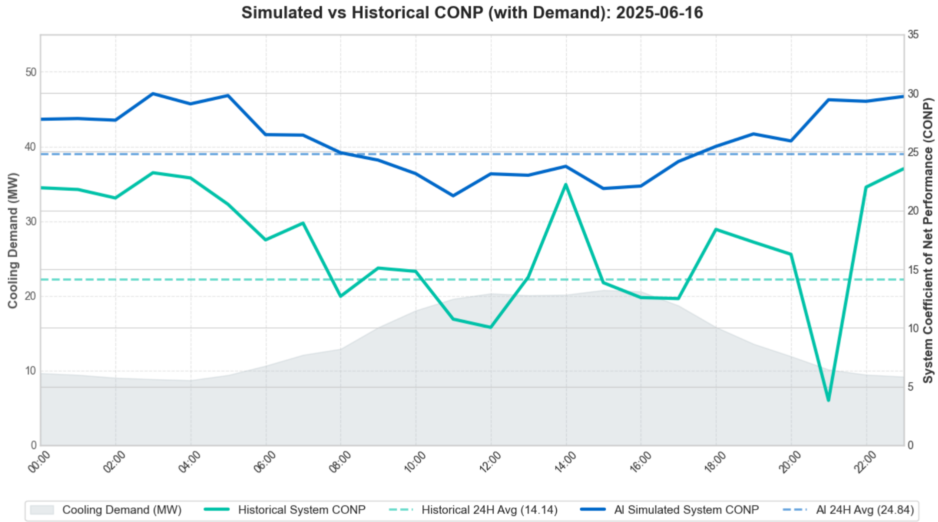
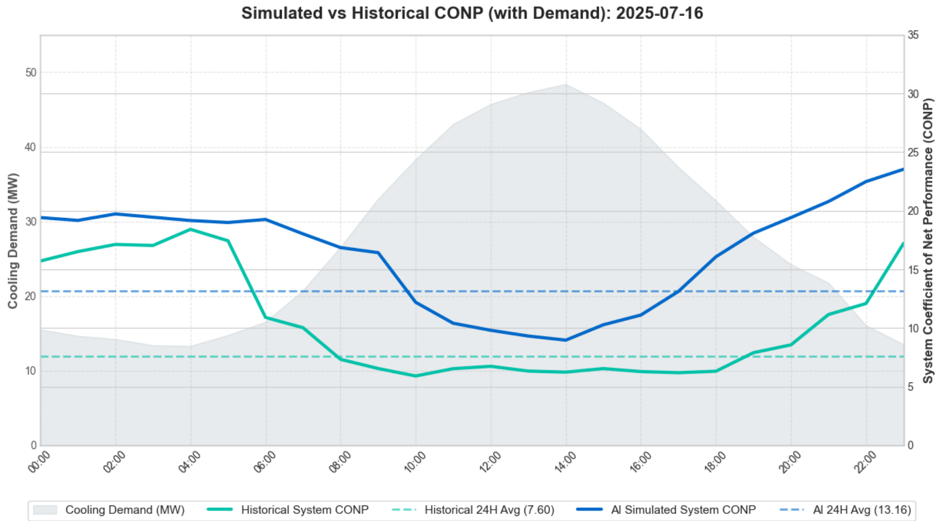


Figure 5.19: Simulated CONP in summer 2025, including cooling demand.

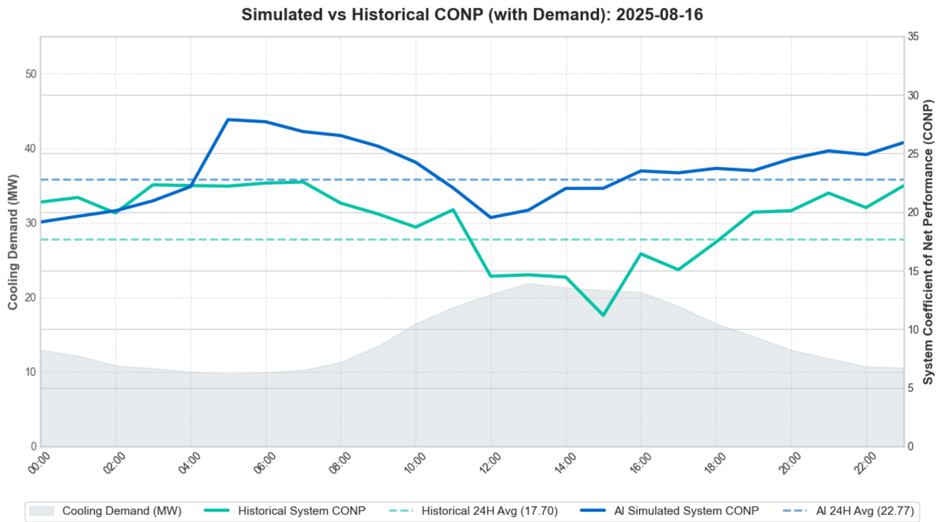
Figure 5.20 shows the same three days as Figure 5.17, but with the simulated and historical values presented together for comparison. As shown in the figures, the simulated operation results in a higher CONP on all three days. More specifically, Figure 5.20a shows that the CONP for 2025-06-18 could be increased by approximately 75%. Similarly, Figure 5.20b and Figure 5.20c show increases in CONP of 73% and 28%, respectively. Detailed chiller dispatch logs, which outline the load allocations, are provided in Appendix C.



(a) 2025-06-16



(b) 2025-07-16



(c) 2025-08-16

Figure 5.20: Comparison between simulated and historical CONP for selected days.

5.4 Quantification of Energy Savings

To translate the theoretical improvements in CONP into tangible operational metrics, the total electrical power consumption of the simulated operation was calculated and directly compared against the historical baseline. Table 5.1 summarizes the total energy consumed, the absolute energy saved (in MWh), and the relative percentage of savings across the evaluated time periods.

While the simulation yielded a 15.81% reduction in electricity use over the full 2025 calendar year, the most significant impact was observed during the peak summer months of June through August. During this period, the automated dispatch strategy reduced electrical consumption by 1,615.31 MWh, corresponding to a 41.69% energy saving. Furthermore, the daily analysis demonstrates that the optimization tool consistently achieved substantial reductions, ranging from 22.2% to 43.1%, even on individual high-demand days.

Table 5.1: Comparison of Historical vs. Simulated Electrical Power Consumption

Time Period	**Historical (MWh)**	**AI Simulated (MWh)**	**Energy Saved (MWh)**	**Savings (%)**
Full Year 2025	8,282.38	6,972.67	1,309.71	15.81%
Summer (Jun–Aug)	3,874.70	2,259.39	1,615.31	41.69%
June 16, 2025	23.69	13.48	10.21	43.1%
July 16, 2025	87.78	50.73	37.05	42.2%
August 16, 2025	19.62	15.27	4.35	22.2%

To provide a multi-criteria evaluation of the system, Table 5.2 outlines the operational compliance, asset wear constraints, and solver robustness corresponding to the time periods evaluated in Table 5.1.

Table 5.2: Operational Performance and Constraint Compliance Across Evaluated Scopes

Time Period	**Demand Tracking Compl. (%)**	**Max Daily Cycles ($S_i \leq 2$)**	**Solver Convergence Rate (Hours)**
Full Year 2025	100.0%	≤ 2	99.52% (8,694/8,736)
Summer (Jun–Aug)	100.0%	≤ 2	98.10% (2,166/2,208)
June 16, 2025	100.0%	≤ 2	100.0% (24/24)
July 16, 2025	100.0%	≤ 2	100.0% (24/24)
August 16, 2025	100.0%	≤ 2	100.0% (24/24)

6. Discussion

6.1 Analysis of Baseline Operational Inefficiencies

As shown in Figure 5.1 and Figure 5.2, river temperature, wet-bulb temperature, and chiller load affect COSP, suggesting that the most efficient start-up order may vary under different operating conditions. Informal conversations with a process engineer and a business manager indicated that operators aim to start and stop the chillers they expect to provide the highest COSP under the current conditions. This interpretation is supported by Figure 5.3 and Figure 5.4, where CONP varies substantially even under relatively similar conditions.

Because the optimal start-up order appears to vary with exogenous conditions, operators cannot always follow the standardized start-up sequence. As a result, chiller dispatch may be formally standardized, but in practice it becomes partly dependent on operator judgement.

Figure 5.4 shows that even when river temperature and wet-bulb temperature are within a narrow range, CONP varies substantially across the system. This indicates that efficiency is influenced by factors beyond weather conditions and cooling demand, and suggests that the current operation is not fully standardized or consistently optimized. The remaining spread in CONP therefore suggests that the variation is more likely related to differences in unit selection, start-up decisions, and part-load operation rather than weather alone.

The dispatch patterns shown in Figure 5.5 and Figure 5.7 to Figure 5.10 further support this interpretation. While the current operation is guided by a predefined start-up ranking, the observed chiller dispatch differs across days with similar maximum outdoor temperature and comparable peak cooling demand. In several of these cases, the observed start-up sequence also appears to deviate from the predefined ranking, suggesting that the practical application of the control strategy is not fully fixed in practice. This indicates that operational decisions are influenced not only by the formal start-up order, but also by situational judgment, local constraints, and the timing of demand changes over the day.

The current level of standardization would likely be more effective if the system operated under stable and repetitive conditions. However, district cooling operation is dynamic, as both cooling demand and exogenous factors vary over time. Because chiller efficiency is influenced by changing environmental conditions, and because demand rises and falls differently from day to day, a purely manual control strategy becomes difficult to apply consistently in an efficient way. Even if operators know the general start-up order of the chillers, it remains challenging to determine the optimal timing for when a unit should be started or stopped. This suggests that the main limitation is not only the existence of a rule-based operating strategy itself, but also its inability to account for continuously changing system conditions in real time. This strengthens the argument for software-based decision support, since such a system can continuously evaluate current operating conditions and support start/stop decisions in a way that is difficult to achieve through manual operation alone.

Taken together, these findings suggest that the main operational limitations of the current control strategy are its reliance on a generalized rule-based start-up order, its dependence on operator judgment, and its lack of real-time adaptation to changing exogenous conditions and demand patterns. The main inefficiencies are reflected in the substantial variation in chiller and network efficiency under otherwise similar operating conditions, indicating that unit selection, start-up timing, and part-load operation are not consistently optimized. RQ1 is therefore answered by showing that the current control strategy is only partly standardized in practice. Although a predefined start-up order exists, the operation remains sensitive to changing exogenous conditions and requires operator judgment to adapt to daily variations in demand and chiller performance. As a result, the current approach does not appear to provide a dispatch of the production units that is consistently optimized for efficiency. These findings provide a clear motivation for the software-based decision support and optimization approach developed in response to RQ2.

6.2 Software-Based Decision Support

Following the analysis of historical operational inefficiencies, this section evaluates the developed software-based artifact as a solution for optimized district cooling dispatch. The discussion assesses the simulation results in terms of CONP and energy savings, the practical utility of the decision support interface, and the methodological limitations of the modeling approach.

6.2.1 Operational Performance and Energy Savings

The summer period provides the most relevant basis for comparison, since chillers are operated more continuously, cooling production is not affected by free cooling, and the availability of waste heat is more consistent. It therefore provides the clearest basis for evaluating the proposed decision support under conditions where chiller selection and start/stop decisions have the greatest impact on electricity use.

