Demand response in a container terminal

A stochastic optimization of the operational planning considering energy consumption

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Preface

With the completion of this thesis, my six-year-long journey at TU Delft comes to a close. Now, I get to join the lineage of TU Delft alumni within my family. I flew through my bachelor's program in Mechanical Engineering with flying colors and sought a new challenge by pursuing a dual master's degree in Multi Machine Engineering and Sustainable Energy Technology. With my master's thesis, I bridged the gap between the different faculties and people of Maritime and Transport Technology & Electrical Sustainable Energy. I hope my thesis serves as a start for future collaborations between these two groups, and helps to shape a more sustainable future for the Maritime industry.

There's no time to wait for future technology to be developed; the energy transition within the Maritime industry must begin today. The focus should be on building out solutions that are already within reach, and resolving the engineering problems that impede their implementation. Many individuals and organizations profess their commitment to the energy transition. Such a transition, however, requires the courage to step out of one's comfort zone and to challenge the status quo. The challenges presented by the energy transition, as well as the opportunities they bring, can only be captured if there is a willingness to change behavior. I hope that with this thesis, I've highlighted one of the many issues that arise from the energy transition, and demonstrated the potential that a change in behavior can have in resolving this issue.

I would like to extend my gratitude to everyone who has supported me over the past seven months. Specifically, I would like to thank my supervisors, Frederik and Milos. Your shared knowledge and expertise were integral to the successful completion of my thesis. The insights you provided were invaluable. Additionally, I would like to thank Michelle, Jorn, and Xinyu. You were always there when I needed someone to brainstorm with or receive critical feedback from. Your help is deeply appreciated.

During this thesis I used Chat-GPT in order to troubleshoot the python code and improve the text written for this report. After using this tool/service, I reviewed and edited the content as needed and take full responsibility for the content that is presented in this report.

Enjoy reading the report.

Jasper Stoter
Delft, June 2023

Abstract

Seaport operators are becoming more environmentally conscious and are looking to electrify their terminals to reduce their greenhouse gas emissions. This leads to higher energy-related costs and more congestion on the electricity grid. This thesis investigates the potential of demand response as a viable strategy to reduce energy-related costs. By modifying operational planning, energy consumption could be deferred from peak to off-peak hours, resulting in cost savings. Different potential ways within the terminal to provide demand response are identified. I propose a two-stage stochastic mixed-integer programming model to optimize operations planning, incorporating energy-related costs. Both energy demand and supply uncertainties are accounted for, exploring various scenarios for vessel arrival times and fluctuating electricity prices. The model is decomposed using a progressive hedging algorithm. Operational aspects considered in this model include vessel arrival scheduling, temperature control of refrigerated containers, allocation of handling capacity across quay cranes, yard cranes, and automated guided vehicles, as well as a charging schedule for the automated guided vehicles. A case study of the Altenwerder container terminal in Hamburg was conducted to test the model. Preliminary results suggest potential cost savings in the range of 12.0-13.2 % with a varying electricity prices based on wholesale market rates. Furthermore, it was found that stochastic modeling improved the solutions found of up to 20.6 % compared to a deterministic model. These findings underscore the substantial potential of demand response strategies in the context of container terminal operations.

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Nomenclature

Abbreviations

Abbreviation	Definition
AGV	Automated Guided Vehicle
BACAP	Berth Allocation and Quay Crane Assignment Problem
BAP	Berth Allocation Problem
BRP	Balancing Responsible Party
CPP	Critical Peak Pricing
CP	Constant Price
CTA	Container Terminal Altenwerder
DLC	Direct Load Control
DR	Demand Response
DSM	Demand Side Management
EEV	Expectation of Expected Value Problem
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicle
EVPI	Expected Value of Perfect Information
HHLA	Hamburger Hafen- und Lagerhaus-Aktiengesellschaft
KPI	Key Performance Indicator
MAS	Multi Agent System
MIP	Mixed Integer Programming
NP	No Price
OPS	On-shore Power Supply
QC	Quay Crane
QCAP	Quay Crane Assignment Problem
QCSP	Quay Crane Scheduling Problem
RTP	Real-Time Price
SP	Stochastic Problem
TEU	Twenty-foot Equivalent Unit
TOU	Time-Of-Use
TOS	Terminal Operation System
TSO	Transmission System Operator
V2G	Vehicle to Grid Charging
VSS	Value of Stochastic Solution
WS	Wait-and-See Problem
YC	Yard Crane

Symbols

Notation	**Description**
Sets	
V	Set of vessels to be served, $i \in 1, 2, \ldots, N$, where N is the number of vessels to be served, 10.
T	Set of time periods (1 hour), $t \in 0, 1, \ldots, H-1$, where H is 48 hours.

Continued on next page

Table 1 – continued from previous page

P_i	Handling rate that can be assigned to a ship $i \in V$, where p is the mininum of $u_{p,m} * h_m$.
M	Types of machinery present in the terminal $m \in QC, YC, AGV$.
S	Set of scenarios $w \in S$.
Parameters	
k_m	Amount of machinery $m \in M$ available .
h_m	Handling rate of machinery m in containers per hour .
$d_{i,w}$	The total demand of containers to be handled (loaded + unloaded) for ship $i \in V$ in scenario $w \in S$.
$u_{p,m}$	The amount of machinery of type m used in pattern p
l_i^{ship}	The quay length that ship i takes up.
l^{total}	The total length of the quay.
eat_i	Expected arrival time of vessel $i \in V$.
eft_i	Expected berthing finishing time of vessel $i \in V$.
$a_{i,w}$	Actual arrival time of vessel $i \in V$ in scenario $w \in S$.
e^{ship}	energy consumption for one hour of a ship using on shore power supply .
$e_m^{machinery}$	Energy consumption of machinery m for operating for one hour
e^{charge}	Energy consumed by one charger.
$e^{charge,max}$	Maximum Energy consumed by all chargers.
b^{min}	Minimum AGV battery level.
b^{max}	Maximum AGV battery level.
η^{charge}	Charging efficiency.
e^{reefer}	Energy consumption of one reefer connection
$e^{reefer,max}$	Maximum energy consumption of all reefer connection
tc^{min}	Minimum reefer temperature.
tc^{max}	Maximum reefer temperature.
η^{reefer}	Cooling efficiency.
ta	Ambient temperature
mc^p	Specific heat capacity of a reefer.
u^a	Heat transfer coefficient of a reefer.
$c_{t,w}^{da}$	Day electricity price at time t in scenario $w \in S$.
c_i^{late}	Penalty cost of exceeding the expected finishing time (EFT) for vessel $i \in V$ for one hour.
$c^{reschedule}{}_i$	cost of changing the initial schedule by one hour.
c^{sur}	cost of having a surplus of energy.
c^{shor}	cost of having a shortage of energy.
M	A large positive number.
ρ_w	Probability of scenario w occurring ($1/S$).
Decision variables	
$S_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing start time of vessel $i \in V$
$S_{i,w} \in \mathbb{Z}^+$	Berthing start time of vessel $i \in V$ in scenario $w \in S$
$S_{i,w}^{early} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives ahead of schedule in scenario $w \in S$
$S_{i,w}^{late} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives behind schedule in scenario $w \in S$
$F_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing end time (time when handling ends) of vessel $i \in V$
$F_{i,w} \in \mathbb{Z}^+$	Berthing end time (time when handling ends) of vessel $i \in V$ in scenario $w \in S$
$L_{i,w} \in \mathbb{Z}^+$	Lateness of operations for ship $i \in V$ in scenario $w \in S$

Continued on next page

Table 1 – continued from previous page

$A_{i,t,w} \in \mathbb{B}$	1 if vessel $i \in V$ is assigned at to a berth in period t in scenario $w \in S$, 0 otherwise
$H_{i,p,t,w} \in \mathbb{B}$	1 if handling rate p is assigned to serve vessel $i \in V$ at time period t in scenario $w \in S$, 0 otherwise
$B_{t,w}^{level} \in \mathbb{R}^{+}$	Battery level at time t in scenario $w \in S$
$TC_{t,w}^{temperature} \in \mathbb{R}$	Reefer temperature at time t in scenario $w \in S$
$E_{t,w}^{charge} \in \mathbb{R}^{+}$	Energy consumed to charge AGVs at time t in scenario $w \in S$
$E_{t,w}^{reefer} \in \mathbb{R}$	Energy consumed to cool the reefers at time t in scenario w S
$P_{t,w}$ $\mathbb{R}^{+}$	Power used from the utility grid at time t in scenario w S
P_{t}^{da} $\mathbb{R}^{+}$	Power purchased at the day ahead market at time t
P_{t}^{sur} $\mathbb{R}^{+}$	Power surplus at time t
P_{t}^{shor} $\mathbb{R}^{+}$	Power shortage at time t
IM_{t}^{state} $\mathbb{B}$	Imbalance state, 1 if there is a surplus and 0 if there is a deficit

1 Introduction

Climate change has become an urgent global challenge, necessitating significant reductions in greenhouse gas (GHG) emissions across all industries and sectors. To address the challenge of climate change and reduce our reliance on fossil fuels, a global energy transition is necessary. This transition will affect every industry and present a host of technological and logistical challenges.

Seaports operators have put greater focus on reducing energy cost and environmental friendly operations due to economic and environmental considerations. The share of the shipping industry in the emissions was 2.89 percent in 2018 [31]. The ESPO periodically publishes a list with the environmental priorities of the European port sector. In 2004 the topic of energy consumption was not in the top ten, while by 2013 it had become the third highest priority [77]. In recent years infrastructure within the port is electrified to reduce energy cost and GHG emissions [59]. In order to make up for the energy gap left by diesel engines, port operations will need to increase their electricity consumption as a result of the port electrification process [59]. To reduce the energy cost it is essential for port operators to manage their electricity consumption.

Grid operators are facing a challenge to provide electricity to everyone due to the integration of large amounts of renewable energy in the grid. Renewable energy from solar and wind is depend on the weather and can vary widely throughout the day. The necessity to maintain the balance between load and generation at all timescales creates technical issues when more uncertain generation from variable renewable energy sources (VRES) is introduced into the grid [47].

An option to deal with the uncertainty of VRES is to mange the demand of electricity to match the generation [47]. Demand side management is the ability for end-use customers to change their normal consumption patterns in response to an incentive to induce less consumption at times of high wholesale market prices or when system reliability is at risk [35].

Seaports could potentially save electricity cost by implementing demand side management strategies. The logistic process within the port are highly dynamical, resulting in a complex planning of operations. The energy consumption that varies widely throughout a day, depending on the planning [2]. By considering electricity prices when determining planning, container terminals can identify different operational schedules that are more cost-effective. This means that by changing their scheduling, container terminals can potentially reduce their costs while helping the grid operator mange the grid.

In this thesis the potential of demand side management in ports will be investigated. First, in section 1.1 the scope of the thesis will be set. Second, in section 1.2 the research gabs that this thesis will fill are identified. Third, the research questions and objective are formulated in section 1.3. Finally the structure of the report is presented in 1.4.

1.1. Scope

The aim of this study is to find the potential of demand response programs within a container terminal. The processes with seaports are complex, making demand response also a complex issue.

The scope of this study is limited to only consider a container terminal within a port. A more in depth analysis of the energy consumption within the container terminal is performed than would not be possible if the entire port was considered. While conducting a literature review on demand response in container terminals the most prominent electrical loads that could provide demand response were identified. Only these loads were considered when optimizing the operational planning.

On-site (renewable) generation and large scale battery storage are considered out of scope for this research. Both methods could provide demand response in the terminal. The potential of batteries and wind turbines or solar panels in a container terminal is consider by various authors researching port micro grids and energy managements systems (EMS). Roy et al. have provided an overview of microgrids in seaport in their literature review [58]. Often the potential of providing demand response by changing operational schedule is ignored or insufficiently investigated. It has therefore been decided to focus on the operational flexibility in this thesis and consider common elements of microgrids / EMS such as battery storage and onsite wind and solar generation out of scope.

The scope is further narrowed down by not considering all forms of demand side management, only demand response. As stated fore demand side management is the ability for end-use customers to change their normal consumption patterns in response to an incentive. Two types of demand side management can be identified; Energy Efficiency (EE) and Demand Response (DR) [35]. Energy efficiency refers to decreasing the overall demand by implementing energy saving measures. Demand response refers to the ability of consumers to shift their electricity usage [35]. Measures to reduce the overall energy consumption are considered out of scope in this thesis.

The scope of this thesis does not include the physical electrical systems involved in the demand response program of a container terminal. It should be noted that in order to implement a demand response program in a container terminal, certain changes to the existing electrical infrastructure may be required, such as the installation of measuring devices. For this thesis we will focus on controlling the active power. Reactive power regulation, voltage regulation and frequency regulation are not considered in this thesis.

1.2. Scientific contribution

This thesis is not the first to investigate the energy consumption in Ports. In a review paper by Iris and Lam different strategies to increase the energy efficiency in ports are presented [32]. Demand response is a widely applied concept in many industries, and therefore also the maritime industry. A literature review was conducted to find what the existing state of research is for demand response programs within container terminals. From the literature review research gabs were identified.

This thesis makes the following 3 contributions to the implementation of DR programs in container terminals:

First, an overview is provided of the potential for DR in container terminals by identifying the factors that drive energy consumption in large electric loads and assessing the feasibility of controlling that consumption. While conduction the literature review no such overview was found. In a review paper by Baker et al. a overview of large electric loads with some factors that could influence their consumption was given [2]. It was however missing what factors influence the consumption the most, over what time periods the consumption happens, and whether the loads are critical, curtail-able or reschedule-able. To be able to find whether a load has the potential for demand response such factors are important.