Figure 5.16 and Figure 5.19 show that the artifact improves start/stop and dispatch decisions, resulting in a 72% increase in CONP over the summer period and corresponding energy savings of 41.69% (Table 5.1). This substantial improvement suggests that the proposed control strategy has strong potential to improve operational efficiency during periods when chiller dispatch is most critical. The improvement in CONP is reflected not only in a higher average value, but also in a more stable performance profile over time. In the simulated operation, the remaining drops in CONP are concentrated around periods of peak demand, when most or all chillers must be activated to satisfy the cooling load. Under such conditions, the opportunity to select only the most efficient chillers is reduced, since additional and less efficient units may also need to be operated. This suggests that the decision support approach is most effective during periods when there is greater flexibility in choosing which chillers to run.

The simulated artifact likely outperforms the historical operation because it systematically incorporates exogenous factors into the dispatch logic and can therefore select the most efficient chillers for the current operating conditions. In addition, it reduces inefficiencies related to suboptimal start/stop decisions by allocating load more consistently, thereby limiting unnecessary part-load operation and improving overall dispatch performance.

6.2.2 Fulfillment of Success Criteria and Practical Utility

The simulation results must be discussed in relation to the success criteria defined in Section 4.3.2. The goal was not only to achieve a higher CONP, but to do so while fully meeting cooling demand and avoiding excessive start/stop events. The results indicate that the artifact improves CONP without introducing obvious trade-offs in these respects, since the simulated operation was mathematically constrained to satisfy demand and limit the chillers daily start/stop events to a maximum of two. This suggests that the reduction in electricity use is mainly due to more efficient dispatch decisions rather than to relaxed operational requirements.

Beyond the mathematical optimization, the practical utility of the developed artifact relies heavily on its user interface. The development of this interface represents the final step in answering RQ2. It transforms the underlying mathematical engine from a theoretical script into an applied software tool. By visualizing the predicted efficiency and generating an explicit hourly start and stop schedule, the dashboard provides a structured method for utilizing exogenous environmental factors in daily operations. This directly addresses the operational inconsistencies identified in the historical baseline by shifting the process from subjective human judgment to a software-based, automated decision tool. Ultimately, this artifact functions as a necessary first step toward full automation by demonstrating how complex dispatch decisions can be systematically generated, evaluated, and presented in a practical environment.

6.2.3 Methodological Limitations and Model Validity

An important limitation of the artifact is that it has been evaluated only through simulation and has not yet been tested in live operation. The results indicate that the artifact would have performed well under the historical conditions of 2025, but they do not demonstrate that the same level of performance would necessarily be achieved in other years. Because the artifact was developed and calibrated using data from 2025, its performance may be partly influenced by the specific operational and environmental characteristics of that year.

A further limitation relates to the underlying assumptions regarding the district heating network. The simulation assumes both an optimal district heating supply temperature and the abstraction of intra-plant hydraulics. These assumptions create more favorable operating conditions for the absorption chillers and reduce the interaction effects between chillers within the same facility. As a result, the simulated performance may be somewhat higher than what would be achievable in real operation.

The hard threshold of 12°C for waste heat availability was established based on discussions with a system engineer at Göteborg Energi due to the lack of detailed data on the actual availability of waste heat. This assumption helps explain why Figure 5.18 shows a relatively high historical CONP compared to the simulated one during March and April. During this period, absorption chillers were used in the historical operation even when the average temperature was below 12°C. At the same time, the threshold does not appear to be fully accurate in the opposite direction either. This is illustrated during April, May, October, and November, when the temperature exceeded 12°C and the simulation produced very high CONP values, while the historical data show no use of absorption chillers. This suggests that waste heat was not actually available during those periods despite the temperature-based assumption. This means that the results for winter, spring, and autumn should be interpreted with greater caution, since part of the difference between simulated and historical CONP in these periods may be caused by the simplified assumption regarding waste heat availability rather than by the dispatch logic alone.

The empirical chiller models demonstrate varying predictive performance across the production fleet. As detailed in Appendix A.1, average prediction errors range from 1.29% to 17.72%, while R^2 values span from 0.356 to 0.934. These variations introduce direct parameter uncertainty into the MINLP framework, as the regressed performance equations populate both the objective function and the non-linear constraints. For units with high statistical accuracy (such as `K08_VKA3` with $R^2 = 0.934$), the solver operates on highly reliable efficiency data. Conversely, units with low explanatory power (such as `K10_VKA2` with $R^2 = 0.356$) introduce prediction errors into the optimization loop.

These model errors directly affect the optimization decisions regarding asset selection and load distribution. If a regression model systematically overestimates a chiller's efficiency under specific ambient conditions, the MINLP solver may incorrectly prioritize its binary commitment variable ($\delta_{i,t}$) or overallocate its continuous cooling load ($P_{i,t}$). On the other hand, underestimating a unit's efficiency can cause the model to prematurely cycle assets or over-rely on less efficient configurations. Although the hard system constraints prevent structural or operational failures, these individual model errors propagate directly into the global objective function. Consequently, there is an unmeasured gap between the calculated CONP in this simulation and how the real cooling network would perform in reality. Therefore, the exact efficiency and savings metrics reported in this study should be interpreted within an inherent uncertainty margin rather than as absolute values.

Finally, an important limitation of the empirical chiller models is their reliance on a restricted set of input features. The regression models were trained exclusively on cooling load and exogenous environmental factors. While these variables capture macro-level efficiency trends, they exclude hydraulic parameters including internal flow rates and the temperature difference (ΔT) between the supply and return water. Because thermodynamic efficiency is sensitive to these specific hydraulic conditions, the predicted COSP values contain an inherent margin of error.

This limitation becomes evident when comparing specific hours where the historical operation shows a higher CONP than the simulated dispatch. During some hours on 2025-08-16, the historical operation outperformed the simulation, suggesting that the fitted models do not always capture the full performance potential of the chillers. For example, in the simulated operation, the absorption chiller R1_QV3 is operated at 4.0 MW with a power input of 0.2 MW, corresponding to a COSP of 20.00 at 100.0% capacity. In the historical data, the same chiller is instead operated at 2.6 MW with a power input of 0.1 MW, corresponding to a COSP of 26.80 at 64.6% capacity. Since absorption chillers often tend to operate more efficiently at higher loads, this comparison indicates that the regression model does not fully reproduce the observed chiller behavior under all hydraulic conditions. In this instance, the simulation assigns a higher load to the unit but still predicts a lower efficiency than what is observed in the historical data, which ultimately contributes to a lower simulated CONP.

6.3 Generalizability of the Developed Artifact

The generalizability of the developed artifact should be understood with caution. The chiller models were developed entirely from historical operational data from Göteborg Energi and fitted to the specific chillers, environmental conditions, and operational characteristics of the Gothenburg district cooling network. The resulting regression coefficients and chiller-specific performance equations are therefore case-specific and cannot be transferred directly to other district cooling systems. However, the overall modeling approach may still be applicable in similar contexts, provided that new chiller models are established using local operational data and adapted to the technical configuration of the system in question. Once such local machine models have been defined, the remaining parts of the tool are more broadly reusable, including the optimization engine, the decision logic, and the interactive dashboard used to visualize electricity use, system efficiency, and proposed start/stop schedules. Furthermore, the modular software architecture allows the system to easily adapt to different chiller configurations by simply adding or removing individual chiller performance equations. The most case-specific components are thus the fitted chiller models and the infrastructure-related assumptions embedded in the present case, such as the use of the Göta Älv river for free cooling and the availability of industrial waste heat. This addresses RQ2.1 by distinguishing between case-specific system inputs and potentially transferable elements of the tool's overall design.

Beyond the specific Göteborg Energi implementation, this architecture provides a formalized design approach and implementation guideline for other district cooling systems seeking automated decision support. While any external deployment requires local configuration of machine performance models and environmental boundaries, the fundamental workflow remains identical. This workflow systematically links historical operational data, empirical component modeling, algebraic optimization logic, and frontend visual feedback. In this context, the transferable value of this research rests on the structural integration of these modules rather than the case-specific parameters of a single district cooling network.

6.4 Future Work

Future work should focus on validating the proposed artifact under real operational conditions. Since the present study evaluates the tool only through simulation based on historical data from 2025, an important next step would be to test the decision support system in live operation or in a pilot environment. This would make it possible to assess how robust the proposed control strategy is under real-time uncertainties and plant-level interactions. Another important direction would be to improve the representation of industrial waste heat availability, since the current model relies on a simplified temperature-based assumption due to limited data. Future work could therefore incorporate direct measurements or predictive models for waste heat and district heating supply temperature. Extending the model to include these dependencies would improve the physical realism of the generated dispatch schedules. Future research could expand the model to include a dynamic thermal storage model to reflect the upcoming infrastructure expansion, as this capacity will alter future chiller dispatch logic and introduce new load-shifting possibilities. In addition, the robustness of the artifact could be strengthened by evaluating it on data from multiple years and by refining the performance models for chillers with limited historical observations. Future work should also investigate whether the inclusion of hydraulic variables, such as internal flow rates and supply-return temperature differences, can improve the predictive accuracy of the chiller models and provide a more complete representation of the factors influencing COSP.

7. Conclusion

The results show that the current control strategy is only partly standardized in practice. Although a predefined start-up order exists, the actual operation remains sensitive to exogenous conditions, varies between similar operating situations, and depends partly on operator judgement.

To address these limitations, the study developed an artifact consisting of empirical chiller performance models, a MINLP optimization engine, and an interactive dashboard. Together, these components enabled automated start/stop and dispatch decisions based on predicted chiller efficiency under varying operating conditions. The simulation results indicate that the proposed control strategy can improve operational efficiency while still meeting cooling demand and limiting daily chiller cycling according to the defined success criteria.

The quantitative evaluation showed that the annual average CONP increased from 8.98 to 10.66, corresponding to an improvement of nearly 19%. During the summer period, the average CONP increased from 10.21 to 17.51, corresponding to an improvement of nearly 72%, while electricity use was reduced by 41.69%. The selected daily comparisons further showed energy savings ranging from 22.2% to 43.1%.

Regarding generalizability, the fitted chiller models and infrastructure-related assumptions are case-specific, while the overall modeling approach, optimization logic, modular software structure, and dashboard-based decision support may be transferable to similar district cooling systems if new local chiller models are established. The study therefore contributes a transferable design approach for software-supported district cooling optimization, demonstrated through a practical prototype.

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A. Appendix

A.1 Machine-Level COSP Equations

The estimated machine-level COSP equations are presented below. Only the non-zero terms from the selected regression model for each unit are shown. In the equations, P denotes machine power/load, WB wet-bulb temperature, R river temperature, A air temperature, H humidity, and A_{roll} rolling air temperature.

A.1.1 Rosenlund units

`R1_QV1` $R^2 = 0.905$, Avg. error $= 3.21\%$

$$\text{COSP} = 1.4772 + 3.1332P - 0.297P^2 - 0.0689R - 0.0446RP - 4.5098\frac{P}{R}$$

Maximum cooling capacity: 5.0 MW

`R1_QV2` $R^2 = 0.701$, Avg. error $= 2.18\%$

$$\text{COSP} = 1.0704 + 1.9148P - 0.245P^2 + 0.6215\frac{P}{R} - 0.0028RA + 0.0276A_{\text{roll}}$$

Maximum cooling capacity: 5.0 MW

`R1_QV3` $R^2 = 0.569$, Avg. error $= 11.49\%$

$$\text{COSP} = 8.1491 + 10.0458P - 78.076\frac{P}{R} - 0.082RA + 0.0174PH + 1.2732A_{\text{roll}}$$

Maximum cooling capacity: 4.0 MW

R1_QV4 $R^2 = 0.729$, Avg. error $= 17.56\%$

$$\text{COSP} = -31.1324 + 17.6378P + 2.4279R - 0.0881R^2 - 0.5464PA + 1.0289A_{\text{roll}}$$

Maximum cooling capacity: 4.0 MW

R1_QV5 $R^2 = 0.637$, Avg. error $= 11.85\%$

$$\text{COSP} = -56.7917 + 28.5528P - 5.636P^2 + 5.2565R - 0.1725R^2 + 0.0232PH$$

Maximum cooling capacity: 4.0 MW

R1_QV6 $R^2 = 0.648$, Avg. error $= 10.86\%$

$$\text{COSP} = -51.0406 + 37.1142P - 7.8536P^2 + 5.5631R - 0.1765R^2 - 0.2776PA$$

Maximum cooling capacity: 3.2 MW

R1_QV7 $R^2 = 0.664$, Avg. error $= 11.17\%$

$$\text{COSP} = -40.6098 + 19.4408P + 4.7218R - 0.1513R^2 - 0.6932PA + 0.824A_{\text{roll}}$$

Maximum cooling capacity: 3.2 MW

R1_QV8 $R^2 = 0.719$, Avg. error $= 10.62\%$

$$\text{COSP} = -59.9254 + 39.314P - 8.0873P^2 + 6.2808R - 0.2R^2 - 0.2712PA$$

Maximum cooling capacity: 3.2 MW

A.1.2 Odinsplatsen units

K01_VKA3 $R^2 = 0.665$, Avg. error = 12.26%

$$\text{COSP} = -19.3974 + 80.5831P - 31.9307P^2 - 0.077WB^2 - 0.0473PH + 0.0113AH$$

Maximum cooling capacity: 2.0 MW

K01_VKA4 $R^2 = 0.799$, Avg. error = 5.62%

$$\text{COSP} = 2.7719 + 9.8732P - 9.2849P^2 - 0.0543A - 0.0042A^2 + 0.1426PA$$

Maximum cooling capacity: 1.3 MW

A.1.3 Arkaden units

K03_VKA1 $R^2 = 0.559$, Avg. error = 8.54%

$$\text{COSP} = 4.2743 + 6.5035P - 0.1346WB + 0.0076A^2 - 0.2419PA - 0.1068A_{\text{roll}}$$

Maximum cooling capacity: 1.3 MW

K03_VKA2 $R^2 = 0.922$, Avg. error = 1.87%

$$\text{COSP} = 0.1963 + 4.1044P - 0.8448P^2 - 0.004WB^2 + 0.0139PWB + 0.0002AH$$

Maximum cooling capacity: 2.9 MW

A.1.4 Gullbergsvass units

K04_VKA1 $R^2 = 0.489$, Avg. error = 7.16%

$$\text{COSP} = 0.0863 + 2.3337P - 0.2736P^2 - 0.2461WB + 0.0002H^2 + 0.1744A_{\text{roll}}$$

Maximum cooling capacity: 5.0 MW

`K04_VKA2` $R^2 = 0.544$, Avg. error = 17.72%

$$\text{COSP} = -3.2367 + 13.9646P - 6.4544P^2 - 0.0024WB^2 + 0.0953A - 0.0971PA$$

Maximum cooling capacity: 1.25 MW

`K04_VKA3` $R^2 = 0.877$, Avg. error = 5.05%

$$\text{COSP} = 2.3353 + 19.2181P - 3.3113P^2 + 1.4719WB - 0.0851WB^2 - 0.38A_{\text{roll}}$$

Maximum cooling capacity: 3.1 MW

`K04_VKA4` $R^2 = 0.370$, Avg. error = 2.99%

$$\text{COSP} = 2.8089 + 4.3658P - 2.1014P^2 - 0.0623WB + 0.0491PWB + 0.0143A_{\text{roll}}$$

Maximum cooling capacity: 1.9 MW

A.1.5 Ceres units

`K06_QV1` $R^2 = 0.640$, Avg. error = 5.44%

$$\text{COSP} = -3.869 + 4.1141P - 0.6225P^2 - 0.0125WB^2 + 0.0411PA + 0.0023AH$$

Maximum cooling capacity: 5.65 MW

A.1.6 Lindholmen units

`K08_VKA1` $R^2 = 0.607$, Avg. error = 6.91%

$$\text{COSP} = 0.5344 + 4.4763P - 0.8044P^2 - 0.0009AH$$

Maximum cooling capacity: 4.0 MW

K08_VKA2 $R^2 = 0.633$, Avg. error = 5.08%

$$\text{COSP} = -1.355 + 11.6875P - 5.5997P^2 - 0.0495PWB + 0.09A - 0.0867A_{\text{roll}}$$

Maximum cooling capacity: 1.25 MW

K08_VKA3 $R^2 = 0.934$, Avg. error = 4.86%

$$\text{COSP} = -20.3862 + 41.0961P - 8.6185P^2 + 1.5618WB - 0.0945WB^2 - 0.3234A_{\text{roll}}$$

Maximum cooling capacity: 3.1 MW

K08_VKA4 $R^2 = 0.465$, Avg. error = 14.44%

$$\text{COSP} = -2.2557 + 6.951P - 1.0891P^2 - 0.0037WB^2 + 0.1286A - 0.0819PA$$

Maximum cooling capacity: 2.3 MW

K08_VKA5 $R^2 = 0.811$, Avg. error = 3.48%

$$\text{COSP} = -3.4874 + 4.5438P - 0.6034P^2 - 0.0027WB^2 + 0.0054H + 0.0368A_{\text{roll}}$$

Maximum cooling capacity: 5.0 MW

A.1.7 Svenska Mässan units

K10_VKA1 $R^2 = 0.807$, Avg. error = 6.98%

$$\text{COSP} = 15.5318 + 44.9608P - 25.9198P^2 - 0.2073PA - 0.005AH - 0.4325A_{\text{roll}}$$

Maximum cooling capacity: 1.2 MW

`K10_VKA2` $R^2 = 0.356$, Avg. error = 13.52%

$$\text{COSP} = 17.3474 - 1.3786P - 0.0479WB^2 + 0.8454A + 0.0063AH - 0.6695A_{\text{roll}}$$

Maximum cooling capacity: 1.2 MW

`K10_VKA3` $R^2 = 0.621$, Avg. error = 8.53%

$$\text{COSP} = 7.6223 + 55.7081P - 43.7433P^2 + 1.22WB - 0.0645WB^2 - 0.3104A_{\text{roll}}$$

Maximum cooling capacity: 1.2 MW

`K10_VKA4` $R^2 = 0.827$, Avg. error = 1.29%

$$\text{COSP} = 7.676 - 11.3372P + 0.0055R^2 - 0.0083RA + 0.514PWB - 0.0015AH$$

Maximum cooling capacity: 1.25 MW

B. Appendix

Table B.1: Summary of valid operational data points (hourly observations) per cooling machine during the 2025 baseline year.

Machine ID	**Valid Observations (n)**
K04_VKA3	3148
R1_QV3	3110
K08_VKA3	2724
K01_VKA3	2634
K10_VKA1	2417
R1_QV6	2294
R1_QV8	1979
R1_QV2	1942
K10_VKA2	1873
R1_QV7	1805
K10_VKA3	1642
R1_QV1	1162
R1_QV5	1147
K08_VKA4	1054
R1_QV4	891
K04_VKA4	822
K04_VKA2	820
K06_QV1	788
K08_VKA5	784
K01_VKA4	563
K08_VKA2	521
K04_VKA1	468
K03_VKA2	322
K03_VKA1	167
K08_VKA1	127
K10_VKA4	44
K01_VKA2	0
K01_VKA1	0

C. Appendix

Dispatch Logs 06-16

Hour 00 00

AI Simulated Dispatch

[STARTED] R1_QV4 (ABS)	3.6 MW	COSP 35.00
[STARTED] R1_QV8 (ABS)	3.0 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.13

AI CONP 27.77 Total Power 0.35 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.1 MW	COSP 22.14
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 28.76
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 25.95
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.97
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 25.80

Hist CONP 21.93 Total Power 0.44 MW

Hour 01 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	3.5 MW	COSP 35.00
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.41

AI CONP 27.83 Total Power 0.34 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 20.99
[HIST] R1_QV8 (ABS)	1.6 MW	COSP 27.24
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.67
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.76

Hist CONP 21.79 Total Power 0.43 MW

Hour 02 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.42

AI CONP 27.69 Total Power 0.33 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 21.49
[HIST] R1_QV8 (ABS)	1.2 MW	COSP 18.74
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.85
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.06

Hist CONP 21.06 Total Power 0.43 MW

Hour 03 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	2.8 MW	COSP 35.00
[STARTED] R1_QV7 (ABS)	3.2 MW	COSP 33.50
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00

AI CONP 29.95 Total Power 0.30 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 26.74
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.25
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.68

Hist CONP 23.21 Total Power 0.38 MW

Hour 04 00

AI Simulated Dispatch

[STARTED] R1_QV6 (ABS)	2.6 MW	COSP 31.70
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.08
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 29.08 Total Power 0.30 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.7 MW	COSP 25.50
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.97
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.99
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.21

Hist CONP 22.77 Total Power 0.38 MW

Hour 05 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 35.00
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.44
[KEPT ON] R1_QV8 (ABS)	3.0 MW	COSP 35.00

AI CONP 29.79 Total Power 0.32 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.5 MW	COSP 21.59
[HIST] R1_QV8 (ABS)	1.1 MW	COSP 15.91
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.68
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 29.91
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.46

Hist CONP 20.53 Total Power 0.46 MW

Hour 06 00

AI Simulated Dispatch

[STARTED] R1_QV5 (ABS)	2.1 MW	COSP 22.21
[KEPT ON] R1_QV6 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.92
[KEPT ON] R1_QV8 (ABS)	2.2 MW	COSP 31.11

AI CONP 26.46 Total Power 0.40 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.5 MW	COSP 18.26
[HIST] R1_QV4 (ABS)	0.5 MW	COSP 05.04
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 21.53
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.63
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 29.98
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 28.29

Hist CONP 17.49 Total Power 0.61 MW

Hour 07 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 23.43
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 34.80
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.26
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 26.42 Total Power 0.46 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 19.21
[HIST] R1_QV4 (ABS)	1.9 MW	COSP 19.65
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 23.10
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.46
[HIST] K04_VKA3 (ABS)	3.0 MW	COSP 29.98
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 28.01
[HIST] K10_VKA1 (ABS)	0.6 MW	COSP 15.95
[HIST] K10_VKA2 (ABS)	0.4 MW	COSP 13.72