Second, this study is the first to consider the impact of DR on an entire container terminal solely in the context of operational flexibility. Previous studies have focused on the flexibility of individual loads [11] [7] [40] [61]. Alternatively studies focus on entire terminal mostly providing demand response with batteries and on-site generation [33] [36]. Most researchers keep the energy flows simple, and therefore do not take into consideration the potential operating flexibility of transportation scheduling, which is key for energy management [50]. Providing DR using the operational flexibility requires less investment compared to on-site generation and battery packs and can be implemented quicker. It is therefore interesting to see what would be the potential of providing DR with solely the operational flexibility to see if some quick and easy gains can be made.

Third, uncertainty is considered in electricity demand and supply. The daily processes in a container terminal are highly dynamical and depended on the number of ships and container to be handled [15]. This makes the forecast of the electricity demand complicated and introduces a lot of uncertainty [15]. Additionally, as stated in the introduction, introducing more variable renewable energy sources like wind and solar into the grid makes the supply of electricity uncertain. Most existing literature does not take this uncertainty into account when optimizing the energy consumption. Some studies on energy consumption took into account uncertainty of supply or demand. Only Iris and Lam considered uncertainty to a limited extend in [33]. Here the authors assumed a uncertain production in the on-site solar generation. However all operations within the terminal were still considered deterministic. Mao et. al. recommend to do conduct more multiscenario seaport energy management studies to analyze the social benefits of optimal scheduling and flexible berth allocation while accounting for different types of uncertainties such as vessel arrival, electricity price, and fuel cost [50]. It can be concluded that considering uncertainty in both supply and demand is needed to accurately estimate the potential of demand response in a container terminal.

Overall, this thesis provides valuable insights into the potential of DR programs in container terminals and attempts to quantify the potential by looking and the cost savings that can be achieved.

1.3. Research question

This section outlines the primary research question and its related sub-questions. For each sub-question, a brief explanation is provided on how to address them and the expected results.

Primary Research Question:

What is the potential of demand response for reducing the energy and operational costs of a container terminal?

Sub-Questions:

1. What demand flexibility exists in a container terminal?

    Literature identifies the primary sources of electricity consumption within a container terminal. For these sources, the factors that most significantly influence consumption were investigated. Based on this, a consumption pattern throughout a day was estimated for every load. Different ways to adjust this consumption were researched to ultimately estimate the potential for flexibility.

2. Which demand response programs would be suitable for a container terminal to participate in?

    Different demand response programs, their characteristics, and operating timescales were identified from the literature. A connection was then made with the demand flexibility found in the first question to identify potential energy markets.

3. How can the energy consumption of terminal operations be modeled and analyzed, given uncertain electricity demand and supply?

    The main sources causing uncertainty in electricity demand and supply were identified. Various methods for creating an optimization model with uncertainty were outlined. The appropriate method was chosen based on the characteristics of the container terminal and the electricity markets. Scenarios representing the uncertainty were created based on these uncertain parameters.

4. What is the impact of demand response in a container terminal on peak energy consumption and energy consumption throughout the day?

    The effects of demand response were identified by comparing the operational planning without considering electricity prices to a situation where a constant price and real-time prices based on wholesale market are considered. The correlation coefficient between electricity consumption and price, as well as the peak-to-average ratio of energy demand, were compared in both situations.

5. How do different electricity prices influence the potential for demand response?

    The potential for demand response was calculated with electricity prices from different years to evaluate the price's influence.

1.4. Thesis outline

In this section, the structure of the thesis is explained, providing an overview of each chapter and its content.

Chapter 2 focuses on investigating the potential of demand response in a container terminal. Firstly, it explores the equipment that contributes to the electricity consumption of a container terminal. Secondly, it identifies the factors influencing the consumption and controllability of electricity usage. Finally, it highlights promising demand response programs that can be implemented.

Chapter 3 presents the optimization model developed in this thesis, outlining the assumptions made in the model and providing a detailed explanation of the mathematical formulation used.

Chapter 4 describes the methodology employed in this thesis. It compares different modeling approaches for dealing with uncertainty and justifies the selection of stochastic programming as the preferred modeling approach.

Chapter 5 presents the results obtained from the model. It begins with the validation of the model, followed by a case study conducted on the HHLA Container Terminal Altenwerder. Various experiments are then performed to analyze the impact of demand response on the container terminal.

Chapter 6 discusses the results in detail. It interprets the findings, addresses the limitations of the research, and provides recommendations for future studies.

Chapter 7 concludes the thesis, summarizing the key findings and contributions made.

Table 1.1 provides an overview of all the chapters and specifies the research questions addressed in each chapter, highlighting the alignment between research questions and chapters.

Chapter	Title	Research Questions
1	Introduction	-
2	Potential of demand response	1,2
3	Problem description	-
4	Solution approach	3
5	Experiments & Results	4,5
6	Discussion	4,5
7	Conclusions	-

Table 1.1: Thesis Structure

2 Potential of demand response in Container terminals

in this chapter we will discuss the potential of demand response (DR) in a container terminal. Firstly, it will be explained what demand response is and how the electricity markets in the netherlands work in section 2.1. In section 2.2, an overview of existing literature on DSM in container terminals is presented. A breakdown of which sources contribute to the energy consumption and the flexibility potential of the main sources is stated in section 2.3 . In section 2.4 it is explained how the flexible loads can be used for demand response. Finally conclusions are drawn in section 2.5.

2.1. Background

Electricity is a highly perishable good, because it needs to be consumed the moment it is produced. At any time the amount of electricity produced has to be equal to the amount consumed, otherwise the grid frequency will deviate from the nominal 50 Hz. The keep the balance either the demand to electricity or the supply of electricity has to adjusted. Demand response is a way to adjust the demand for electricity to be able prevent/restore system imbalances.

In section 2.1.1 an overview will be given on the different demand response programs that exist. Different markets exist on which electricity can be bought or sold. An explanation of the dutch electricity markets will be given in section 2.1.2.

2.1.1. Demand Response programs

Demand response, or demand-side flexibility, refers to consumers' ability to adjust their electricity usage from their planned consumption. Electricity prices fluctuate significantly throughout the day, week, and year due to the uncertainty of the amount of electricity produced and consumed. With demand response, it is possible for consumers to reduce their electricity costs by shifting their consumption from times with high prices to times with low prices. Simultaneously, they aid in balancing supply and demand and reducing peak loads on the electricity grid.

Two types of demand response programs exist: price-based programs and incentive-based programs. These can be further divided into different types of demand response strategies as detailed below [53] [1] [35] [17]. Incentive-based programs can be further split into direct load control, interruptible/curtailable rates, Emergency Demand Response programs, Demand bidding/buyback, Capacity market programs, and Ancillary services. Time-based programs can be divided into Time-of-use rates, Critical peak pricing, and Real-time pricing.

Incentive-based demand response programs reward consumers for altering their consumption upon request [66]. These programs help maintain reliable system operations [66]. Based on papers from Albadi and El-Saadany (2007), Han and Piette (2008), and Jordehi (2019), descriptions are formulated for each of the demand response programs [1] [17] [35].

Direct load control (DLC) allows the utility grid operator to remotely shut down customers' loads on short notice. DLC programs are typically implemented for residential and small commercial customers.

Interruptible/curtailable rates offer customers a discount on their electricity rate if they agree to reduce load during contingencies. Customers are penalized if they do not comply.

Emergency Demand Response is a program similar to the one described above, where customers get paid to reduce their load during contingencies. The difference, however, is that curtailing loads is voluntary.

Demand bidding/buyback is a demand response program where large customers offer load reductions in the wholesale market based on their willingness to curtail their operations. These programs are typically called on a day ahead based on demand predictions.

Capacity market programs allow consumers to commit to a pre-specified load reduction in case the system is overloaded. Consumers usually receive a one-day advance notice. Even if the system is not overloaded, consumers still get paid. If a contingency occurs and customers do not reduce their load, they are penalized.

Ancillary services are services that a consumer can deliver to the grid operator to balance the grid. An auction is held one day ahead, during which consumers can offer reserve capacity. If their bid is accepted, they get paid and must stand by to deliver balancing services. Additionally, consumers are paid based on the load reduction that is requested by the grid operator.

In price-based demand response (DR) programs, consumers pay a time-varying electricity rate [66]. This provides a price incentive for them to shift consumption away from times with high prices [66]. With price-based incentives, consumers respond based on their willingness and capability [66]. Descriptions of each of the DR programs are formulated based on papers from Albadi and El-Saadany (2007), Han and Piette (2008), and Jordehi (2019) [1] [17] [35].

Time-of-use rates (TOU) are based on historical pricing experience, with electricity rates set high during times of high demand and low during off-peak times. TOU is the oldest and most used DR program. TOU rates may vary based on daily or seasonal cycles.

Critical peak pricing (CPP) is a program in which consumers are charged high electricity rates during critical peaks. This typically happens a few times a year.

Real-time pricing (RTP) charges the wholesale market electricity price directly to customers. To allow consumers the opportunity to plan their demand, RTP signals can be given from one hour up to one day in advance.

Not all loads are suitable for demand response. Generally, three types of loads exist [60]. First, critical loads are those that must be met at all times. Second, curtailable loads are those that can be temporarily switched off or lowered. Lastly, reschedulable loads can be shifted in time. Among these, curtailable and reschedulable loads can participate in demand response, while critical loads cannot [60]. An overview of all the DR programs along with the timescale at which they operate can be found in Figure 2.1.

2.1.2. Dutch electricity markets

To facilitate the trade of electricity production and consumption several markets exist. Each markets has different characteristics, and therefore different requirements for demand response.

There are two types of markets of interest for this thesis, the wholesale and balancing market. All consumers and producers need to purchase their electricity consumption and production on the wholesale market for specific time slots. In case an actor didn't produce/consume as much as contracted a imbalance occurs. Additional reserved electricity from balancing market is used to restore this imbalance, The actor causing the imbalance has to pay for the additional electricity based on the imbalance price. The balancing market is operated by the Transmission System Operator (TSO) of each country. In the Netherlands the TSO is Tennet [68]. To be allowed to trade on the wholesale market an actor needs to be either a Balance Responsible Party (BRP) or have a external BRP balance on their behalf [70]. The wholesale market in the Netherlands consists out of the forward and futures market, the day-ahead market and the intraday market [70]. Below a description is given of the different types of markets

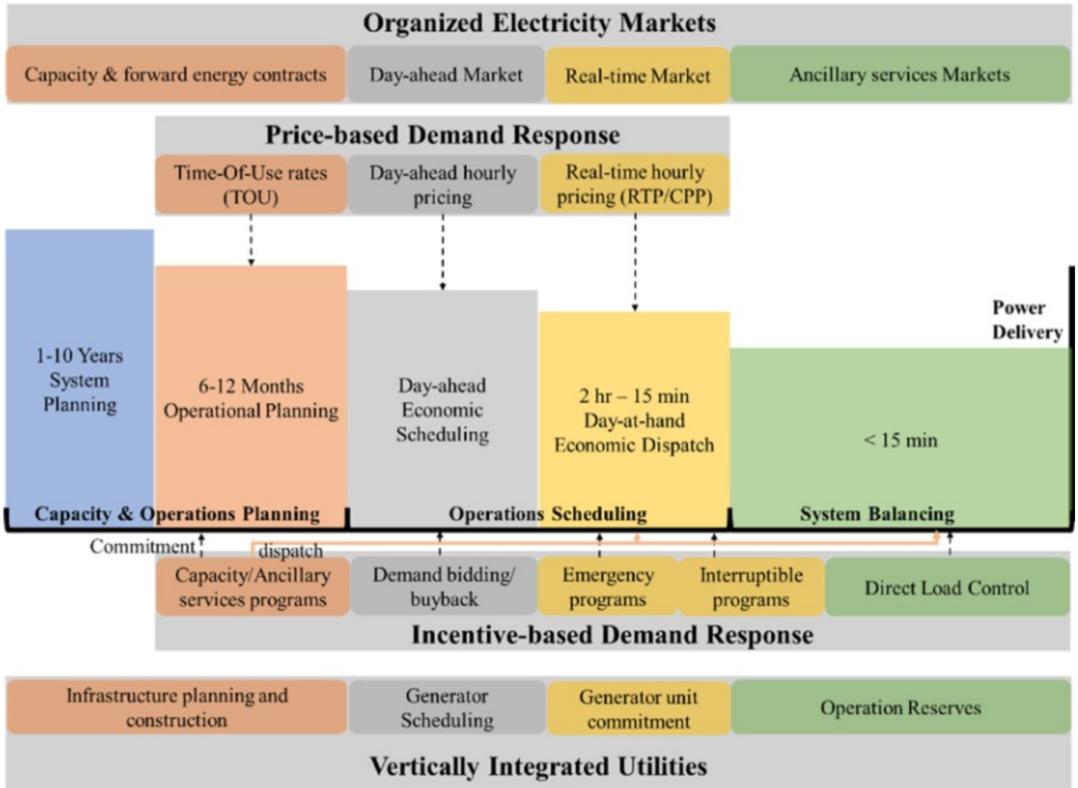


Figure 2.1: Electric Power System and Demand Response implementation timescales [65]

based on information provided by Tennet [71][68]. An overview of all the electricity markets is shown in figure 2.1.

Forward and future market On this market long term agreements between producers and consumers are made. Any time between four year and one month before delivery the electricity can be traded. The time over which a contract can last differs per contract. The Forward and futures market is used to protect producers and consumers from the volatility of the prices of the Day-ahead and Intraday market.

Day-ahead market In the day ahead markets electricity is purchased and sold for the next day. Every day at 12:00 an auction is held. During the auction electricity bids are made for every hour of the next day. All the bid to consume and produce energy and ranked the clearing price comes about if the marginal bid to produce electricity is equal to the bid to consume. All bids lower then the clearing price are automatically accepted for the clearing price as well.

Intraday market After the Day-ahead market closes the Intraday market opens. If actors on the Day-ahead market didn't estimate their power consumption/ production correctly they can buy or sell extra capacity on this market. In the Intraday market it is possible to trade electricity in 15 minute time slots. all bids need to be made at least 5 minutes before the power is scheduled to be consumed. A pay-as-bid principle is present on the Intraday market were individual producers and consumers make a deal between the two of them. This means that there is not a single electricity price on the Intraday market but instead it is a range.