Hist CONP 18.92 Total Power 0.64 MW

Hour 08 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.3 MW	COSP 21.12
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.85
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.49
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 34.19

AI CONP 24.92 Total Power 0.52 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 19.26
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 20.01
[HIST] R1_QV8 (ABS)	1.4 MW	COSP 22.84
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.20
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.90
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 26.88
[HIST] K08_VKA4 (KOMP)	0.4 MW	COSP 01.25
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 20.08
[HIST] K10_VKA2 (ABS)	0.7 MW	COSP 18.05

Hist CONP 12.69 Total Power 1.02 MW

Hour 09 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.1 MW	COSP 21.87
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.18
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.00
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.93
[STARTED] K04_VKA3 (ABS)	3.1 MW	COSP 26.37

AI CONP 24.29 Total Power 0.65 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.4 MW	COSP 21.81
[HIST] R1_QV4 (ABS)	2.3 MW	COSP 22.07
[HIST] R1_QV8 (ABS)	1.8 MW	COSP 25.77
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 27.59
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.56
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.53
[HIST] K08_VKA4 (KOMP)	1.7 MW	COSP 05.19
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 18.68
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.70
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 24.23

Hist CONP 15.09 Total Power 1.05 MW

Hour 10 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.7 MW	COSP 22.90
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.54
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.42
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.76
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.96
[STARTED] K08_VKA3 (ABS)	2.6 MW	COSP 23.24

AI CONP 23.14 Total Power 0.78 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 20.55
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 20.22
[HIST] R1_QV6 (ABS)	1.3 MW	COSP 19.15
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 23.98
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.77
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.20
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 26.08
[HIST] K08_VKA4 (KOMP)	1.7 MW	COSP 05.17
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 18.65
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.15
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 25.33

Hist CONP 14.81 Total Power 1.22 MW

Hour 11 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.8 MW	COSP 17.89
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.80
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.65
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.68
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.66
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 21.68

AI CONP 21.25 Total Power 0.92 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.9 MW	COSP 19.41
[HIST] R1_QV4 (ABS)	2.5 MW	COSP 19.22
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 22.18
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 21.95
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.01
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.37
[HIST] K06_QV1 (KOMP)	0.4 MW	COSP 00.77
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.70
[HIST] K08_VKA4 (KOMP)	1.8 MW	COSP 05.29
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 18.40
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.07
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.38

Hist CONP 10.75 Total Power 1.82 MW

Hour 12 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.9 MW	COSP 22.48
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.53
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.29
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.29
[STARTED] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.58
[KEPT ON] K08_VKA3 (ABS)	2.9 MW	COSP 22.52

AI CONP 23.12 Total Power 0.88 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.4 MW	COSP 19.19
[HIST] R1_QV4 (ABS)	2.3 MW	COSP 19.53
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 22.39
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.24
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 25.87
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 27.51
[HIST] K06_QV1 (KOMP)	2.8 MW	COSP 05.81
[HIST] K08_VKA1 (KOMP)	0.4 MW	COSP 01.53
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 25.40
[HIST] K08_VKA4 (KOMP)	1.4 MW	COSP 04.14
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 17.43
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 15.88
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.09

Hist CONP 10.04 Total Power 2.02 MW

Hour 13 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 22.75
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.63
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.43
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.47
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.06
[KEPT ON] K08_VKA3 (ABS)	2.7 MW	COSP 22.23

AI CONP 23.00 Total Power 0.87 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 18.61
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 18.51
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 22.16
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.01
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.25
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 27.92
[HIST] K06_QV1 (KOMP)	1.7 MW	COSP 03.41
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 25.21
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 17.92
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 16.21
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.27

Hist CONP 14.32 Total Power 1.40 MW

Hour 14 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 22.49
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.48
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.29
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.31
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.54
[KEPT ON] K08_VKA3 (ABS)	2.8 MW	COSP 22.61

AI CONP 23.76 Total Power 0.85 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.6 MW	COSP 19.64
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 19.80
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 22.84
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 22.59
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.74
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.68
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.69
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 18.42
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 16.48
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.55

Hist CONP 22.21 Total Power 0.91 MW

Hour 15 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.1 MW	COSP 20.84
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 29.44
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 28.34
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 29.12
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.35
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 22.23

AI CONP 21.87 Total Power 0.95 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 18.83
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 18.84
[HIST] R1_QV5 (ABS)	1.3 MW	COSP 10.41
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 21.72
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 21.52
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.50
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.92
[HIST] K08_VKA1 (KOMP)	2.0 MW	COSP 05.38
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.82
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 19.10
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.37
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 25.75

Hist CONP 13.85 Total Power 1.50 MW

Hour 16 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.0 MW	COSP 21.38
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.38
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.13
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.90
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 27.24
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 23.36

AI CONP 22.08 Total Power 0.93 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	2.0 MW	COSP 03.93
[HIST] R1_QV3 (ABS)	2.5 MW	COSP 17.76
[HIST] R1_QV4 (ABS)	2.2 MW	COSP 17.81
[HIST] R1_QV5 (ABS)	2.4 MW	COSP 17.54
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 20.19
[HIST] R1_QV8 (ABS)	2.0 MW	COSP 20.08
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.18
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.21
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.56
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 19.54
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.89
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 26.36

Hist CONP 12.58 Total Power 1.64 MW

Hour 17 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.3 MW	COSP 21.77
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.12
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.78
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.75
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	2.8 MW	COSP 26.67
[KEPT ON] K08_VKA3 (ABS)	2.1 MW	COSP 25.08

AI CONP 24.17 Total Power 0.77 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	1.2 MW	COSP 02.22
[HIST] R1_QV3 (ABS)	2.1 MW	COSP 19.40
[HIST] R1_QV4 (ABS)	2.2 MW	COSP 20.06
[HIST] R1_QV5 (ABS)	2.0 MW	COSP 19.03
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 22.55
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.50
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 27.52
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.17
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.54
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 20.11
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 17.12
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 26.97

Hist CONP 12.50 Total Power 1.50 MW

Hour 18 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.74
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.39
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.78
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	2.2 MW	COSP 25.15
[KEPT ON] K08_VKA3 (ABS)	2.1 MW	COSP 25.26

AI CONP 25.46 Total Power 0.62 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.8 MW	COSP 18.21
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 19.05
[HIST] R1_QV5 (ABS)	1.8 MW	COSP 18.01
[HIST] R1_QV6 (ABS)	1.3 MW	COSP 22.19
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 22.18
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.66
[HIST] K04_VKA3 (ABS)	2.5 MW	COSP 28.41
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.48
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 19.88
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 17.10
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 23.69

Hist CONP 18.39 Total Power 0.86 MW

Hour 19 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.66
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.20
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 32.90
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K08_VKA3 (ABS)	2.2 MW	COSP 25.28

AI CONP 26.52 Total Power 0.51 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.9 MW	COSP 17.61
[HIST] R1_QV4 (ABS)	1.9 MW	COSP 18.33
[HIST] R1_QV5 (ABS)	1.7 MW	COSP 17.23
[HIST] R1_QV6 (ABS)	1.4 MW	COSP 21.32
[HIST] R1_QV8 (ABS)	1.6 MW	COSP 21.31
[HIST] K01_VKA3 (ABS)	0.8 MW	COSP 17.53
[HIST] K04_VKA3 (ABS)	2.4 MW	COSP 28.13
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.25
[HIST] K10_VKA1 (ABS)	0.2 MW	COSP 05.45

Hist CONP 17.31 Total Power 0.78 MW

Hour 20 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	1.7 MW	COSP 25.25
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.51
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 33.50
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K08_VKA3 (ABS)	2.0 MW	COSP 24.24

AI CONP 25.92 Total Power 0.46 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.9 MW	COSP 17.15
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 17.88
[HIST] R1_QV5 (ABS)	1.2 MW	COSP 08.71
[HIST] R1_QV6 (ABS)	1.4 MW	COSP 20.76
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 20.75
[HIST] K04_VKA3 (ABS)	2.3 MW	COSP 27.83
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.82

Hist CONP 16.27 Total Power 0.73 MW

Hour 21 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 34.41
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 32.65
[KEPT ON] R1_QV8 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] K01_VKA3 (ABS)	0.6 MW	COSP 35.00

AI CONP 29.43 Total Power 0.34 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.2 MW	COSP 20.60
[HIST] R1_QV4 (ABS)	0.4 MW	COSP 00.20
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 26.03
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 26.03
[HIST] K04_VKA3 (ABS)	2.2 MW	COSP 28.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.67

Hist CONP 03.82 Total Power 2.65 MW

Hour 22 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	2.7 MW	COSP 32.74
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.09
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00
[KEPT ON] K01_VKA3 (ABS)	0.6 MW	COSP 35.00

AI CONP 29.30 Total Power 0.32 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 21.62
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 27.62
[HIST] R1_QV8 (ABS)	1.4 MW	COSP 22.04
[HIST] K04_VKA3 (ABS)	2.2 MW	COSP 28.33
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.40

Hist CONP 21.98 Total Power 0.43 MW

Hour 23 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.0 MW	COSP 33.83
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 32.76
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 29.71 Total Power 0.31 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.7 MW	COSP 24.76
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 29.55
[HIST] K04_VKA3 (ABS)	2.5 MW	COSP 29.74
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.11

Hist CONP 23.55 Total Power 0.39 MW

Dispatch Logs 07-16

Hour 00 00

AI Simulated Dispatch

[STARTED] R1_QV3 (ABS)	4.0 MW	COSP 18.52
[STARTED] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[STARTED] R1_QV6 (ABS)	2.6 MW	COSP 23.10
[STARTED] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 20.12

AI CONP 19.42 Total Power 0.80 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.6 MW	COSP 22.81
[HIST] R1_QV4 (ABS)	2.7 MW	COSP 23.67
[HIST] R1_QV5 (ABS)	2.5 MW	COSP 23.28
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 22.56
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 22.55
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 13.08
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 15.52
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 11.18
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 17.68

Hist CONP 15.72 Total Power 0.99 MW

Hour 01 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.57
[KEPT ON] R1_QV4 (ABS)	2.5 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 25.15
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 20.54

AI CONP 19.18 Total Power 0.77 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 25.18
[HIST] R1_QV4 (ABS)	3.0 MW	COSP 26.25
[HIST] R1_QV6 (ABS)	2.1 MW	COSP 25.35
[HIST] R1_QV8 (ABS)	2.2 MW	COSP 25.43
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 12.90
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 15.98
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 11.37
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 17.76

Hist CONP 16.52 Total Power 0.89 MW

Hour 02 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.55
[KEPT ON] R1_QV4 (ABS)	2.1 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 25.70
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 21.15

AI CONP 19.73 Total Power 0.72 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 26.17
[HIST] R1_QV4 (ABS)	3.0 MW	COSP 27.48
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 26.44
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 26.29
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 13.28
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 16.81
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 11.68
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 17.95

Hist CONP 17.13 Total Power 0.83 MW

Hour 03 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.73
[KEPT ON] R1_QV4 (ABS)	1.2 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 26.29
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 21.75