Balancing market Balacing in the Netherlands is done re-actively based on disturbances. In the Netherlands the main there products for balancing that are offered are; Frequency Containment Reserve (FCR), automatic Frequency Restoration Reserve (aFRR) and manual Frequency Restoration Reserve (mFRR). Each product different minimum bid sizes, activation duration and ramp up/down rates.

To be keep the electricity grid stable and operating several so called Ancillary services are needed. Tennet lists 5 ancillary services in the netherlands; Balancing reserves (the traded capacity on the balancing market), Reactive power, Redispatch, Black start facility and Guarantees of Origin [69].

2.2. Demand Response in container terminals

The daily operations in a container terminal are dynamic, resulting in quickly changing electricity demand. If this demand can be managed, a beneficial electricity consumption pattern can be achieved. A literature review was conducted to find the current state of research into Demand Response (DR) within container terminals. Three fields of research were identified: energy management systems, peak shaving, and vehicle-to-grid charging within container terminals.

2.2.1. Energy management systems in container terminals

A field of research was found for the integration of energy management systems (EMS) in container terminals. EMSs are defined as automated systems that collect data on energy measurements and make it available to operators, thus enabling the management of energy resources [64]. An EMS consists of energy demand planning, energy supply planning, and a system linking demand and supply [32]. Demand response is therefore an important aspect of an EMS since it dictates the planning of demand. For the supply side of the EMS, often distributed energy resources, like wind turbines and PV panels, are used in combination with a grid connection. The term EMS is sometimes used to refer to the supervisory controller of a microgrid, and both terms are often used interchangeably [51]. Below, the main literature on EMSs in container terminals is discussed, and the important conclusions are mentioned.

Iris and Lam (2021) discussed an EMS in a seaport considering the uncertainty of renewable energy generation [33]. This EMS consists of the energy consumption of on-shore power supply (OPS) for berthed ships, quay cranes (QC), yard cranes (YC), and refrigerated containers (reefers). Iris and Lam used a Mixed Integer Programming (MIP) model to solve the integrated operations planning and energy management problem. The objective of the model was to minimize the cost related to the purchasing of electricity as well as the lateness cost related to ships departing the terminal later than scheduled. Iris and Lam compared different energy pricing strategies. The strategies used were based on a constant electricity price, a time of use price, and a real-time pricing scheme where day-ahead wholesale market energy prices are directly used. The authors found that the costs of the market pricing scheme are 18.5-21 percent lower compared to a constant electricity price. This shows that significant cost savings can be achieved with an EMS.

Pu et al. (2020) investigated EMS in ports in general [55]. Their study considered an integrated energy system with electricity, heat, and cooling demand. Various installations such as a combined cooling, heating, and power plant, electric coolers/boilers, and heat exchangers were used to link the different energy flows to each other. A MIP model was used to optimize the energy demand. Pu et al. categorized all the loads in the container terminal into fixed, reducible, and shiftable loads. Fixed loads consist of port machinery and lighting, reducible loads are reefers and continuous operation loads, and shiftable loads include OPS for ships, QC , YC, other lifting machinery, electric tractors, electric vehicles (EVs), and so on. They found a cost reduction between 5 and 19 percent if demand response is done with a time-of-use pricing scheme.

In a similar vein, Mao et al. (2022) conducted a study on EMS in ports, also taking into consideration an integrated energy system with electricity, heat, and cooling demand [50]. Their research considered the power supply to container and cruise ships specifically. The container ships had an additional cooling demand due to the reefers onboard, and the cruise ships had an additional heating demand. Mao et al. compared a constant electricity price with a dynamic price based on the real-time day-ahead energy price. Their findings revealed that the yearly costs are 5-6 percent lower when using a dynamic pricing scheme.

Another author suggesting EMS in container terminals is Kanellos (2017-2019) [37] [38] [36] [12]. Kanellos investigates multi agent systems with decentralized demand response with flexible loads and power generation from renewable energy. Different agents represent different loads within the terminal. The loads considered are reefer containers, EVs that is Automated Guided Vehicles (AGVs) and OPS for berthed ships [38]. Furthermore Kanellos designed a real time controller for reefers and EVs to react to fast power fluctuations of wind turbines [37]. In the same paper it was found that the proposed system

Source	Method	Energy Load
Gennitsaris and Kanellos . (2019) [12]	Multi-Agent Systems	Reefer, OPS
Iris and Lam (2021) [33]	Two stage stochastic . Mixed Integer Programming	OPS, QC, YC, Reefer
Kanellos (2019) [36]	Multi-Agent Systems	Reefer, OPS, EV
Kanellos (2017) [37]	Multi-Agent Systems	Reefer, EV
Kanellos et al. (2019) [38]	Multi-Agent Systems	Reefer, EV, OPS
Mao et al. (2022) [50]	Mixed Integer Programming	OPS, heating / cooling demand
Pei et al. (2021) [54]	Two stage hierarchical controller	Reefer
Pu et al. (2020) [55]	Mixed Integer Programming	Port, heating / cooling demand
Wang et al. (2019) [75]	Two stage stochastic simulation	OPS, QC, YC

Table 2.1: EMS in container terminals

was very efficient in providing ancillary services to the electricity grid.

In the paper from Wang et al. (2019) a two stage optimization is proposed to optimize the energy consumption and generation of a container terminal [75]. In the first stage the installed capacity of wind turbines, energy storage systems and on-shore power supply are determined. In the second stage stochastics of wind generation and loads are considered. In the end the goal is to minimize the operation cost.

Pei et al. (2021) also propose a multi stage EMS, similar to Wang [54]. Pei et al. attempt to manage the energy demand from a reefer container park. In the first stage day-ahead electricity prices are considered and in the second stage intraday price. Finally, a emergency control unit is present to make sure that the temperature of the reefers is always within the bounds. Time of use critical peak pricing schemes are used for the electricity supply. The proposed energy management system reduces the overall operating cost by about 14.7-18 percent.

Table 2 provides a comprehensive overview of research conducted on energy management systems within container terminals. The table highlights the methods employed and the energy loads considered in these studies. The commonly utilized methods include Multi-Agent Systems (MAS) and Mixed Integer Programming (MIP). Among the various energy loads proposed in energy management systems, Reefers, Quay Cranes (QCs), Yard Cranes (YCs), Electric Vehicles (EVs), and On-shore Power Supply (OPS) are frequently addressed.

In conclusion, The findings suggest that implementing demand-side management through an energy management system in container terminals can lead to a significant reduction in operating costs. By effectively managing and optimizing energy consumption, container terminals can enhance their cost efficiency and sustainability. The research highlights the potential benefits of deploying energy management systems in container terminals, with demand-side management playing a vital role in achieving substantial cost reductions.

2.2.2. Peak shaving in container terminals

Peak shaving refers to operational strategies aimed at reducing peak energy consumption in ports [32]. High energy demand peaks are undesirable as they increase the risk of power system failure and inflate supply costs, due to the necessity of occasionally activating expensive generators [72]. The electricity bill for ports and other consumers comprises a variable portion that depends on the peak power consumption for the year [32]. For ports, this consumption accounts for 25-30 percent of the monthly bill [11]. The three major strategies for peak load shaving are Demand Response (DR), Energy Storage Systems (ESS), and the integration of electric vehicles into the grid as mobile energy storage [72]. Two

Source	Method	Energy Load
Geerlings et al. (2018) [11]	Discrete event simulation	QC
Kermani et al. (2018) [41]	Particle swarm optimization	QC
Kermani et al. (2018) [42]	Particle swarm optimization	QC
Kermani et al. (2019) [40]	Particle swarm optimization	QC
Kermani et al. (2022) [43]	Economic evaluation	QC, YC, OPS, AGV, SC & Reefer
Van Duin et al. (2018) [7]	Discrete event simulation	Reefer

Table 2.2: Peak shaving in container terminals

opportunities to perform peak shaving in a container terminal using DR are discussed below.

Kermani et al. (2018) explore the potential to apply DR for peak shaving of Quay Cranes (QCs) using particle swarm optimization [41]. They reduced the peak load by coordinating the duty cycles of different cranes to prevent simultaneous lifting. This delay in duty cycle led to a peak load reduction of 17.7 percent. In subsequent research, Kermani incorporated a Flywheel ESS or ultracapacitor and a Hybrid ESS to further decrease the peak load [42] [40].

Geerlings et al. (2018) also examined operational strategies to reduce the peak load of quay cranes, similar to Kermani [11]. They proposed two rules of operation: limiting the number of lifting cranes and capping the maximal energy demand. They observed a reduction in peak energy demand of 38 percent for the former strategy and 50 percent for the latter, while the handling time increased by less than half a minute per hour.

In a study by van Duin et al. (2018), peak shaving is investigated in the context of reefer stacks [7]. They examined two operational strategies: intermittent power distribution among reefer racks and restriction of peak power consumption. The first strategy showed a significant reduction in peak energy, up to 80 percent.

Table 3 provides an overview of the research conducted on peak shaving. The most commonly considered loads for peak shaving are reefers and quay cranes. The methods used for peak shaving include particle swarm optimization and discrete event simulation.

In conclusion, peak loads contribute significantly to the energy-related costs of a container terminal. Substantial reductions in peak consumption can be achieved by preventing individual quay cranes or reefer containers from consuming energy simultaneously. By implementing effective peak shaving strategies, container terminals can effectively manage their energy consumption and reduce costs associated with peak demand.

2.2.3. Vehicle-to-grid charging in container terminals

Another research community focused on demand-side management within container terminals is the Vehicle-to-grid (V2G) charging community. V2G refers to the use of batteries in electric vehicles to provide services to the grid. V2G charging offers various services to the grid operator, such as regulation of active and reactive power, load balancing, peak load shaving, and current harmonics filtering [16]. Electric vehicles hold substantial potential for Demand Response (DR) [52]. Several papers were found utilizing V2G charging with a fleet of Battery Electric Automated Guided Vehicles (B-AGV) to provide DR in a container terminal.

Schmidt et al. (2015) proposed six potential business cases for using V2G to save costs for the terminal operator [61]. The first two cases involve modifying the company's load curve to reduce the grid fees dependent on peak loads, a strategy known as peak shaving. The third business case employs the batteries in AGVs to balance other loads due to uncertainties within the terminal. The fourth case controls the charging process based on the variable electricity prices throughout the day. This control aims to charge the batteries during times of low electricity prices. The last two business cases involve

Source	Method	Energy Load
Schmidt et al. (2015) [61]	Economical evaluation DR methods	AGV
Schmidt et al. (2014) [62]	Economical evaluation . charging strategies	AGV
Ihle et al. (2016) [30]	Logistic simulation + . Energy optimization	AGV
Kolenc et al. (2019) [45]	Experimental setup	AGV
Holly et al. (2020) [29]	Review ongoing work	AGV
Harnischmacher et al. . (2023) [18]	Rain flow counting analysis	AGV

Table 2.3: V2G charging in container terminals

providing ancillary services to the grid operator, where the batteries are used to balance the electricity grid in real-time based on the grid operator's needs. Schmidt et al. identified charging during tines of low electricity prices and peak shaving as the most promising and easiest to implement. Moreover, they found that peak shaving with AGVs can reduce the annual grid fees by up to 80 percent.

Several papers on the implementation of V2G charging at the Container Terminal Altenwerder (CTA) in Hamburg were found [30] [45] [29] [18]. Ihle et al. (2016) reported that the charging cost of B-AGV can be lowered by 10 percent with V2G [30]. Kolenc et al. (2019) investigated a communication protocol between a virtual power plant and an AGV to reliably provide ancillary services to the grid [45]. They found that ramping and latency could be potential issues for AGVs providing V2G services. Holly et al. (2020) reviewed ongoing work and proposed a method to manage the uncertainty and variability of AGV scheduling logistics while maintaining high reliability for ancillary services like frequency containment reserve [29]. Harnischmacher et al. (2023) found that AGVs are only operational between 12 and 13 hours per day [18]. Therefore, they proposed a secondary use for the AGV fleet, providing ancillary services to the grid for additional profit during the AGVs' downtime. Harnischmacher et al. demonstrated that V2G services with AGVs are both economically and ecologically feasible.

Table 4 provides an overview of V2G charging with AGVs. Due to different research objectives, the presented methods vary widely. The table highlights the methods employed and the energy loads considered in these studies. All research on V2G charging in container terminals only considers AGVs.

In conclusion, vehicle-to-grid charging with AGVs can be utilized for demand response in container terminals in several ways. Promising implementations include charging the batteries during off-peak hours to provide demand response and performing peak shaving for other loads within the terminal. Additionally, the CTA terminal is working on using AGVs to provide ancillary services to the grid operator.

2.3. Flexibility Potential for Demand Response

The presence of flexible loads is key for effective Demand Response (DR) [38]. In addition to flexibility, the cycle time of the load is also of interest. This can provide an indication over which time period a load can be shifted. Section 2.3.1 first identifies the most relevant loads for DR. The subsequent section 2.3.2 discusses the flexibility for each load.

2.3.1. Identifying Major Energy Loads

Only a limited number of container terminals track their energy consumption [76]. Tracking loads is important because, without it, effective measures to increase energy efficiency cannot be taken [76]. The distribution of loads can vary significantly from terminal to terminal [76]. When investigating electricity consumption, it's important to consider whether certain equipment runs on electricity or fuel.

In a paper by Baker et al. (2021), different loads within container terminals are identified, along with the factors that affect energy consumption [2]. An overview of these loads is given in Table 5.