AI CONP 19.45 Total Power 0.69 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	3.0 MW	COSP 26.69
[HIST] R1_QV4 (ABS)	3.1 MW	COSP 27.70
[HIST] R1_QV6 (ABS)	2.1 MW	COSP 26.75
[HIST] R1_QV8 (ABS)	2.2 MW	COSP 26.72
[HIST] K01_VKA3 (ABS)	0.6 MW	COSP 07.49
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 17.37
[HIST] K10_VKA2 (ABS)	0.2 MW	COSP 04.71

Hist CONP 17.04 Total Power 0.79 MW

Hour 04 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.70
[KEPT ON] R1_QV4 (ABS)	3.0 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 26.51
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 22.28

AI CONP 19.17 Total Power 0.69 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	3.1 MW	COSP 26.80
[HIST] R1_QV4 (ABS)	3.2 MW	COSP 27.85
[HIST] R1_QV6 (ABS)	2.3 MW	COSP 27.25
[HIST] R1_QV8 (ABS)	2.5 MW	COSP 27.14
[HIST] K01_VKA3 (ABS)	0.2 MW	COSP 04.75
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 17.91

Hist CONP 18.42 Total Power 0.72 MW

Hour 05 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.82
[KEPT ON] R1_QV4 (ABS)	1.3 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 26.77
[STARTED] R1_QV7 (ABS)	3.2 MW	COSP 25.22
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 22.62

AI CONP 19.00 Total Power 0.78 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.9 MW	COSP 25.96
[HIST] R1_QV4 (ABS)	3.1 MW	COSP 26.97
[HIST] R1_QV6 (ABS)	2.1 MW	COSP 26.11
[HIST] R1_QV7 (ABS)	0.5 MW	COSP 08.57
[HIST] R1_QV8 (ABS)	2.2 MW	COSP 26.12
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 22.20
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 18.52
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 12.31

Hist CONP 17.45 Total Power 0.85 MW

Hour 06 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 19.06
[KEPT ON] R1_QV4 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 26.95
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 25.42
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 22.67

AI CONP 19.26 Total Power 0.86 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 23.77
[HIST] R1_QV4 (ABS)	2.9 MW	COSP 24.64
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 23.11
[HIST] R1_QV7 (ABS)	1.9 MW	COSP 23.98
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 23.26
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 24.27
[HIST] K06_QV1 (KOMP)	0.9 MW	COSP 01.50
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 18.68
[HIST] K10_VKA2 (ABS)	0.7 MW	COSP 13.70
[HIST] K10_VKA3 (ABS)	0.4 MW	COSP 17.75

Hist CONP 10.91 Total Power 1.52 MW

Hour 07 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.78
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[STARTED] R1_QV5 (ABS)	3.3 MW	COSP 18.81
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 25.64
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 24.23
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 21.85

AI CONP 18.03 Total Power 1.15 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.7 MW	COSP 18.87
[HIST] R1_QV4 (ABS)	2.9 MW	COSP 19.54
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 19.37
[HIST] R1_QV7 (ABS)	2.0 MW	COSP 19.78
[HIST] R1_QV8 (ABS)	2.2 MW	COSP 19.47
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 23.70
[HIST] K04_VKA4 (KOMP)	0.4 MW	COSP 03.03
[HIST] K06_QV1 (KOMP)	3.9 MW	COSP 05.99
[HIST] K08_VKA2 (KOMP)	0.4 MW	COSP 02.73
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 17.91
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 12.41
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 19.17

Hist CONP 10.03 Total Power 2.07 MW

Hour 08 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.60
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	2.9 MW	COSP 19.91
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 23.44
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 22.32
[STARTED] R1_QV8 (ABS)	3.2 MW	COSP 23.16
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 19.47
[STARTED] K08_VKA3 (ABS)	2.9 MW	COSP 16.09

AI CONP 16.86 Total Power 1.58 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.9 MW	COSP 18.44
[HIST] R1_QV4 (ABS)	3.2 MW	COSP 19.09
[HIST] R1_QV6 (ABS)	2.2 MW	COSP 18.68
[HIST] R1_QV7 (ABS)	2.1 MW	COSP 18.72
[HIST] R1_QV8 (ABS)	2.5 MW	COSP 18.84
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 21.39
[HIST] K03_VKA1 (KOMP)	0.3 MW	COSP 02.13
[HIST] K04_VKA1 (KOMP)	1.3 MW	COSP 02.12
[HIST] K04_VKA2 (KOMP)	0.5 MW	COSP 02.76
[HIST] K04_VKA4 (KOMP)	0.7 MW	COSP 04.37
[HIST] K06_QV1 (KOMP)	4.9 MW	COSP 05.04
[HIST] K08_VKA2 (KOMP)	1.0 MW	COSP 03.85
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 17.24
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 11.28
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 18.08

Hist CONP 07.33 Total Power 3.63 MW

Hour 09 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.52
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	3.8 MW	COSP 16.70
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 22.70
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 21.70
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 22.08
[STARTED] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 18.47
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 15.18
[STARTED] K10_VKA1 (ABS)	1.2 MW	COSP 13.29
[STARTED] K10_VKA2 (ABS)	1.2 MW	COSP 11.52
[STARTED] K10_VKA3 (ABS)	1.2 MW	COSP 09.26

AI CONP 16.43 Total Power 2.01 MW

Historical Operator Dispatch

[HIST] R1_QV2 (KOMP)	2.7 MW	COSP 03.78
[HIST] R1_QV3 (ABS)	2.8 MW	COSP 18.32
[HIST] R1_QV4 (ABS)	3.0 MW	COSP 18.95
[HIST] R1_QV6 (ABS)	2.1 MW	COSP 18.11
[HIST] R1_QV7 (ABS)	2.0 MW	COSP 18.03
[HIST] R1_QV8 (ABS)	0.6 MW	COSP 01.93
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 19.54
[HIST] K03_VKA1 (KOMP)	1.2 MW	COSP 04.14
[HIST] K04_VKA1 (KOMP)	3.3 MW	COSP 04.40
[HIST] K04_VKA2 (KOMP)	0.9 MW	COSP 03.19
[HIST] K04_VKA3 (ABS)	2.1 MW	COSP 17.33
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.63
[HIST] K06_QV1 (KOMP)	4.9 MW	COSP 04.97
[HIST] K08_VKA2 (KOMP)	1.0 MW	COSP 03.82
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 16.34
[HIST] K10_VKA1 (ABS)	0.2 MW	COSP 05.37
[HIST] K10_VKA2 (ABS)	0.6 MW	COSP 10.35
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 17.00

Hist CONP 06.55 Total Power 5.04 MW

Hour 10 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.37
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.70
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 21.98
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 21.08
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 21.04
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 24.69
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 17.76
[STARTED] K06_QV1 (KOMP)	4.9 MW	COSP 05.13
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 14.67
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 13.03
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.40
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 09.10

AI CONP 12.20 Total Power 3.14 MW

Historical Operator Dispatch

[HIST] R1_QV2 (KOMP)	4.7 MW	COSP 04.47
[HIST] R1_QV3 (ABS)	2.9 MW	COSP 20.85
[HIST] R1_QV4 (ABS)	3.2 MW	COSP 21.64
[HIST] R1_QV6 (ABS)	2.3 MW	COSP 20.80
[HIST] R1_QV7 (ABS)	2.2 MW	COSP 20.54
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 17.71
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 04.11
[HIST] K04_VKA1 (KOMP)	3.8 MW	COSP 04.19
[HIST] K04_VKA2 (KOMP)	0.9 MW	COSP 03.13
[HIST] K04_VKA3 (ABS)	2.6 MW	COSP 16.39
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.82
[HIST] K06_QV1 (KOMP)	4.9 MW	COSP 04.93
[HIST] K08_VKA2 (KOMP)	0.3 MW	COSP 00.93
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 14.62
[HIST] K08_VKA4 (KOMP)	1.3 MW	COSP 03.10
[HIST] K08_VKA5 (KOMP)	1.1 MW	COSP 01.69
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 11.85
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.98
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 15.60

Hist CONP 05.91 Total Power 6.48 MW

Hour 11 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.15
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.63
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 21.05
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 20.26
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 20.02
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 23.50
[STARTED] K04_VKA1 (KOMP)	5.0 MW	COSP 05.04
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 16.57
[KEPT ON] K06_QV1 (KOMP)	4.7 MW	COSP 05.25
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 13.70
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.61
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.14
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 08.69

AI CONP 10.41 Total Power 4.13 MW

Historical Operator Dispatch

[HIST] R1_QV2 (KOMP)	4.7 MW	COSP 04.46
[HIST] R1_QV3 (ABS)	2.9 MW	COSP 20.75
[HIST] R1_QV4 (ABS)	3.2 MW	COSP 21.55
[HIST] R1_QV5 (ABS)	0.3 MW	COSP 03.85
[HIST] R1_QV6 (ABS)	2.4 MW	COSP 20.70
[HIST] R1_QV7 (ABS)	2.2 MW	COSP 20.44
[HIST] R1_QV8 (ABS)	1.2 MW	COSP 11.29
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 15.98
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 03.95
[HIST] K04_VKA1 (KOMP)	4.3 MW	COSP 04.76
[HIST] K04_VKA2 (KOMP)	1.0 MW	COSP 03.18
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 15.68
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.91
[HIST] K06_QV1 (KOMP)	4.8 MW	COSP 04.87
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 14.22
[HIST] K08_VKA4 (KOMP)	1.8 MW	COSP 04.20
[HIST] K08_VKA5 (KOMP)	4.1 MW	COSP 05.22
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 11.95
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 09.02
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 15.68

Hist CONP 06.54 Total Power 6.58 MW

Hour 12 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.04
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.52
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 20.71
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 19.96
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 19.51
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 22.84
[KEPT ON] K04_VKA1 (KOMP)	5.0 MW	COSP 05.07
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 16.20
[KEPT ON] K06_QV1 (KOMP)	4.2 MW	COSP 05.41
[STARTED] K08_VKA1 (KOMP)	3.2 MW	COSP 05.29
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 13.48
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.47
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.07
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 08.63

AI CONP 09.81 Total Power 4.66 MW

Historical Operator Dispatch

[HIST] R1_QV2 (KOMP)	4.3 MW	COSP 04.27
[HIST] R1_QV3 (ABS)	2.9 MW	COSP 17.53
[HIST] R1_QV4 (ABS)	3.1 MW	COSP 18.04
[HIST] R1_QV5 (ABS)	2.7 MW	COSP 18.67
[HIST] R1_QV6 (ABS)	2.3 MW	COSP 17.62
[HIST] R1_QV7 (ABS)	2.1 MW	COSP 17.55
[HIST] R1_QV8 (ABS)	2.3 MW	COSP 17.46
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 16.10
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 03.88
[HIST] K04_VKA1 (KOMP)	4.3 MW	COSP 04.67
[HIST] K04_VKA2 (KOMP)	0.9 MW	COSP 03.14
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 14.94
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.92
[HIST] K06_QV1 (KOMP)	4.7 MW	COSP 04.84
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 13.99
[HIST] K08_VKA4 (KOMP)	1.9 MW	COSP 04.18
[HIST] K08_VKA5 (KOMP)	4.1 MW	COSP 05.15
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 11.81
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 09.04
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 15.17