Seaport's services	Load	Factor Influnece Energy Consumption
Vessel	Passenger ships (cruise, ferry), container ships, electric ships, tugs, gliders, bunkers, boats, tankers, hovercraft, sailboats, submarines, yachts	Size of the ship, activity conduct on the ship, time of operation, weather, wave, speed
Goods handling	Cargo, container, quay, logistic, freight forwarder, customs warehouse, storage, security, loading-unloading	Number of cranes, amount of cargo, hours of operation
Administration	Management and administrative building, planning, service solution, IT, monitoring	Type of electrical equipment, weather, building material, hours of operation, occupant behavior
Transportation	Electric vehicles, cranes, trucks, yard tractors, trains	Number of transportation, hours of consumption
Electric Facility	Cold ironing, charging station for electric vehicles	Time of berthing, number of ships per berthing, size, and ship's load
Maintenance	Repair and maintenance	Type of maintenance

Table 2.4: Seaport activities and loads variation [2]

Due to variations in the degree of electrification and the size of container terminals, different authors have found varying distributions of energy loads. In a paper by Iris and Lam, an overview of different studies into greenhouse gas emissions and energy consumption within ports is provided [32]. Commonly mentioned sources of energy demand include cargo handling cranes, (yard) vehicles, trucks, reefer cooling, buildings, lighting, hoteling, maneuvering, and the arrival and departure of ships. For estimating the potential for DR, only energy consumption in the form of electricity is of interest.

Based on the reviews by Baker et al. and Iris and Lam, the largest electrical loads were found to be on-shore power supply for ships, quay cranes, yard cranes, reefer containers, buildings, lighting, and battery electric automated guided vehicles. The consumption patterns for each of these sources are investigated in the next section.

2.3.2. Consumption Patterns

Very limited understanding exists within the container terminal industry regarding energy consumption patterns [76]. Unlike other industries, container terminals do not have continuous and recurrent production cycles [15]. Instead, daily processes are highly dynamic due to their dependency on the number of containers and ships arriving [15]. This makes the forecasting of electricity demand difficult [15].

Due to highly dynamic and stochastic logistics, it is not possible to plan detailed transportation and handling activities for more than 5-10 minutes ahead [15]. Therefore, logistic processes are usually controlled in real-time [15]. Not every detail of the logistic processes needs to be known to estimate energy demand. Short term deviations in planning can impact logistic processes but not so much the energy consumption if a 15-minute mean power demand is taken [15]. Below, the consumption patterns of the largest loads are explained.

Ships

predominantly use auxiliary engines to provide electricity to the loads on the ship. To reduce environmental pollution, it is possible for ships to receive electricity from the grid through On-shore Power Supply (OPS). The power consumption of a ship mostly depends on their load and size [2]. The cruising speed of a ship can be considered as a demand response tool [10]. By changing the speed, the

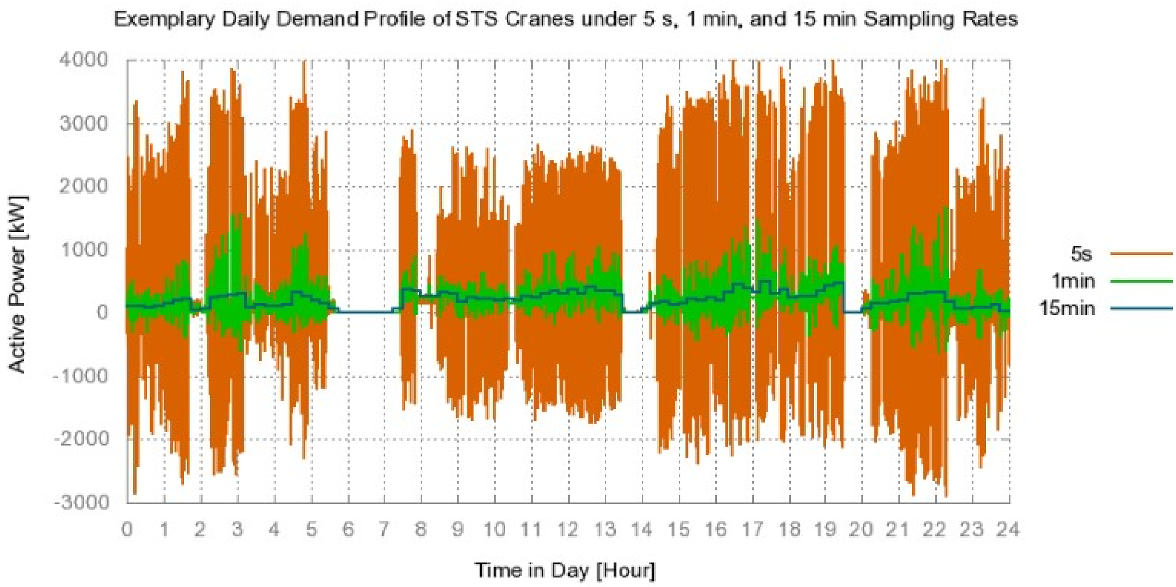


Figure 2.2: Electricity consumption of Quay Crane in a typical day [67]

arrival time of a ship can be changed. The departure and arrival times of a ship dictate the consumption pattern [2]. The average berthing duration for a container ship is 21 hours [4], and the average power requirement of a container ship ranges from 1 to 4 MW [4]. The total load of the OPS can be divided into essential and time-shiftable loads [23]. Vessels with long berthing times can provide flexibility by shifting their demand to more economically advantageous operating hours [23]. It was not found what percentage of the OPS load can be shifted to different berthing hours, so additional research is required.

Quay Cranes
(QCs) contribute significantly to the total energy consumption of a container terminal, accounting for up to 20-30 percent depending on the traffic volume [63]. Quay cranes, in particular, have a substantial impact on the peak power consumption. In the Port of Long Beach, for instance, 36.6 percent of the maximum power consumption is due to QCs [43]. The energy consumption of a QC varies widely between different movements of the crane . Six movements necessary to move a container from a ship to the shore, of these movements, hoisting the container requires the most energy [11]. One container cycle takes around 112 seconds [41]. The energy consumption of a quay crane also depends on the handling rate [10]. By reviewing several papers about berth assignment and quay crane scheduling problems, it was assumed that the handling rate is constant for one hour. Quay cranes operate only when a ship is berthed, so their energy consumption is dependent on the berthing schedule. A simulation by Tao et al. (2014) for the Container Terminal Altenwerder in Hamburg illustrates the consumption pattern (Figure 2.2) [67]. The frequent spikes (orange line) represent the hoisting, traveling, and lowering of a container. When a sample time of 15 minutes is used (blue line), most of these peaks are smoothed out. Quay cranes are most suited for providing very short-term flexibility because their operation is subject to strict time constraints [37].

Yard Cranes
(YCs) have an energy consumption pattern similar to quay cranes. The energy consumption is cyclical, based on the container movements and handling rate. Like QCs, YCs also have a high peak power load. In the Port of Long Beach, YCs account for 34.2 percent of the peak load of the terminal [43]. The berthing of ships influences the consumption pattern of YCs in a similar manner to QCs. Additionally, YCs can consume energy by re-marshalling containers even when no ship is present. Re-marshalling is mostly done when there are not many ships berthed and there is additional capacity left for the yard cranes to move the containers. Figure 2.3 shows the daily demand profile of a YC.

Reefers

consume between 26 and 48 percent of the energy within a container terminal [14] [76] [67]. The temperature within the reefer has to be controlled precisely to prevent the contents from spoiling. When a reefer's cooling is turned off, it will heat up approximately 1°C every 9 hours [37]. The mass of a container is the factor that affects temperature fluctuations the most [7]. Containers with a high mass experience slower temperature variations. The electricity consumption can be controlled by managing the times at which the cooling is turned on. The reefers are then used as so-called heat storage. The characteristics of reefers in terms of heat storage are similar to that of buildings [54]. Reefers are very flexible loads, but their potential for DR is underutilized [37]. Most reefers stay within the terminal for two to three days [37]. Furthermore, one cycle of a reefer heating up and cooling down lasts between 7-40 hours [7]. During this time cycle, the energy consumption is zero most of the time when the reefer is heating up. The energy consumption pattern of reefers also depends on the day-night cycle. More energy is needed for cooling during the day when ambient temperatures are higher. A simulation of the energy consumption of a reefer park throughout a day is shown in Figure 2.4.

Lighting

is required to illuminate the container yard at night. The energy consumption depends on the time of day, with consumption only during the night. Lighting contributes 7 to 21 percent of the total electricity consumption of a container terminal [14] [76] [67]. Lighting can be considered a critical load. As explained in Section 2.1.1, it is therefore not suited for DR. The energy consumption of lighting over a day is shown in Figure 2.5.

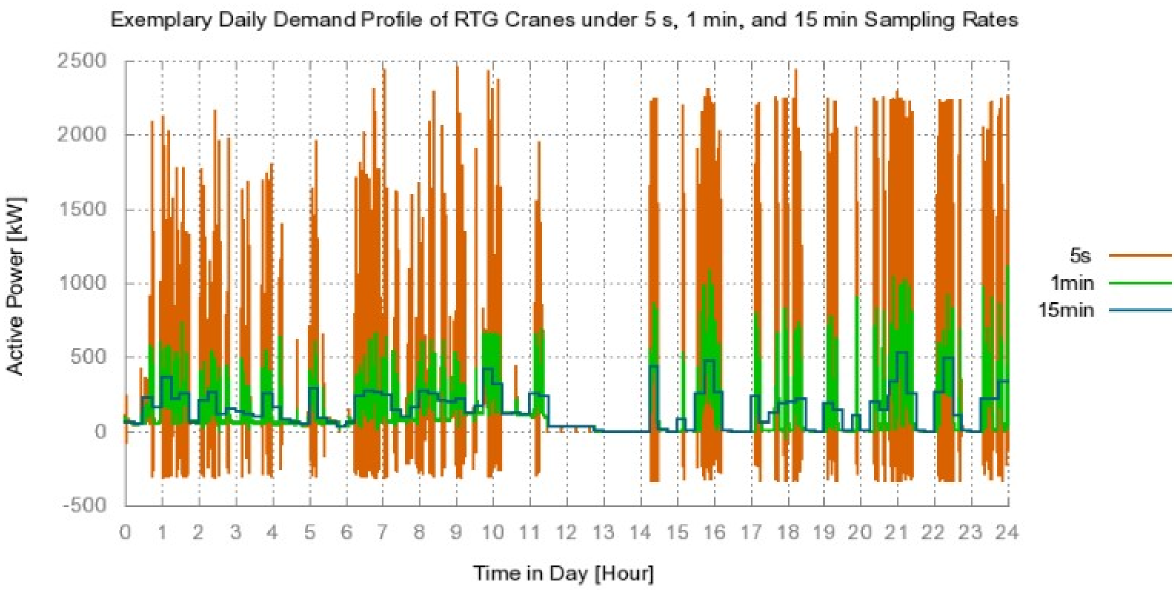


Figure 2.3: Electricity consumption of Yard Crane in a typical day [67]

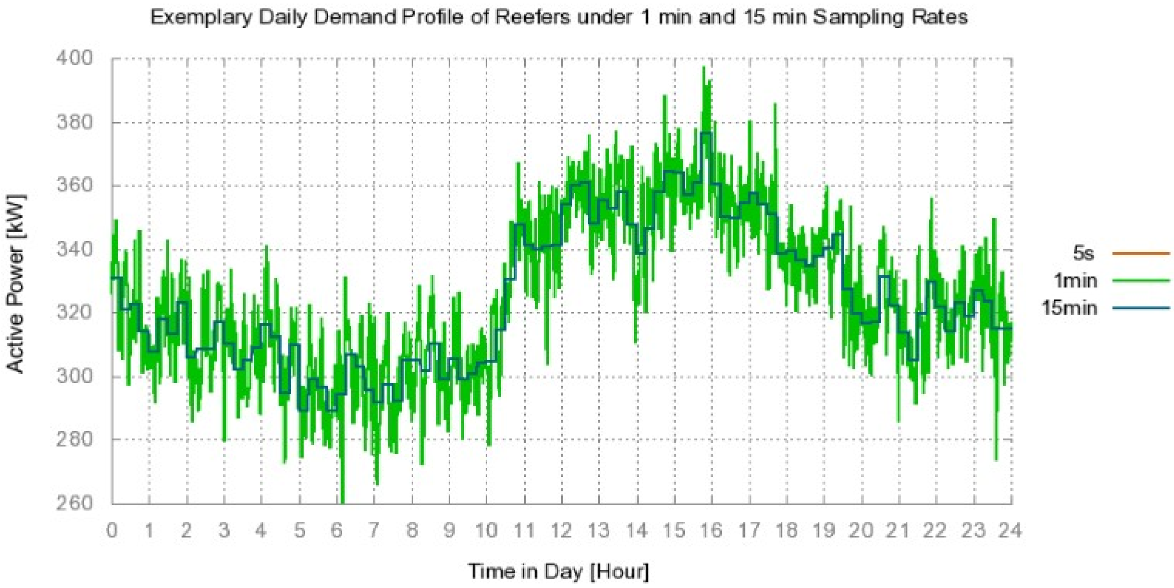


Figure 2.4: Electricity consumption of Reefer in a typical day [67]

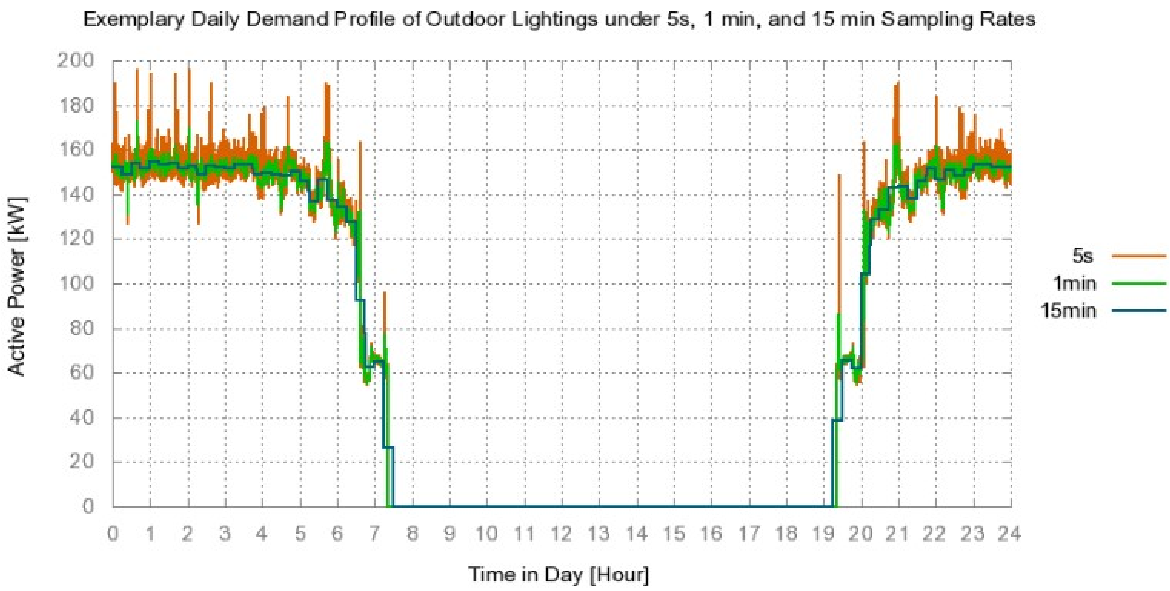


Figure 2.5: Electricity consumption of Lighting in a typical day [67]

Buildings

are a significant energy consumer within container terminals, responsible for between 3 to 20 percent of the total electricity consumption [14] [76] [67]. The electricity demand of buildings also follows a day-night cycle [67]. The electricity within buildings is predominantly consumed by lighting, heating, ventilation, and air conditioning (HVAC) [2]. While lighting cannot be controlled since it is considered critical, HVAC systems can be managed by allowing the temperature in the building to fluctuate by a few degrees throughout the day. Building energy management systems can be used to optimize the demand for buildings [37]. A graph of the electricity consumption of buildings within a port is shown in figure 2.6.

Automated Guided Vehicles

(AGVs), or more precisely Battery-electric Automated Guided Vehicles (B-AGVs) and other electric vehicles, can be considered as flexible loads. Future ports may be able to provide a substantial portion of demand flexibility by controlling the charging cycles of AGVs [37] [38]. AGVs only operate between 12 and 13 hours per day [18], and charging them takes around 6 hours [62]. AGVs could be used for demand response during the times of day when they are not operating [18]. Besides the charging schedule, the charging rate can also be used to control energy consumption. The charging rate can even be negative, allowing the batteries to provide power to the terminal or grid. Batteries can be discharged during peak consumption hours to reduce peak loads [61]. Additionally, batteries can be used to reduce imbalances between the scheduled and actual energy consumption of the container terminal during an Imbalance Settlement Period [61]. In the Netherlands, one Imbalance Settlement Period is 15 minutes [70]. By controlling the charging rate of the battery, it is possible to provide ancillary services to the grid operator [61]. To provide ancillary balancing services to the grid operator, the charging rate has to be controlled within 30 seconds, 5 minutes, or longer, depending on the type of balancing being performed [69]. Several business cases exist for making use of the flexibility potential of AGVs. In a paper by Schmidt et al. (2015), six were identified, ranging from flexibility in the microseconds to provide ancillary services, to flexibility over a day to take advantage of price fluctuations in the day-ahead market [61].

Container Terminal

The consumption patterns within the port vary significantly, suggesting a great potential for DR. In Figure 2.7, the average electricity demand of a container terminal over a day is depicted. This figure does not

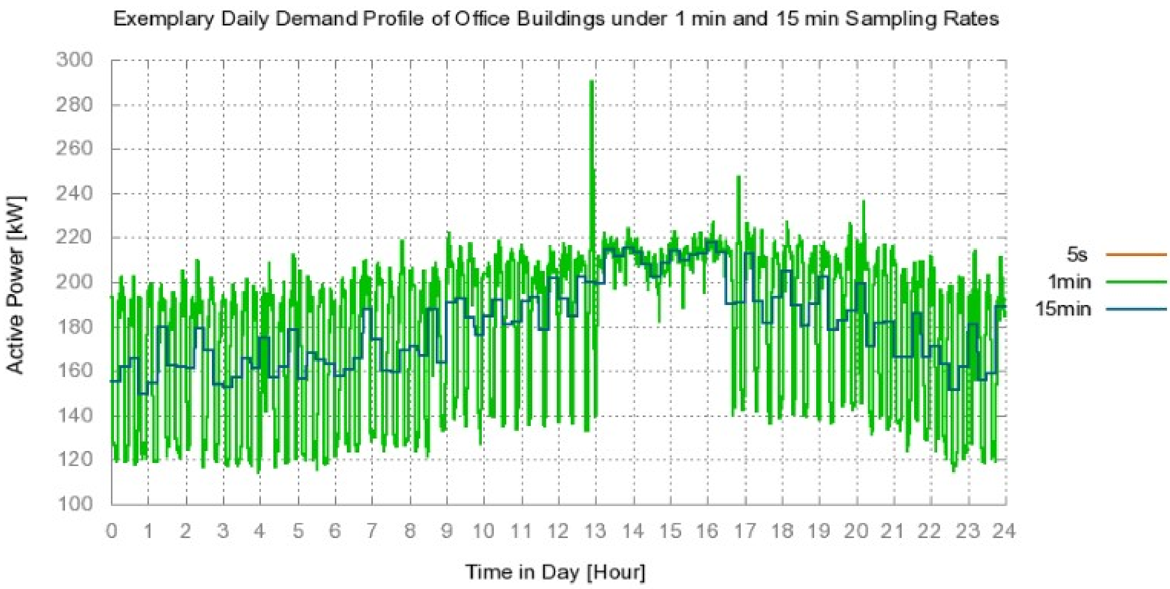


Figure 2.6: Electricity consumption of Buildings in a typical day [67]

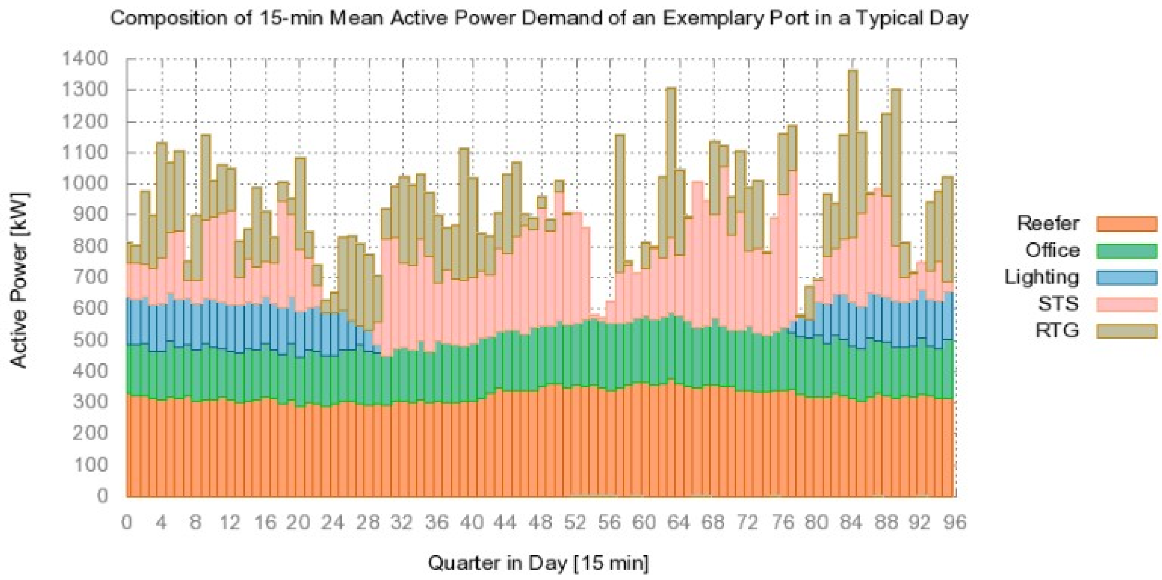


Figure 2.7: Electricity consumption of the entire port in a typical day [67]

include the energy consumption of OPS and AGVs. The most considerable variation in consumption is observed in quay and yard cranes.
In conclusion, there is significant flexibility in the loads within a terminal, but different loads have flexibility over different time periods. The energy consumption of ships, quay cranes, yard cranes, reefers, buildings, and automated guided vehicles can all be considered reschedulable to some extent. However, due to the critical nature of the load, lighting is not suited for DR. The berthing schedule is one of the major factors influencing the energy consumption within the terminal.

2.4. Demand response programs in container terminals

There are several ways through which a container terminal can reduce their electricity costs by managing their consumption. As discussed in 2.1, different demand response programs exist in which a container terminal can participate. Not all programs are as well-suited for a container terminal. In this section, the different demand response programs and electricity markets found in 2.1 will be compared with the demand flexibility found in **??**. Interesting demand response programs will be identified.

In a paper by Jordehi et al., a review is conducted on demand response optimization [35]. Jordehi found that real-time pricing is most commonly used in demand response optimization research, followed by direct load control and time-of-use pricing. Jordehi concluded that most research into demand response focuses on residential customers, and more research into industrial and commercial demand response is recommended.

Research on demand response within container terminals mostly focuses on price-based demand response programs. As explained in 2.1, demand response programs can be categorized as price-based and incentive-based. Most of the literature presented in section **??** (implicitly) used a price-based incentive for demand response, with time-of-use rates or real-time pricing being employed. Only researchers investigating Vehicle-to-Grid charging of AGVs considered an incentive-based demand response program in the form of ancillary services. No argumentation was found in any of the research as to why a particular type of demand response was chosen.

The issue of precise forecasting of future energy consumption poses a significant hurdle for many demand response programs, as highlighted by Schmidt et al. in their research [61]. This is particularly challenging in terminal operations, where factors such as fluctuating operations and changing conditions can lead to unpredictable changes in electricity demand, resulting in imbalances. Section 2.3.2 further explains that forecasting electricity demand far ahead is difficult due to the uncertainty associated with consumption patterns.

To address this challenge, terminal operators should strive to improve their demand forecasting capabilities to accurately contract the required amount of electricity. Additionally, utilizing the intraday market can be a viable option to buy additional electricity or sell surplus electricity to mitigate electricity imbalances.

Certain demand response programs, such as capacity market programs, demand bidding, and ancillary services, face even greater complexities as they require commitments to be made at least one day prior to delivery. In a study by Holly et al., it is investigated how BAGVs can be used to provide a frequency containment reserve (an ancillary service) on the balancing market [29]. Holly noted that the major challenge is to provide a critical grid service, requiring high reliability, with a process that is characterized by high uncertainty and variability. By taking measures like improving the forecast on the availability of AGVs and integrating the AGV fleet in a pool with other distributed energy resources, among others, Holly found that it was possible to provide ancillary services with AGVs. For other loads in the container terminal, it might be harder to achieve the forecast accuracy required for capacity market programs, demand bidding, and ancillary services.

Since price-based demand response programs do not require any upfront commitment in electricity consumption, they are considered better suited for most loads within the container terminal. For these programs, port operators are notified upfront about the electricity prices for every hour, and they have to pay more if the prices are high. However, they do not receive any fines in case they don't deliver the required capacity, as would be the case for some of the incentive-based programs. Alternatively, demand response programs without upfront commitment, such as Emergency DR or Direct load control, can be used in a port.

For this thesis, it has been decided to focus on real-time pricing demand response. This type of demand response is in line with other research done on demand response in container terminals. The price signals on which the demand response program will work will be based on the day-ahead electricity price and the imbalance (surplus and shortage) price.

2.5. Conclusion potential of demand response

In this chapter, the potential for demand response in container terminals has been investigated by examining existing research on demand response in container terminals. energy consumption patterns and the major energy loads within these terminals were identified. The objective was to determine the sources of demand flexibility and explore the suitability of different demand response programs for container terminals to answer the first two research questions presented in 1.3.

Through the literature review, three topics of research were found considering demand response within container terminals. First, several papers about energy management systems showed that demand side management can significantly reducing the operating cost of a terminal. Second, peak shaving which showed that that reducing the peak power consumption can reduce the grid usage fees from the grid operator. Within the terminal Quay cranes and reefer are mostly responsible for the peak loads. Lastly, with the switch to an electric AGV fleet vehicle to grid charging can provide additional revenue to the terminal operator, by providing ancillary services, peak shaving, the reduction of imbalances and with off-peak charging.

Form the literature review several research gabs where found. First, no review was found on all the ways the ways demand response can be applied in a container terminal. Second, most studies on demand response in a container terminal either focus on a single load or on a micro grid the major loads and a battery and onsite generation. No studies have been found focusing solely on demand response potential of the entire terminal. Third, no studies into demand response do not consider the uncertainty in both the energy supply and demand. The uncertainty in the energy consumption is often not taken into account in research into demand response within a container terminal. Often the loads

Load	Factors to control Energy Consumption	cycle time
Vessel	Berthing schedule ,	21h
	flexible loads on the ship	-
Quay crane	Berthing schedule	21h
	handling rate	1h
	lifting speed	120s
Yard crane	Berthing (+ re-marshaling) schedule	21h
	handling rate	1h
	lifting speed	120s
Reefer	Heating/Cooling rate	7h-40h
Building	Heating/Cooling rate	24h
AGV	Charging rate	24h - 30s

Table 2.5: Methods to control the energy consumption with a container terminal

are considered deterministic, leading to a incomplete picture when estimating the potential for demand response. More information on how these research gabs found are solved in this thesis can be found in 1.2.