Hist CONP 06.74 Total Power 6.78 MW

Hour 13 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 17.82
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.37
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 20.46
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 19.72
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 19.11
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 22.48
[KEPT ON] K04_VKA1 (KOMP)	5.0 MW	COSP 05.11
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 15.95
[KEPT ON] K06_QV1 (KOMP)	4.9 MW	COSP 05.08
[KEPT ON] K08_VKA1 (KOMP)	4.0 MW	COSP 04.96
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 13.33
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.39
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.00
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 08.59

AI CONP 09.32 Total Power 5.08 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	3.0 MW	COSP 03.36
[HIST] R1_QV2 (KOMP)	3.5 MW	COSP 04.19
[HIST] R1_QV3 (ABS)	2.8 MW	COSP 16.67
[HIST] R1_QV4 (ABS)	2.9 MW	COSP 17.09
[HIST] R1_QV5 (ABS)	2.5 MW	COSP 17.66
[HIST] R1_QV6 (ABS)	1.9 MW	COSP 17.29
[HIST] R1_QV7 (ABS)	2.0 MW	COSP 17.75
[HIST] R1_QV8 (ABS)	2.0 MW	COSP 17.18
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 15.12
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 03.84
[HIST] K04_VKA1 (KOMP)	4.5 MW	COSP 05.10
[HIST] K04_VKA2 (KOMP)	1.0 MW	COSP 03.20
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 15.31
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.86
[HIST] K06_QV1 (KOMP)	4.7 MW	COSP 04.83
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 13.48
[HIST] K08_VKA4 (KOMP)	1.9 MW	COSP 04.17
[HIST] K08_VKA5 (KOMP)	4.1 MW	COSP 05.10
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 11.27
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.78
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 13.94

Hist CONP 06.33 Total Power 7.47 MW

Hour 14 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 17.89
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.29
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 20.64
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 19.90
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 19.16
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 22.51
[KEPT ON] K04_VKA1 (KOMP)	5.0 MW	COSP 05.18
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 16.37
[KEPT ON] K06_QV1 (KOMP)	5.1 MW	COSP 05.01
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 13.78
[STARTED] K08_VKA5 (KOMP)	4.9 MW	COSP 04.69
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.55
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.14
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 08.83

AI CONP 08.97 Total Power 5.39 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	3.2 MW	COSP 03.38
[HIST] R1_QV2 (KOMP)	3.7 MW	COSP 04.20
[HIST] R1_QV3 (ABS)	2.7 MW	COSP 17.13
[HIST] R1_QV4 (ABS)	2.9 MW	COSP 17.62
[HIST] R1_QV5 (ABS)	2.6 MW	COSP 18.28
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 18.06
[HIST] R1_QV7 (ABS)	2.0 MW	COSP 18.54
[HIST] R1_QV8 (ABS)	2.0 MW	COSP 18.22
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 15.02
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 03.85
[HIST] K04_VKA1 (KOMP)	4.2 MW	COSP 04.55
[HIST] K04_VKA2 (KOMP)	0.9 MW	COSP 03.09
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 14.38
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.67
[HIST] K06_QV1 (KOMP)	4.7 MW	COSP 04.85
[HIST] K08_VKA1 (KOMP)	1.0 MW	COSP 05.45
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 12.73
[HIST] K08_VKA4 (KOMP)	1.7 MW	COSP 04.04
[HIST] K08_VKA5 (KOMP)	3.9 MW	COSP 05.09
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 10.84
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.90
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 14.00

Hist CONP 06.24 Total Power 7.75 MW

Hour 15 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.05
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	4.0 MW	COSP 15.49
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 23.03
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 22.08
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 20.96
[KEPT ON] K01_VKA3 (ABS)	2.0 MW	COSP 25.00
[KEPT ON] K04_VKA1 (KOMP)	4.8 MW	COSP 05.47
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 17.57
[KEPT ON] K06_QV1 (KOMP)	3.9 MW	COSP 05.59
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 14.76
[KEPT ON] K08_VKA5 (KOMP)	3.8 MW	COSP 05.18
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.95
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 11.14
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 09.25

AI CONP 10.28 Total Power 4.46 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	2.7 MW	COSP 03.46
[HIST] R1_QV2 (KOMP)	3.2 MW	COSP 04.27
[HIST] R1_QV3 (ABS)	2.5 MW	COSP 17.65
[HIST] R1_QV4 (ABS)	2.7 MW	COSP 18.23
[HIST] R1_QV5 (ABS)	1.6 MW	COSP 07.23
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 17.31
[HIST] R1_QV7 (ABS)	1.8 MW	COSP 17.93
[HIST] R1_QV8 (ABS)	0.9 MW	COSP 07.75
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 15.92
[HIST] K03_VKA1 (KOMP)	1.3 MW	COSP 03.98
[HIST] K04_VKA1 (KOMP)	4.8 MW	COSP 05.97
[HIST] K04_VKA2 (KOMP)	1.0 MW	COSP 03.30
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 16.15
[HIST] K04_VKA4 (KOMP)	0.8 MW	COSP 04.89
[HIST] K06_QV1 (KOMP)	4.7 MW	COSP 04.87
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 13.32
[HIST] K08_VKA4 (KOMP)	1.8 MW	COSP 04.13
[HIST] K08_VKA5 (KOMP)	3.9 MW	COSP 05.20
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 10.67
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 09.32
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 15.28

Hist CONP 06.54 Total Power 7.01 MW

Hour 16 00

AI Simulated Dispatch

[KEPT ON]	R1_QV3 (ABS)	4.0 MW	COSP 17.83
[KEPT ON]	R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON]	R1_QV5 (ABS)	4.0 MW	COSP 15.62
[KEPT ON]	R1_QV6 (ABS)	3.2 MW	COSP 22.22
[KEPT ON]	R1_QV7 (ABS)	3.2 MW	COSP 21.31
[KEPT ON]	R1_QV8 (ABS)	3.2 MW	COSP 20.61
[KEPT ON]	K01_VKA3 (ABS)	2.0 MW	COSP 24.69
[KEPT ON]	K04_VKA1 (KOMP)	5.0 MW	COSP 05.25
[KEPT ON]	K04_VKA3 (ABS)	3.1 MW	COSP 16.56
[KEPT ON]	K06_QV1 (KOMP)	4.0 MW	COSP 05.47
[KEPT ON]	K08_VKA3 (ABS)	3.1 MW	COSP 13.72
[KEPT ON]	K10_VKA1 (ABS)	1.2 MW	COSP 12.59
[KEPT ON]	K10_VKA2 (ABS)	1.2 MW	COSP 10.88
[KEPT ON]	K10_VKA3 (ABS)	1.2 MW	COSP 08.70

AI CONP 11.11 Total Power 3.81 MW

Historical Operator Dispatch

[HIST]	R1_QV1 (KOMP)	2.6 MW	COSP 03.68
[HIST]	R1_QV2 (KOMP)	3.1 MW	COSP 04.59
[HIST]	R1_QV3 (ABS)	2.5 MW	COSP 25.00
[HIST]	R1_QV4 (ABS)	2.6 MW	COSP 26.07
[HIST]	R1_QV6 (ABS)	1.6 MW	COSP 23.09
[HIST]	R1_QV7 (ABS)	0.6 MW	COSP 06.71
[HIST]	K01_VKA3 (ABS)	1.3 MW	COSP 16.03
[HIST]	K03_VKA1 (KOMP)	1.2 MW	COSP 04.12
[HIST]	K03_VKA2 (KOMP)	0.5 MW	COSP 01.05
[HIST]	K04_VKA1 (KOMP)	4.1 MW	COSP 05.24
[HIST]	K04_VKA2 (KOMP)	0.9 MW	COSP 03.12
[HIST]	K04_VKA3 (ABS)	2.6 MW	COSP 14.85
[HIST]	K04_VKA4 (KOMP)	0.8 MW	COSP 04.84
[HIST]	K06_QV1 (KOMP)	4.7 MW	COSP 04.89
[HIST]	K08_VKA3 (ABS)	2.4 MW	COSP 13.33
[HIST]	K08_VKA4 (KOMP)	1.8 MW	COSP 04.13
[HIST]	K08_VKA5 (KOMP)	4.0 MW	COSP 05.18
[HIST]	K10_VKA1 (ABS)	0.7 MW	COSP 10.83
[HIST]	K10_VKA2 (ABS)	0.5 MW	COSP 08.97
[HIST]	K10_VKA3 (ABS)	0.4 MW	COSP 15.33

Hist CONP 06.29 Total Power 6.74 MW

Hour 17 00

AI Simulated Dispatch

[KEPT ON]	R1_QV3 (ABS)	4.0 MW	COSP 17.85
[KEPT ON]	R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON]	R1_QV5 (ABS)	4.0 MW	COSP 15.68
[KEPT ON]	R1_QV6 (ABS)	3.2 MW	COSP 22.17
[KEPT ON]	R1_QV7 (ABS)	3.2 MW	COSP 21.24
[KEPT ON]	R1_QV8 (ABS)	3.2 MW	COSP 20.81
[KEPT ON]	K01_VKA3 (ABS)	2.0 MW	COSP 24.88
[KEPT ON]	K04_VKA3 (ABS)	3.1 MW	COSP 16.62
[KEPT ON]	K06_QV1 (KOMP)	3.9 MW	COSP 05.45
[KEPT ON]	K08_VKA3 (ABS)	3.1 MW	COSP 13.71
[KEPT ON]	K10_VKA1 (ABS)	1.2 MW	COSP 12.62
[KEPT ON]	K10_VKA2 (ABS)	1.2 MW	COSP 10.90
[KEPT ON]	K10_VKA3 (ABS)	1.2 MW	COSP 08.66

AI CONP 13.12 Total Power 2.84 MW

Historical Operator Dispatch

[HIST]	R1_QV1 (KOMP)	1.9 MW	COSP 03.53
[HIST]	R1_QV2 (KOMP)	2.3 MW	COSP 04.30
[HIST]	R1_QV3 (ABS)	2.7 MW	COSP 22.34
[HIST]	R1_QV4 (ABS)	2.8 MW	COSP 23.24
[HIST]	R1_QV6 (ABS)	1.9 MW	COSP 21.43
[HIST]	K01_VKA3 (ABS)	1.3 MW	COSP 13.45
[HIST]	K03_VKA1 (KOMP)	1.2 MW	COSP 04.28
[HIST]	K03_VKA2 (KOMP)	2.6 MW	COSP 04.54
[HIST]	K04_VKA1 (KOMP)	4.3 MW	COSP 04.95
[HIST]	K04_VKA2 (KOMP)	0.9 MW	COSP 03.14
[HIST]	K04_VKA3 (ABS)	2.6 MW	COSP 14.22
[HIST]	K04_VKA4 (KOMP)	0.8 MW	COSP 04.80
[HIST]	K06_QV1 (KOMP)	4.6 MW	COSP 04.93
[HIST]	K08_VKA3 (ABS)	0.5 MW	COSP 05.58
[HIST]	K08_VKA5 (KOMP)	3.7 MW	COSP 05.14
[HIST]	K10_VKA1 (ABS)	0.7 MW	COSP 10.83
[HIST]	K10_VKA2 (ABS)	0.5 MW	COSP 08.79
[HIST]	K10_VKA3 (ABS)	0.5 MW	COSP 14.47