By investigating the energy consumption, it was found that container terminals have several major energy loads, including ships, quay cranes, yard cranes, reefers, buildings, lighting, and battery-electric automated guided vehicles (AGVs). These loads contribute significantly to the overall energy consumption of container terminals. The consumption patterns of these loads were analyzed, revealing various factors that can be controlled to adjust energy consumption. For example, ships' energy consumption is influenced by factors such as size, load, cruising speed, and berthing schedule. Quay cranes and yard cranes exhibit cyclic energy consumption patterns based on container movements, while reefers have temperature-dependent consumption patterns. Buildings and AGVs offer potential for demand response through temperature control and charging schedule optimization, respectively. An overview of all the methods to control the energy consumption is shown in table 2.5.

It was observed that different loads exhibit flexibility over different time periods, with some offering short-term flexibility and others having the potential for longer-term adjustments. However, it is important to note that critical loads, such as lighting, may not be suitable for demand response due to their essential nature. Future research is needed to determine the specific extent of flexibility for each load and develop effective demand response strategies in container terminals.

After reviewing different demand response programs, it was found that price-based demand response programs, such as real-time pricing, are well-suited for container terminals. These programs provide price signals based on day-ahead electricity prices, allowing terminals to adjust their consumption accordingly without upfront commitments. Incentive-based programs, such as capacity market programs and ancillary services, present challenges in terms of forecasting and reliability requirements. However, price-based programs offer a practical and feasible approach for container terminals to manage their electricity costs and contribute to a more efficient energy system.

In conclusion, container terminals demonstrate a significant potential for demand response through the flexibility of their energy loads. Ships, quay cranes, yard cranes, reefers, buildings, and AGVs can be adjusted or rescheduled to some extent, providing opportunities for demand response. Price-based demand response programs, particularly real-time pricing, offer a suitable framework for container terminals to optimize their energy consumption and contribute to a sustainable energy future. Future research should address the research gaps identified in this thesis and further explore the implementation and effectiveness of demand response in container terminals.

3

Problem description

As has been explained in chapter 2 there is a potential for demand response in a container terminal. To quantify the potential a energy-aware optimization of operations is conducted. As explained in 2 both the energy consumption of a container terminals and energy prices are highly dynamic and unpredictable. To get a accurate result the uncertainty in both energy demand and supply should be taken into account in the when formulating the problem.

In this section a stochastic model is formulated. First the outline of the model is given in section 3.1. Here the structure of the model is explained and the assumptions are stated. Second the mathematical formulation of the model is given in section 3.2.

3.1. Model description

The aim of the optimization model is to quantify the potential of demand response in a container terminal. To do so, a model is developed to optimize the operational planning in a container terminal. Based on the timing of operations, the energy consumption can be calculated. An energy-aware optimization of container terminal planning is conducted, by considering energy-related costs in the model. By using price-based demand response, it is possible to reduce energy-related costs.

This section first explains how demand response is modeled in 3.1.1. Then, it describes how uncertainty is included in the model in 3.1.2. Finally, the main assumptions are highlighted in 3.1.3.

3.1.1. Outline

For this thesis, the energy consumption of vessels, quay cranes (QCs), yard cranes (YCs), reefers, and automated guided vehicles (AGVs) in the container terminal is considered. As explained in Chapter 2, the energy consumption of buildings in the terminal can also be used for demand response. However, it is ignored in this thesis. It can be argued that the building energy management system in a container terminal is similar to that of other office buildings. The energy consumption of terminal buildings is also expected to be independent of other operations in the terminal and can therefore be studied separately. Demand response in office buildings is a well-studied problem, and it has been decided not to consider it in this thesis. Figure 3.2 provides an overview of all the energy loads considered.

All the operations are controlled by the Terminal Operations System (TOS). The energy consumption of all different loads is mangaged by the energy mangement system (EMS). In figure 3.2 the information and energy flows are shown between all the considered energy loads and the TOS and EMS.

In a container terminal, various planning problems can be identified. These problems can be categorized into three levels: strategic, tactical, and operational planning, each with a different time frame. This thesis focuses on operational planning, as it has the most significant impact on energy consumption. Moreover, the planning problems can be distinguished based on their location: seaside, yard, and landside. For this thesis, the focus is on the seaside and yard, as it is what makes a container terminal unique compared to the rest of the transportation industry. This focus means that the energy consumption related to the transportation of containers out of the terminal with trucks and rail is not considered. Figure 3.1 provides an overview of all the planning problems in a container terminal.

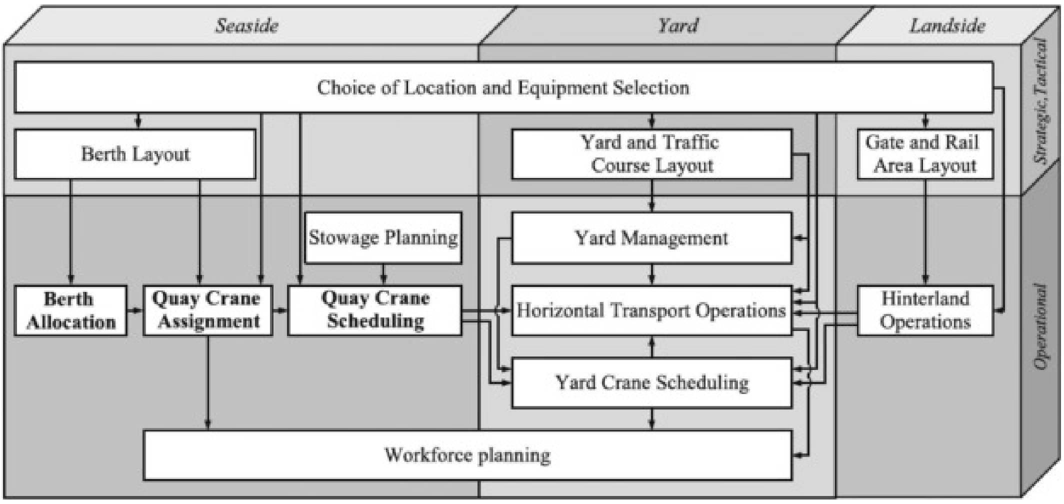


Figure 3.1: Planning problems in container terminals [3]

Some modifications are made to the QCAP to include the assignment of Yard Cranes (YCs) and Automated Guided Vehicles (AGVs). Instead of assigning a specific number of Quay Cranes (QCs) to a ship, a handling rate is assigned. For each handling rate, a specific number of QCs, YCs, and AGVs are required. The handling rate is calculated by taking the minimum handling capacity among the three types of machinery assigned. The handling rate can be calculated using Equation 3.1, where p represents the handling rate, N is the number of each type of machinery assigned, and h is the handling capacity of each individual type of machinery.

$$p = \min(N_{QC} \cdot h_{QC}, N_{YC} \cdot h_{YC}, N_{AGV} \cdot h_{AGV}) \tag{3.1}$$

Based on the number of AGVs assigned in the QCAP problem, the energy consumption of the AGVs is calculated. An Electric Vehicle (EV) charging scheduling problem is formulated, similar to the one presented in [73]. The AGV assignment problem and the EV charging scheduling problem are combined to control the charging rate.

As stated in Section 2.3, the energy consumption of reefer containers depends on heat transfer with the environment. A problem is formulated to control the reefer containers temperature, similar to the problem mentioned by Verzijlbergh and Lukszo in [74] problem is formulated. This formulation allows for the determination of the optimal control of the cooling rate.

The operational planning problems considered in this thesis were selected based on the factors that can control energy consumption, as stated in Chapter 2. Table 3.1 relates the planning problems to the factors that can control energy consumption. All the operational problems considered was simplified as much as possible by ignoring everything that doesn't influence the energy consumption. All planning problems considered are shown in Figure 3.2.

3.1.2. Uncertainty

In Chapter 2, it was mentioned that uncertainty has a significant impact when scheduling the energy demand of a container terminal. The uncertainty in logistics supply chains leads to unpredictable electricity demand for a container terminal, while uncertainty in the power system results in unpredictable electricity supply. Therefore, when developing a model for demand response in a container terminal, it

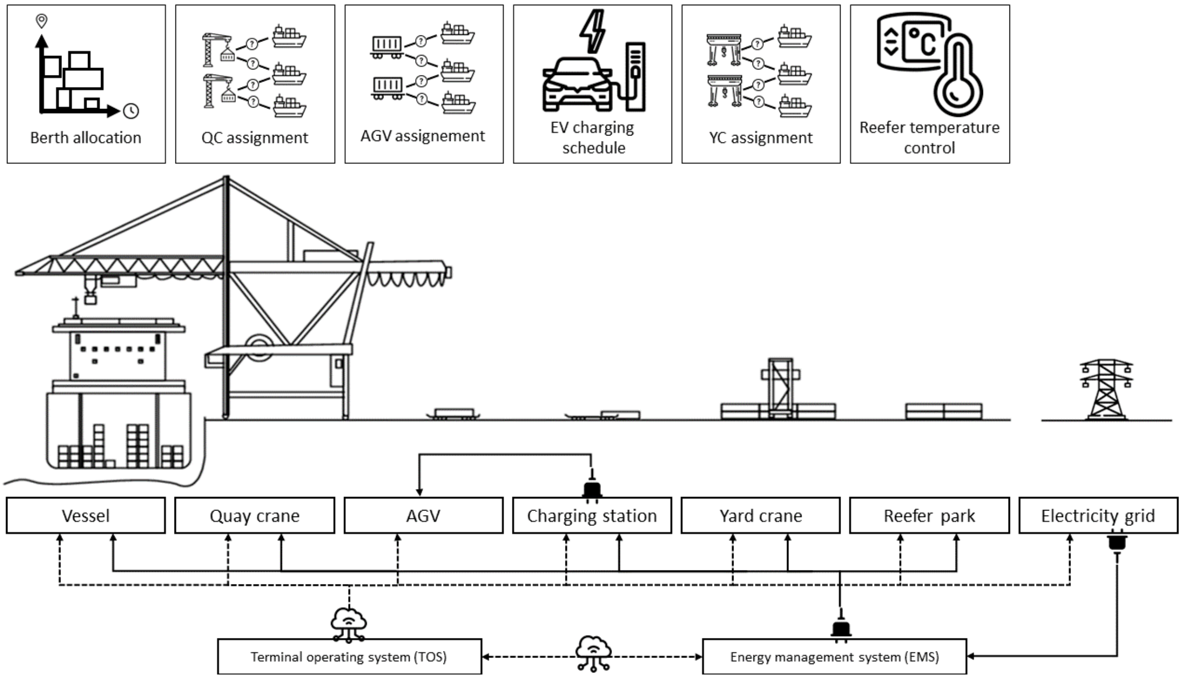


Figure 3.2: Operational problems, Energy loads and Information and Energy flows within the terminal

Load	Factors to control Energy Consumption	Planning problem
Vessel	Berthing schedule	Berth Assignment problem
Quay crane	Berthing schedule handling rate	Berth Assignment problem Quay Crane Assignment Problem
Yard crane	Berthing (+ re-marshaling) schedule handling rate	Berth Assignment problem Yard Crane Assignment Problem
Reefer	Heating/Cooling rate	Temperature control problem
AGV	Charging rate	AGV Assignment Problem+ EV charging schedule problem

Table 3.1: Planning problems

is crucial to consider uncertainty.

In a review paper by Roald et al., an overview is provided of the main sources of uncertainty in power systems [56]. Roald mentions renewable energy generation, component outages, the price of electricity, precipitation (for hydro power plants), ambient conditions, and the occurrence of extreme weather as sources of uncertainty in power systems. Given the scope of this thesis, the uncertainty of the price of electricity is most relevant when optimizing the operational planning of a container terminal.

Complex supply chains introduce uncertainty in container terminal operations in several ways. The arrival times of ships have been identified as the most significant factor of uncertainty in container terminal operations. Ksciuk et al. consider unexpected ship delays and uncertain demand or supply of empty containers as the primary sources of operational uncertainty for ship routing and scheduling [48]. In a review paper by Rodrigues and Agra, the most prominent sources of uncertainty considered in the Berth Assignment Problem (BAP) and Quay Crane Assignment Problems (QCAP) were found to be ship arrival times and handling times [57].

For this thesis, it has been assumed that the arrival times of ships and the electricity prices are uncertain. To deal with this uncertainty a so called two stage stochastic model is formulated. In Chapter 4, will be discussed why this is the best approach. Based on predicted arrival times and electricity prices, a here-and-now decision is made for the electricity consumption and a berthing schedule in the first stage of the two-stage stochastic optimization model. Afterwards, in the second stage, a wait-and-see decision is made to change the initial consumption and schedule based on the specific scenario parameters of the arrival times and electricity prices. Additionally, a decision is made for the assignment of the quay cranes, yard cranes, and automatic guided vehicles. The cooling and charging rate of the reefers and AGVs are also decided in this stage. A diagram with all the decisions and their respective stages is shown in Figure 3.3.

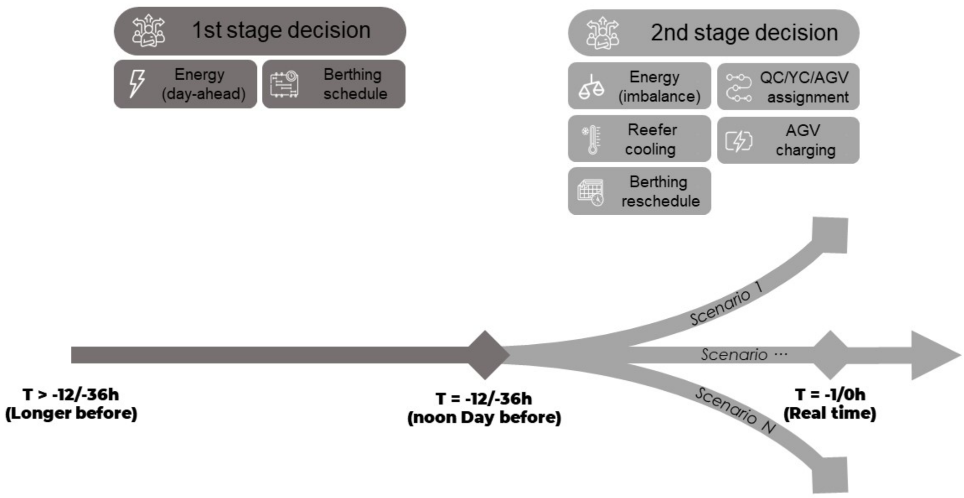


Figure 3.3: Decision timeline

3.1.3. Assumptions

To formulate the model several assumptions had to be made. Below list of the main assumptions is shown.