Hist CONP 06.19 Total Power 6.02 MW

Hour 18 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 17.76
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	3.6 MW	COSP 17.35
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 21.70
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 20.81
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 20.40
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 16.27
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 13.39
[KEPT ON] K10_VKA1 (ABS)	1.2 MW	COSP 12.48
[KEPT ON] K10_VKA2 (ABS)	1.2 MW	COSP 10.84
[KEPT ON] K10_VKA3 (ABS)	1.2 MW	COSP 08.52

AI CONP 16.08 Total Power 2.04 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	1.2 MW	COSP 02.41
[HIST] R1_QV3 (ABS)	2.6 MW	COSP 22.07
[HIST] R1_QV4 (ABS)	2.8 MW	COSP 22.86
[HIST] R1_QV5 (ABS)	0.1 MW	COSP 02.13
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 22.04
[HIST] R1_QV7 (ABS)	0.7 MW	COSP 08.88
[HIST] R1_QV8 (ABS)	0.4 MW	COSP 05.11
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 13.15
[HIST] K03_VKA1 (KOMP)	0.6 MW	COSP 02.49
[HIST] K03_VKA2 (KOMP)	1.4 MW	COSP 02.82
[HIST] K04_VKA1 (KOMP)	4.6 MW	COSP 06.48
[HIST] K04_VKA2 (KOMP)	0.3 MW	COSP 01.06
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 14.68
[HIST] K04_VKA4 (KOMP)	0.5 MW	COSP 03.94
[HIST] K06_QV1 (KOMP)	4.3 MW	COSP 04.93
[HIST] K08_VKA3 (ABS)	1.7 MW	COSP 11.53
[HIST] K08_VKA5 (KOMP)	2.9 MW	COSP 05.06
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 10.58
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 09.30
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 12.82

Hist CONP 06.32 Total Power 5.19 MW

Hour 19 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 17.92
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	2.7 MW	COSP 19.58
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 22.78
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 21.80
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 21.26
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 17.20
[KEPT ON] K08_VKA3 (ABS)	2.7 MW	COSP 13.98

AI CONP 18.09 Total Power 1.54 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.5 MW	COSP 19.77
[HIST] R1_QV4 (ABS)	2.7 MW	COSP 20.58
[HIST] R1_QV5 (ABS)	2.4 MW	COSP 21.55
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 19.66
[HIST] R1_QV7 (ABS)	1.7 MW	COSP 19.87
[HIST] R1_QV8 (ABS)	1.8 MW	COSP 19.52
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 15.02
[HIST] K04_VKA1 (KOMP)	0.9 MW	COSP 01.58
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 16.05
[HIST] K06_QV1 (KOMP)	4.3 MW	COSP 05.31
[HIST] K08_VKA1 (KOMP)	1.0 MW	COSP 05.89
[HIST] K08_VKA3 (ABS)	1.1 MW	COSP 09.00
[HIST] K08_VKA5 (KOMP)	3.1 MW	COSP 05.08
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 10.08
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.27
[HIST] K10_VKA3 (ABS)	0.4 MW	COSP 13.94

Hist CONP 07.90 Total Power 3.53 MW

Hour 20 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 17.97
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	2.5 MW	COSP 19.15
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 23.58
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 22.49
[KEPT ON] R1_QV8 (ABS)	2.4 MW	COSP 20.44
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 18.08

AI CONP 19.42 Total Power 1.25 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 19.50
[HIST] R1_QV4 (ABS)	2.5 MW	COSP 20.26
[HIST] R1_QV5 (ABS)	2.2 MW	COSP 21.32
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 19.14
[HIST] R1_QV7 (ABS)	1.8 MW	COSP 20.07
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 19.30
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 15.20
[HIST] K04_VKA3 (ABS)	3.1 MW	COSP 16.62
[HIST] K06_QV1 (KOMP)	2.3 MW	COSP 03.55
[HIST] K08_VKA1 (KOMP)	1.1 MW	COSP 04.82
[HIST] K08_VKA3 (ABS)	1.8 MW	COSP 12.99
[HIST] K08_VKA5 (KOMP)	2.3 MW	COSP 03.61
[HIST] K10_VKA1 (ABS)	0.6 MW	COSP 10.58
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.59
[HIST] K10_VKA3 (ABS)	0.4 MW	COSP 14.05

Hist CONP 08.57 Total Power 2.83 MW

Hour 21 00

AI Simulated Dispatch

[KEPT ON] R1_QV3 (ABS)	4.0 MW	COSP 18.28
[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	2.4 MW	COSP 19.28
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 24.44
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 23.26
[KEPT ON] R1_QV8 (ABS)	3.1 MW	COSP 22.77
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00

AI CONP 20.79 Total Power 1.05 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.4 MW	COSP 20.12
[HIST] R1_QV4 (ABS)	2.6 MW	COSP 21.03
[HIST] R1_QV5 (ABS)	1.0 MW	COSP 05.64
[HIST] R1_QV6 (ABS)	1.7 MW	COSP 19.80
[HIST] R1_QV7 (ABS)	1.7 MW	COSP 20.36
[HIST] R1_QV8 (ABS)	1.8 MW	COSP 19.89
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 16.91
[HIST] K04_VKA3 (ABS)	3.1 MW	COSP 17.33
[HIST] K06_QV1 (KOMP)	0.4 MW	COSP 00.66
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 14.24
[HIST] K10_VKA1 (ABS)	0.6 MW	COSP 11.16
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 08.58
[HIST] K10_VKA3 (ABS)	0.4 MW	COSP 15.13

Hist CONP 11.16 Total Power 1.95 MW

Hour 22 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	4.0 MW	COSP 35.00
[KEPT ON] R1_QV5 (ABS)	2.4 MW	COSP 19.14
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 25.55
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 24.23
[KEPT ON] R1_QV8 (ABS)	1.4 MW	COSP 17.66
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00

AI CONP 22.49 Total Power 0.71 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.1 MW	COSP 23.10
[HIST] R1_QV4 (ABS)	2.3 MW	COSP 24.35
[HIST] R1_QV6 (ABS)	1.4 MW	COSP 22.22
[HIST] R1_QV7 (ABS)	1.1 MW	COSP 14.67
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 19.96
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 20.65
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 19.11
[HIST] K08_VKA1 (KOMP)	0.4 MW	COSP 01.03
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 16.95
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 12.49
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 10.55
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 17.54

Hist CONP 12.09 Total Power 1.33 MW

Hour 23 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	2.1 MW	COSP 35.00
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 25.47
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 24.13
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 24.50
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00

AI CONP 23.54 Total Power 0.58 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 24.73
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 25.79
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 24.25
[HIST] K01_VKA3 (ABS)	1.2 MW	COSP 21.88
[HIST] K04_VKA3 (ABS)	2.5 MW	COSP 21.00
[HIST] K08_VKA3 (ABS)	2.7 MW	COSP 17.18
[HIST] K10_VKA1 (ABS)	0.7 MW	COSP 13.18
[HIST] K10_VKA2 (ABS)	0.5 MW	COSP 11.31
[HIST] K10_VKA3 (ABS)	0.5 MW	COSP 18.19

Hist CONP 17.22 Total Power 0.79 MW

Dispatch Logs 08-16

Hour 00 00

AI Simulated Dispatch

[STARTED] R1_QV4 (ABS)	3.6 MW	COSP 35.00
[STARTED] R1_QV8 (ABS)	3.0 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.13

AI CONP 27.77 Total Power 0.35 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.1 MW	COSP 22.14
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 28.76
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 25.95
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.97
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 25.80

Hist CONP 21.93 Total Power 0.44 MW

Hour 01 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	3.5 MW	COSP 35.00
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.41

AI CONP 27.83 Total Power 0.34 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 20.99
[HIST] R1_QV8 (ABS)	1.6 MW	COSP 27.24
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.67
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.76

Hist CONP 21.79 Total Power 0.43 MW

Hour 02 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.42

AI CONP 27.69 Total Power 0.33 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 21.49
[HIST] R1_QV8 (ABS)	1.2 MW	COSP 18.74
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.85
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.06

Hist CONP 21.06 Total Power 0.43 MW

Hour 03 00

AI Simulated Dispatch

[KEPT ON] R1_QV4 (ABS)	2.8 MW	COSP 35.00
[STARTED] R1_QV7 (ABS)	3.2 MW	COSP 33.50
[KEPT ON] R1_QV8 (ABS)	2.8 MW	COSP 35.00

AI CONP 29.95 Total Power 0.30 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 26.74
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.25
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 30.00
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.68

Hist CONP 23.21 Total Power 0.38 MW

Hour 04 00

AI Simulated Dispatch

[STARTED] R1_QV6 (ABS)	2.6 MW	COSP 31.70
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.08
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 29.08 Total Power 0.30 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.7 MW	COSP 25.50
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.97
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.99
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.21

Hist CONP 22.77 Total Power 0.38 MW

Hour 05 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 35.00
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.44
[KEPT ON] R1_QV8 (ABS)	3.0 MW	COSP 35.00

AI CONP 29.79 Total Power 0.32 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.5 MW	COSP 21.59
[HIST] R1_QV8 (ABS)	1.1 MW	COSP 15.91
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.68
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 29.91
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.46

Hist CONP 20.53 Total Power 0.46 MW

Hour 06 00

AI Simulated Dispatch

[STARTED] R1_QV5 (ABS)	2.1 MW	COSP 22.21
[KEPT ON] R1_QV6 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.92
[KEPT ON] R1_QV8 (ABS)	2.2 MW	COSP 31.11

AI CONP 26.46 Total Power 0.40 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.5 MW	COSP 18.26
[HIST] R1_QV4 (ABS)	0.5 MW	COSP 05.04
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 21.53
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.63
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 29.98
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 28.29

Hist CONP 17.49 Total Power 0.61 MW

Hour 07 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 23.43
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 34.80
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.26
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 26.42 Total Power 0.46 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 19.21
[HIST] R1_QV4 (ABS)	1.9 MW	COSP 19.65
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 23.10
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.46
[HIST] K04_VKA3 (ABS)	3.0 MW	COSP 29.98
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 28.01
[HIST] K10_VKA1 (ABS)	0.6 MW	COSP 15.95
[HIST] K10_VKA2 (ABS)	0.4 MW	COSP 13.72

Hist CONP 18.92 Total Power 0.64 MW

Hour 08 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.3 MW	COSP 21.12
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.85
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.49
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 34.19

AI CONP 24.92 Total Power 0.52 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.0 MW	COSP 19.26
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 20.01
[HIST] R1_QV8 (ABS)	1.4 MW	COSP 22.84
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 28.20
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.90
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 26.88
[HIST] K08_VKA4 (KOMP)	0.4 MW	COSP 01.25
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 20.08
[HIST] K10_VKA2 (ABS)	0.7 MW	COSP 18.05

Hist CONP 12.69 Total Power 1.02 MW

Hour 09 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.1 MW	COSP 21.87
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.18
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.00
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.93
[STARTED] K04_VKA3 (ABS)	3.1 MW	COSP 26.37

AI CONP 24.29 Total Power 0.65 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.4 MW	COSP 21.81
[HIST] R1_QV4 (ABS)	2.3 MW	COSP 22.07
[HIST] R1_QV8 (ABS)	1.8 MW	COSP 25.77
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 27.59
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 29.56
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.53
[HIST] K08_VKA4 (KOMP)	1.7 MW	COSP 05.19
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 18.68
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.70
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 24.23