- Ships only use energy when they are berthed.
- The energy consumption is the same for every ship and constant over time.
- The location where a ship is berthed does not influence the energy consumption.
- Berthing space is available if the combined length of all berthed ships is less then the quay length.
- The energy consumption of QCs, YCs and AGVs only depends on the handling rate.
- The loading and unloading consume the same amount of energy for QCs and YCs.
- Every container consumes the same amount of energy for loading and unloading (so no influence on the mass).
- The energy needed move QCs to the correct location is negligible.
- The amount of reefers in the yard is constant throughout the day.
- The reefer cooling requirements are the same for every container.
- The reefer park can be modeled as one large refrigerated storage.
- The reefer energy consumption is dependent on the ambient temperature.
- The ambient temperature is considered to be constant.
- The AGV fleet can be modeled with one large battery.
- The energy consumption of the container terminal does not influence the electricity price.

3.2. Mathematical formulation

In this section, a model is presented that builds upon the work of Iris and Lam [33]. While the basic framework of the model remains the same, several enhancements have been made. These include the addition of AGV operations, improved reefer operations, and the incorporation of uncertainty in ship arrival times and electricity prices. Table 3.2 provides an overview of all the sets, parameters, and decision variables used in the model, along with their descriptions.

The section begins by explaining the objective function employed in the model. Subsequently, it proceeds to describe the constraints that bound the model and ensure its validity.

Notation	**Description**
Sets	
V	Set of vessels to be served, $i \in 1, 2, \ldots, N$, where N is the number of vessels to be served, 10.
T	Set of time periods (1 hour), $t \in 0, 1, \ldots, H-1$, where H is 48 hours.
P_i	Handling rate that can be assigned to a ship $i \in V$, where p is the mininum of $u_{p,m} * h_m$.
M	Types of machinery present in the terminal $m \in QC, YC, AGV$.
S	Set of scenarios $w \in S$.
Parameters	
k_m	Amount of machinery $m \in M$ available .
h_m	Handling rate of machinery m in containers per hour .
$d_{i,w}$	The total demand of containers to be handled (loaded + unloaded) for ship $i \in V$ in scenario $w \in S$.
$u_{p,m}$	The amount of machinery of type m used in pattern p
l_i^{ship}	The quay length that ship i takes up.
l^{total}	The total length of the quay.
eat_i	Expected arrival time of vessel $i \in V$.
eft_i	Expected berthing finishing time of vessel $i \in V$.
$a_{i,w}$	Actual arrival time of vessel $i \in V$ in scenario $w \in S$.
e^{ship}	energy consumption for one hour of a ship using on shore power supply .
$e_m^{machinery}$	Energy consumption of machinery m for operating for one hour
e^{charge}	Energy consumed by one charger.
$e^{charge,max}$	Maximum Energy consumed by all chargers.
b^{min}	Minimum AGV battery level.
b^{max}	Maximum AGV battery level.
η^{charge}	Charging efficiency.
e^{reefer}	Energy consumption of one reefer connection
$e^{reefer,max}$	Maximum energy consumption of all reefer connection
tc^{min}	Minimum reefer temperature.
tc^{max}	Maximum reefer temperature.
η^{reefer}	Cooling efficiency.
ta	Ambient temperature
mc^p	Specific heat capacity of a reefer.
u^a	Heat transfer coefficient of a reefer.
$c_{t,w}^{da}$	Day electricity price at time t in scenario $w \in S$.
c_i^{late}	Penalty cost of exceeding the expected finishing time (EFT) for vessel $i \in V$ for one hour.
$c^{reschedule}{}_i$	cost of changing the initial schedule by one hour.
c^{sur}	cost of having a surplus of energy.
c^{shor}	cost of having a shortage of energy.

Continued on next page

Table 3.2 – continued from previous page

M	A large positive number.
ρ_w	Probability of scenario w occurring ($1/S$).
Decision variables	
$S_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing start time of vessel $i \in V$
$S_{i,w} \in \mathbb{Z}^+$	Berthing start time of vessel $i \in V$ in scenario $w \in S$
$S_{i,w}^{early} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives ahead of schedule in scenario $w \in S$
$S_{i,w}^{late} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives behind schedule in scenario $w \in S$
$F_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing end time (time when handling ends) of vessel $i \in V$
$F_{i,w} \in \mathbb{Z}^+$	Berthing end time (time when handling ends) of vessel $i \in V$ in scenario $w \in S$
$L_{i,w} \in \mathbb{Z}^+$	Lateness of operations for ship $i \in V$ in scenario $w \in S$
$A_{i,t,w} \in \mathbb{B}$	1 if vessel $i \in V$ is assigned at to a berth in period t in scenario $w \in S$, 0 otherwise
$H_{i,p,t,w} \in \mathbb{B}$	1 if handling rate p is assigned to serve vessel $i \in V$ at time period t in scenario $w \in S$, 0 otherwise
$B_{t,w}^{level} \in \mathbb{R}^+$	Battery level at time t in scenario $w \in S$
$TC_{t,w}^{temperature} \in \mathbb{R}$	Reefer temperature at time t in scenario $w \in S$
$E_{t,w}^{charge} \in \mathbb{R}^+$	Energy consumed to charge AGVs at time t in scenario $w \in S$
$E_{t,w}^{reefer} \in \mathbb{R}$	Energy consumed to cool the reefers at time t in scenario $w \quad S$
$P_{t,w} \quad \mathbb{R}^+$	Power used from the utility grid at time t in scenario $w \quad S$
$P_t^{da} \quad \mathbb{R}^+$	Power purchased at the day ahead market at time t
$P_t^{sur} \quad \mathbb{R}^+$	Power surplus at time t
$P_t^{shor} \quad \mathbb{R}^+$	Power shortage at time t
$IM_t^{state} \quad \mathbb{B}$	Imbalance state, 1 if there is a surplus and 0 if there is a deficit

Table 3.2: Sets, Parameters, and Decision Variables

3.2.1. Objective

There is an inherent tradeoff between the optimal operating schedule and the optimal electricity consumption schedule in an energy-aware optimization of operations. Both the scheduling cost and the energy cost are considered in the objective function.

In a review paper by Jordehi [35], four different objectives for demand response (DR) optimization problems are mentioned. First, bill saving maximization aims to reduce the cost of purchasing electricity. Second, comfort maximization focuses on minimizing the inconvenience of DR for the consumer. Third, generation cost minimization considers both the cost of purchasing electricity and the cost of onsite generation. Lastly, peak average ratio minimization is commonly used to minimize peak demand.

Rodrigues and Agra [57] conducted a review paper on Berth Assignment Problems (BAPs) under uncertainty, where they identified different objectives used in BAPs. These objectives were categorized into four categories: Services, Deviations, Cranes, and performance measures. Services refers to the time a ship spends in a port. Objectives in this class are waiting times before being berthed, handling times, completions times (sum of waiting and handling times) and Lateness of delays between the planned and actual departure time. Deviations refers to the difference between the obtained and reference solution. Here the authors consider berth position deviations, deviations in the start time of operations and finish time deviations. In the third category the number of quay cranes and the number of crane movements between vessels are considered as objectives. The the last category consists of objectives of risk measures and robustness criteria.

For the demand response in this thesis, the focus is on maximizing bill savings and comfort. This objective is reformulated as a minimization problem, considering the cost of purchasing electricity and the inconvenience experienced by the terminal operator due to DR. The purchasing cost of electricity is quantified by the cost needed to buy electricity on the day-ahead electricity market. Inconvenience is quantified based on common objectives in BAPs, where the cost due to lateness is used. Waiting time is ignored as cruising speed is considered a tool for providing DR by adjusting the actual arrival time to the planned arrival time.

Additional objectives need to be considered to minimize deviations between the day-ahead schedule made in the first stage and the real-time schedule made in the second stage. A penalty is added to the objective function to minimize deviations in power consumption and berthing start. In case of a power imbalance, additional power can be bought in the case of a shortage, and extra power can be sold in the case of a surplus. Similar to Crespo-Vazquez et al. and Tajeddini et al., the cost of power imbalance is quantified by multiplying a factor with the day-ahead electricity price. This factor is less than one for a shortage and greater than one for a surplus.

In Equation 3.2, the objective function is shown. The first two terms represent the scheduling cost of a container terminal, taking into consideration the cost of ships departing later than expected and the cost of rescheduling ships. The last two terms represent the cost related to energy. The first term represents the cost of purchasing power on the day-ahead market, while the last two terms represent the cost of having a power surplus or deficit. In the equation, **V** represents the set of all vessels, and **T** represents the set of all time periods.

$$\begin{aligned}\min_{\mathbf{V},\mathbf{T}} \sum_{w\in\mathbf{S}} \pi_w \Bigg(& \sum_{i\in\mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i\in\mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) + \\ & \sum_{t\in\mathbf{T}} c_{t,w}^{\text{da}} P_t^{\text{da}} + \sum_{t\in\mathbf{T}} c_{t,w}^{\text{da}} (c^{\text{shor}} P_{t,w}^{\text{shor}} - c^{\text{sur}} P_{t,w}^{\text{sur}}) \Bigg)\end{aligned} \tag{3.2}$$

3.2.2. Constraints

In this section, we present the constraints that govern the mathematical model for container terminal operations and energy consumption. These constraints ensure the feasibility and optimization of the system. Each constraint is listed below, along with a brief explanation of its purpose and interpretation. Constraint 3.3 ensures that the energy consumed by the ships, quay cranes (QCs), yard cranes (YCs), automated guided vehicle (AGV) charging, and reefer cooling matches the power drawn from the grid.

$$\begin{aligned}& \sum_{i\in V} e_{ship}\ A_{i,t} + \sum_{i\in V} \sum_{p\in P_i} u_{p,'QC'}\ H_{i,p,t}\ e_{'QC'} + \\ & \sum_{i\in V} \sum_{p\in P_i} u_{p,'YC'}\ H_{i,p,t}\ e_{'YC'} + E_t^{reefer} + E_t^{charge} = P_t\end{aligned} \tag{3.3}$$

Constraints 3.4 - 3.12 are associated with the berth assignment of ships and the handling capacity assignment. For example, Constraint 3.4 guarantees that the start time of vessel operation is either equal to or later than its expected arrival time. Constraint 3.5 defines the lateness time, which is the time a ship departs after the expected departure time. To ensure that the ships are berthed during every hour between the berthing start time and end time, Constraints 3.6, 3.8, and **??** are introduced. Constraint 3.9 prevents overcrowding of the berth by ensuring that the length of all berthed vessels is shorter than the quay length. A handling rate is assigned to every ship for every hour it is berthed. This is accomplished by Constraints 3.10 and 3.11. Constraint 3.12 guarantees that the machinery capacity is not exceeded for QCs, YCs, and AGVs.

$$S_{i,w} \geq a_{i,w} \qquad \forall i \in V, \forall w \in S \tag{3.4}$$

$$L_{i,w} \geq F_{i,w} - eft_i \qquad \forall i \in V, \forall w \in S \tag{3.5}$$

$$\sum_{t\in T} A_{i,t,w} = F_{i,w} - S_{i,w} \qquad \forall i \in V, \forall w \in S \tag{3.6}$$

$$(t+1)A_{i,t,w} \leq F_{i,w} \qquad \forall i \in V, t \in T, \forall w \in S \tag{3.7}$$

$$tA_{i,t,w} + t_{max}(1 - A_{i,t,w}) \geq S_i \qquad \forall i \in V, t \in T, \forall w \in S \tag{3.8}$$

$$\sum_{i \in V} A_{i,t,w} l_i^{ship} \leq l_{total} \qquad \forall t \in T, \forall w \in S \tag{3.9}$$

$$\sum_{p \in \Pi_i} H_{i,p,t,w} = A_{i,t,w} \qquad \forall i \in V, t \in T, \forall w \in S \tag{3.10}$$

$$\sum_{p \in \Pi_i} pH_{i,p,t,w} \geq d_i \qquad \forall i \in V, t \in T, \forall w \in S \tag{3.11}$$

$$\sum_{i \in V} \sum_{p \in P_i} u_{p,m} H_{i,p,t,w} \leq k_m \qquad \forall t \in T, m \in M, \forall w \in S \tag{3.12}$$

A day-ahead schedule is formulated for both the arrivals of the ships and power consumption. Constraint 3.13 establishes the day-ahead start time of the ships, which remains consistent across all scenarios. The difference between the start time and day-ahead start time is equivalent to the deviation of start time. Similarly, Constraint 3.16 defines this for the day-ahead energy consumption. It is impossible to have a surplus and a deficit in energy consumption simultaneously. A binary variable IM_t^{state} is used to keep track of whether there is a surplus or shortage, with Constraints 3.14 and 3.15 capturing this dynamic.

$$S^{late}i,w - S^{early}i,w = S_i,w - S_i^{da} \qquad \forall i \in V, \forall w \in S \tag{3.13}$$

$$P^{shor}t,w - P^{sur}t,w = P_t,w - P_t^{da} \qquad \forall t \in T, \forall w \in S \tag{3.14}$$

$$P^{sur}t,w \leq M \cdot IM^{state}t,w \qquad \forall t \in T, \forall w \in S \tag{3.15}$$

$$P^{shor}t,w \leq M \cdot (1 - IM^{state}t,w) \qquad \forall t \in T, \forall w \in S \tag{3.16}$$