Hist CONP 15.09 Total Power 1.05 MW

Hour 10 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.7 MW	COSP 22.90
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.54
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.42
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.76
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.96
[STARTED] K08_VKA3 (ABS)	2.6 MW	COSP 23.24

AI CONP 23.14 Total Power 0.78 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 20.55
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 20.22
[HIST] R1_QV6 (ABS)	1.3 MW	COSP 19.15
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 23.98
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.77
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.20
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 26.08
[HIST] K08_VKA4 (KOMP)	1.7 MW	COSP 05.17
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 18.65
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.15
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 25.33

Hist CONP 14.81 Total Power 1.22 MW

Hour 11 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.8 MW	COSP 17.89
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.80
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.65
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.68
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.66
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 21.68

AI CONP 21.25 Total Power 0.92 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.9 MW	COSP 19.41
[HIST] R1_QV4 (ABS)	2.5 MW	COSP 19.22
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 22.18
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 21.95
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.01
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.37
[HIST] K06_QV1 (KOMP)	0.4 MW	COSP 00.77
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.70
[HIST] K08_VKA4 (KOMP)	1.8 MW	COSP 05.29
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 18.40
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.07
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.38

Hist CONP 10.75 Total Power 1.82 MW

Hour 12 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.9 MW	COSP 22.48
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.53
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.29
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.29
[STARTED] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.58
[KEPT ON] K08_VKA3 (ABS)	2.9 MW	COSP 22.52

AI CONP 23.12 Total Power 0.88 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.4 MW	COSP 19.19
[HIST] R1_QV4 (ABS)	2.3 MW	COSP 19.53
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 22.39
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.24
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 25.87
[HIST] K04_VKA3 (ABS)	2.7 MW	COSP 27.51
[HIST] K06_QV1 (KOMP)	2.8 MW	COSP 05.81
[HIST] K08_VKA1 (KOMP)	0.4 MW	COSP 01.53
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 25.40
[HIST] K08_VKA4 (KOMP)	1.4 MW	COSP 04.14
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 17.43
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 15.88
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.09

Hist CONP 10.04 Total Power 2.02 MW

Hour 13 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 22.75
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.63
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.43
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.47
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.06
[KEPT ON] K08_VKA3 (ABS)	2.7 MW	COSP 22.23

AI CONP 23.00 Total Power 0.87 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 18.61
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 18.51
[HIST] R1_QV6 (ABS)	1.6 MW	COSP 22.16
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.01
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.25
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 27.92
[HIST] K06_QV1 (KOMP)	1.7 MW	COSP 03.41
[HIST] K08_VKA3 (ABS)	2.4 MW	COSP 25.21
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 17.92
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 16.21
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.27

Hist CONP 14.32 Total Power 1.40 MW

Hour 14 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.8 MW	COSP 22.49
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 30.48
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 29.29
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.31
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 25.54
[KEPT ON] K08_VKA3 (ABS)	2.8 MW	COSP 22.61

AI CONP 23.76 Total Power 0.85 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.6 MW	COSP 19.64
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 19.80
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 22.84
[HIST] R1_QV8 (ABS)	1.9 MW	COSP 22.59
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.74
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.68
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.69
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 18.42
[HIST] K10_VKA2 (ABS)	0.9 MW	COSP 16.48
[HIST] K10_VKA3 (ABS)	0.8 MW	COSP 25.55

Hist CONP 22.21 Total Power 0.91 MW

Hour 15 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.1 MW	COSP 20.84
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 29.44
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 28.34
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 29.12
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 26.35
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 22.23

AI CONP 21.87 Total Power 0.95 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.8 MW	COSP 18.83
[HIST] R1_QV4 (ABS)	2.4 MW	COSP 18.84
[HIST] R1_QV5 (ABS)	1.3 MW	COSP 10.41
[HIST] R1_QV6 (ABS)	2.0 MW	COSP 21.72
[HIST] R1_QV8 (ABS)	2.1 MW	COSP 21.52
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 26.50
[HIST] K04_VKA3 (ABS)	2.9 MW	COSP 28.92
[HIST] K08_VKA1 (KOMP)	2.0 MW	COSP 05.38
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 25.82
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 19.10
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.37
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 25.75

Hist CONP 13.85 Total Power 1.50 MW

Hour 16 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	3.0 MW	COSP 21.38
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.38
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.13
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 30.90
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	3.1 MW	COSP 27.24
[KEPT ON] K08_VKA3 (ABS)	3.1 MW	COSP 23.36

AI CONP 22.08 Total Power 0.93 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	2.0 MW	COSP 03.93
[HIST] R1_QV3 (ABS)	2.5 MW	COSP 17.76
[HIST] R1_QV4 (ABS)	2.2 MW	COSP 17.81
[HIST] R1_QV5 (ABS)	2.4 MW	COSP 17.54
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 20.19
[HIST] R1_QV8 (ABS)	2.0 MW	COSP 20.08
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 27.18
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.21
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.56
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 19.54
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 16.89
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 26.36

Hist CONP 12.58 Total Power 1.64 MW

Hour 17 00

AI Simulated Dispatch

[KEPT ON] R1_QV5 (ABS)	2.3 MW	COSP 21.77
[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.12
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.78
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.75
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	2.8 MW	COSP 26.67
[KEPT ON] K08_VKA3 (ABS)	2.1 MW	COSP 25.08

AI CONP 24.17 Total Power 0.77 MW

Historical Operator Dispatch

[HIST] R1_QV1 (KOMP)	1.2 MW	COSP 02.22
[HIST] R1_QV3 (ABS)	2.1 MW	COSP 19.40
[HIST] R1_QV4 (ABS)	2.2 MW	COSP 20.06
[HIST] R1_QV5 (ABS)	2.0 MW	COSP 19.03
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 22.55
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 22.50
[HIST] K01_VKA3 (ABS)	1.4 MW	COSP 27.52
[HIST] K04_VKA3 (ABS)	2.8 MW	COSP 29.17
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.54
[HIST] K10_VKA1 (ABS)	0.9 MW	COSP 20.11
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 17.12
[HIST] K10_VKA3 (ABS)	0.7 MW	COSP 26.97

Hist CONP 12.50 Total Power 1.50 MW

Hour 18 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 31.74
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 30.39
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 31.78
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K04_VKA3 (ABS)	2.2 MW	COSP 25.15
[KEPT ON] K08_VKA3 (ABS)	2.1 MW	COSP 25.26

AI CONP 25.46 Total Power 0.62 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.8 MW	COSP 18.21
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 19.05
[HIST] R1_QV5 (ABS)	1.8 MW	COSP 18.01
[HIST] R1_QV6 (ABS)	1.3 MW	COSP 22.19
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 22.18
[HIST] K01_VKA3 (ABS)	1.3 MW	COSP 26.66
[HIST] K04_VKA3 (ABS)	2.5 MW	COSP 28.41
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.48
[HIST] K10_VKA1 (ABS)	0.8 MW	COSP 19.88
[HIST] K10_VKA2 (ABS)	0.8 MW	COSP 17.10
[HIST] K10_VKA3 (ABS)	0.6 MW	COSP 23.69

Hist CONP 18.39 Total Power 0.86 MW

Hour 19 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 32.66
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.20
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 32.90
[KEPT ON] K01_VKA3 (ABS)	1.8 MW	COSP 35.00
[KEPT ON] K08_VKA3 (ABS)	2.2 MW	COSP 25.28

AI CONP 26.52 Total Power 0.51 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.9 MW	COSP 17.61
[HIST] R1_QV4 (ABS)	1.9 MW	COSP 18.33
[HIST] R1_QV5 (ABS)	1.7 MW	COSP 17.23
[HIST] R1_QV6 (ABS)	1.4 MW	COSP 21.32
[HIST] R1_QV8 (ABS)	1.6 MW	COSP 21.31
[HIST] K01_VKA3 (ABS)	0.8 MW	COSP 17.53
[HIST] K04_VKA3 (ABS)	2.4 MW	COSP 28.13
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.25
[HIST] K10_VKA1 (ABS)	0.2 MW	COSP 05.45

Hist CONP 17.31 Total Power 0.78 MW

Hour 20 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	1.7 MW	COSP 25.25
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 31.51
[KEPT ON] R1_QV8 (ABS)	3.2 MW	COSP 33.50
[KEPT ON] K01_VKA3 (ABS)	1.9 MW	COSP 35.00
[KEPT ON] K08_VKA3 (ABS)	2.0 MW	COSP 24.24

AI CONP 25.92 Total Power 0.46 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	1.9 MW	COSP 17.15
[HIST] R1_QV4 (ABS)	2.0 MW	COSP 17.88
[HIST] R1_QV5 (ABS)	1.2 MW	COSP 08.71
[HIST] R1_QV6 (ABS)	1.4 MW	COSP 20.76
[HIST] R1_QV8 (ABS)	1.5 MW	COSP 20.75
[HIST] K04_VKA3 (ABS)	2.3 MW	COSP 27.83
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 26.82

Hist CONP 16.27 Total Power 0.73 MW

Hour 21 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.2 MW	COSP 34.41
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 32.65
[KEPT ON] R1_QV8 (ABS)	3.1 MW	COSP 35.00
[KEPT ON] K01_VKA3 (ABS)	0.6 MW	COSP 35.00

AI CONP 29.43 Total Power 0.34 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.2 MW	COSP 20.60
[HIST] R1_QV4 (ABS)	0.4 MW	COSP 00.20
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 26.03
[HIST] R1_QV8 (ABS)	1.7 MW	COSP 26.03
[HIST] K04_VKA3 (ABS)	2.2 MW	COSP 28.00
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.67

Hist CONP 03.82 Total Power 2.65 MW

Hour 22 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	2.7 MW	COSP 32.74
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 33.09
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00
[KEPT ON] K01_VKA3 (ABS)	0.6 MW	COSP 35.00

AI CONP 29.30 Total Power 0.32 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.3 MW	COSP 21.62
[HIST] R1_QV6 (ABS)	1.5 MW	COSP 27.62
[HIST] R1_QV8 (ABS)	1.4 MW	COSP 22.04
[HIST] K04_VKA3 (ABS)	2.2 MW	COSP 28.33
[HIST] K08_VKA3 (ABS)	2.5 MW	COSP 27.40

Hist CONP 21.98 Total Power 0.43 MW

Hour 23 00

AI Simulated Dispatch

[KEPT ON] R1_QV6 (ABS)	3.0 MW	COSP 33.83
[KEPT ON] R1_QV7 (ABS)	3.2 MW	COSP 32.76
[KEPT ON] R1_QV8 (ABS)	2.9 MW	COSP 35.00

AI CONP 29.71 Total Power 0.31 MW

Historical Operator Dispatch

[HIST] R1_QV3 (ABS)	2.7 MW	COSP 24.76
[HIST] R1_QV6 (ABS)	1.8 MW	COSP 29.55
[HIST] K04_VKA3 (ABS)	2.5 MW	COSP 29.74
[HIST] K08_VKA3 (ABS)	2.6 MW	COSP 27.11

Hist CONP 23.55 Total Power 0.39 MW