Constraint 3.17 - 3.22 concern the operation of AGVs and regulate their charging and discharging procedures. The total power used to charge the AGVs is constraint based on the number of charging stations and the number of AGVs available for charging. These restrictions are described by Constraints 3.17 and 3.18. Constraint 3.19 ensures that the battery level always remains within the minimum and maximum allowed levels. The state of battery charge should fluctuate based on the amount of energy charged and discharged. This principle is captured by Constraints 3.20 and 3.21 for time periods 1 to H and for time period zero respectively. Constraint 3.22 asserts that the battery level at the start of the day should be equivalent to the level at the end of the day, thereby preventing overcharging. It also ensures that over one day, the amount of energy consumed equals the energy charged.

$$E_{t,w}^{charge} \leq e^{charge,max} \qquad \forall t \in T, \forall w \in S \tag{3.17}$$

$$E_{t,w}^{charge} \leq (k_m - \sum_{i \in V} \sum_{p \in P_i} u_{i,p,m} \cdot H_{i,p,t}) \cdot e_{charge} \qquad m = \{AGV\},\ \forall t \in T,\ \forall w \in S \tag{3.18}$$

$$b^{min} \leq B_{t,w} \leq b^{max} \qquad \forall t \in T,\ \forall w \in S \tag{3.19}$$

$$\begin{aligned} &B_{t,w} = B_{t-1,w} + \eta_{charge} \cdot E_{t,w}^{charge} - \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m,w} \cdot H_{i,p,t,w} \\ &m = \{AGV\},\ \forall t \in T,\ \forall w \in S \end{aligned} \tag{3.20}$$

$$c \qquad \begin{aligned} &B_{t,w} = b_{min} + \eta_{charge} \cdot E^{charge}_{t,w} - \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m,t} \cdot H_{i,p,t,w} \\ &m = \{AGV\},\ t = \{0\},\ \forall w \in S \end{aligned} \tag{3.21}$$

$$\sum_{t \in T} \eta^{charge} \cdot E^{charge}_{t,w} = \sum_{t \in T} \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m} \cdot H_{i,p,t,w} \qquad m = \{AGV\},\ \forall w \in S \tag{3.22}$$

The following five constraints ensure the proper operation of the reefers. The temperature of the reefers, represented by TC_t, should always be within the minimum and maximum temperature levels to ensure the quality of the stored goods, as indicated by Constraint 3.23. The energy consumed by the reefers at any time should not exceed the rated power of all the reefer connections, as dictated by Constraint 3.24. The reefers lose heat to the environment through convection. This heat loss depends on the temperature difference between the container and the environment, both of which are assumed to be constant for every hour. Constraint 3.25 is the cooling balance constraint, which stipulates that the temperature change of the reefer container depends on the heat loss and the cooling energy supplied. Constraint 3.27 is the reefer energy constraint, which ensures that the total energy lost through heat transfer equals the total energy consumed by cooling.

$$tc^{min} \le TC_{t,w} \le tc^{max} \qquad \forall t \in T, \forall w \in S \tag{3.23}$$

$$E^{reefer}_{t,w} \le e^{reefer,max} \qquad \forall t \in T, \forall w \in S \tag{3.24}$$

$$mc_p \cdot (TC_{t,w} - TC_{t-1,w}) = ua \cdot (ta - (tc^{min} + tc^{max})/2) - \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad \forall t \in T, \forall w \in S \tag{3.25}$$

$$mc_p \cdot (TC_{t,w} - tc_{max}) = ua \cdot (ta - (tc^{min} + tc^{max})/2) - \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad t = \{0\}, \forall w \in S \tag{3.26}$$

$$\sum_{t \in T} ua \cdot (ta - (tc^{min} + tc^{max})/2) = \sum_{t \in T} \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad \forall w \in S \tag{3.27}$$

These constraints together manage the energy consumption of ships, quay cranes, yard cranes, automated guided vehicles, and reefer containers, while adhering to the constraints based on the operational planning.

4

Solution approach

The problem described in section 3 is difficult to solve due to the considered uncertainty. In this chapter it will be explained how to problem presented can be solved, given this uncertainty.

In section 4.1 different methods of dealing with uncertainty are discussed, and it is argued why stochastic programming is the most suited. Afterwards techniques to improve the solving speed of the stochastic model are discussed in section 4.2. Finally it is explained how scenarios for the optimization model can be generated based on historical data and how the amount of scenarios can be reduced in section 4.3.

4.1. Uncertainty modeling

The problem described in Chapter 3 is difficult to solve due to the considered uncertainty. The addition of several scenarios to the problem significantly increases the computational load, making it impractical to solve the extensive form of the problem. Various modeling approaches exist to deal with this, which will be discussed below.

Rodrigues and Agra presented three general approaches to dealing with uncertainty [57]. These approaches differ in terms of when decisions are made and when the operational planning is executed. Firstly, in a proactive approach, all decisions are made at the beginning of the time horizon when the uncertainty is still present. Secondly, a reactive approach involves making decisions after some uncertain parameters become known. Finally, a combination of the two can be employed, where an initial planning is made considering the uncertainty, and recourse actions are taken once the uncertainty is resolved.

The sequential nature of electricity markets and container terminal planning makes the proactive/reactive approach the preferred choice. The container terminal needs to purchase electricity when the exact amount required is uncertain. Bids on the day-ahead market must be made without perfect information on electricity prices, power demand, and available flexibility [66]. These bids can later be adjusted by buying or selling electricity on the intraday market. Decisions on one market will influence decisions on subsequent markets and must be taken into account [66]. In a survey by Bierwirth and Meisel, different planning problems for seaside operations are considered. They suggest that Berth Assignment Problems (BAP), Quay Crane Assignment Problems (QCAP), and Quay Crane Scheduling Problems (QCSP) can be integrated by considering them sequentially [3]. The initial berthing plan from the BAP can be used to assign quay cranes, and then the QC assignment can be used for the scheduling of the cranes. An overview of the sequential planning of seaside operations is shown in Figure 4.1. Having an optimization method that allows for proactive bids on the day-ahead market and reactive bids on the intraday market is best suited for this problem.

For the proactive/reactive approach, a two (or more) stage optimization problem can be formulated. The first stage represents the proactive decision, known as the ”here-and-now” decision, where deci-

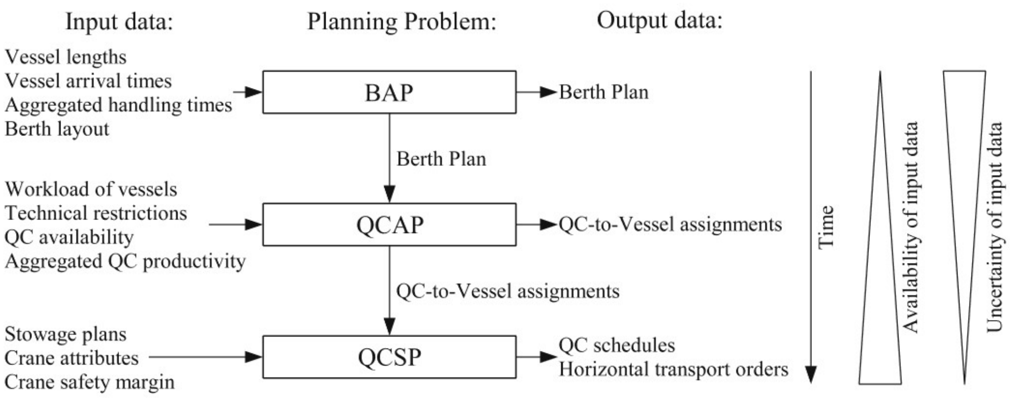


Figure 4.1: Sequential planning of seaside operations [3]

sions are made before the values of uncertain parameters are known. The second stage represents the reactive decision, also known as the "wait-and-see" decision, where decisions are made in response to the realization of the uncertain parameters. A generalized two-stage optimization problem is shown in Equation 4.1. Here, x represents the first stage decision variables, y_ξ represents the second stage decision variables, and ξ represents the uncertain parameters. The objective consists of a first stage cost and a second stage cost, where $\mathbb{R}_{cost}$ is an operator quantifying the risk of excessive costs. Similarly, for the constraints, first stage equality and inequality constraints (h^F and g^F) and a second stage (h^S and g^S) exist.

$$
\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{y}_{\boldsymbol{\xi}}} \quad & f^F(\boldsymbol{x}) + \mathbb{R}_{cost}[f^S(\boldsymbol{x},\boldsymbol{y}_{\boldsymbol{\xi}},\boldsymbol{\xi})] && \text{(4.1a)}\\
\text{s.t.} \quad & \boldsymbol{h}^F(\boldsymbol{x}) = 0, && \text{(4.1b)}\\
& \boldsymbol{g}^F(\boldsymbol{x}) \geq 0, && \text{(4.1c)}\\
& \boldsymbol{h}^S(\boldsymbol{x},\boldsymbol{y}_{\boldsymbol{\xi}},\boldsymbol{\xi}) = 0, && \text{(4.1d)}\\
& \boldsymbol{g}^S(\boldsymbol{x},\boldsymbol{y}_{\boldsymbol{\xi}},\boldsymbol{\xi}) \geq 0 && \text{(4.1e)}
\end{aligned}
$$

There are four commonly used formulations that explicitly consider the impact of uncertainty in the objective [56]. Stochastic optimization considers the expected cost and tries to minimize that cost across all realizations of the uncertain parameters. Similarly, a risk-averse version of stochastic optimization can be formulated by considering the variance, value at risk, or conditional value at risk. For the value at risk, it bounds the largest cost that will occur with a probability higher than a preset level. Similarly, the conditional value minimizes the expected value of a portion of the worst realizations. Robust optimization considers the worst-case cost and tries to minimize that. Robust optimization can be used in case only the bounds of the uncertain parameter are known but not the distribution. Finally, distributionally robust optimization considers the worst-case expected cost of different potential uncertainty distributions. An overview of the four methods is shown in Figure **??**. Additional information on how these methods work can be found in [56].

For this thesis, it has been decided to use the expected cost as a second-stage objective. The most common approach used in the literature on BAP is a stochastic optimization approach where the expected cost is optimized [57]. For both of the uncertain parameters considered in this thesis, ship arrival times and electricity prices, sufficient historical data is available. With this data, a probability density function can be created. Only considering the bounds of the uncertain parameters, as done in (distributionally) robust optimization, would therefore discard valuable information that is known. Using risk-averse optimization is predominantly interesting when best-case and worst-case realizations are not considered to have the same weight. In this thesis, all the different objectives present can be calcu-

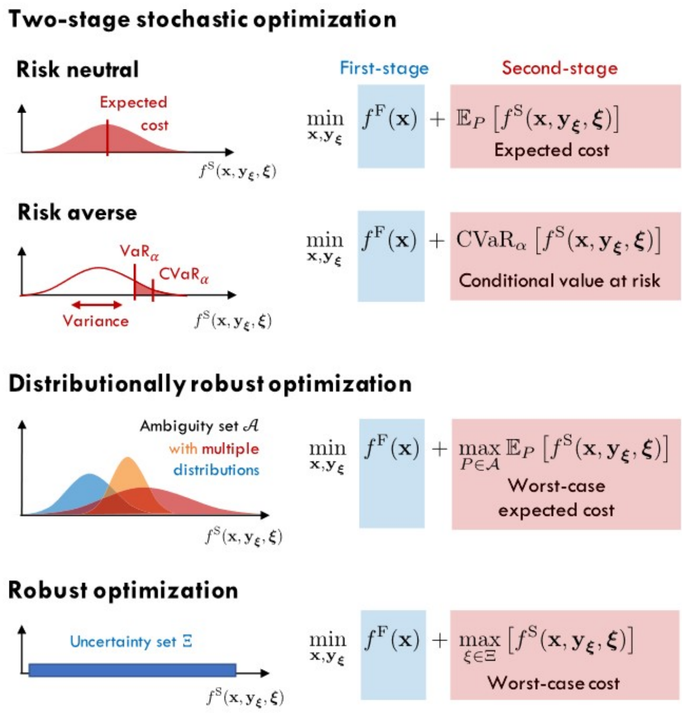


Figure 4.2: An overview of optimization methods under uncertainty [56]

lated back to costs for the terminal operator, which in the end should be minimized. Bad results of one day can easily be compensated with days with good results. If every day is considered independent from the other, the total cost over the year depends on the expected cost of all the days.

No BAP or QCAP papers using the (conditional) value at risk were found, and it is unclear why this has not been considered. Rodrigues and Agra reviewed 62 papers about BAP and QCAP and found stochastic programming and robust optimization to be the most commonly used approaches [57]. Rodrigues and Agra state that the choice between robust and classical stochastic optimization depends on the risk the decision-maker is willing to take, with robust being strongly risk-averse and stochastic programming being risk-tolerant [57]. Rodrigues only mentioned two papers considering risk in the optimization, namely Golias [13] and Karafa et al. [39]. However, both papers didn't use value at risk but instead used a bi-objective model. Having a method like the conditional value at risk could be a good middle ground between expected value stochastic optimization and robust optimization, where you can quantify the level of risk. It could be interesting to research.

To conclude, the best approach for a model optimizing the operational planning while considering energy consumption is found to be a two-stage stochastic optimization model. This model first makes an initial here-and-now decision considering the uncertainty of electricity prices and the arrival times of ships. Afterwards, this decision can be changed based on the realization of the uncertain parameters. The stochastic optimization model should optimize based on the expected cost across all realizations of the uncertain parameters.

4.2. Stochastic decomposition

Optimization problems that involve uncertainty can be complex and challenging to solve, both theoretically and numerically. One strategy for solving such problems is to use decomposition strategies for stochastic programming models. This involves breaking down the problem into smaller subproblems that are easier to solve individually, leading to a simpler overall optimization process and reduced computational complexity. By using decomposition strategies, we can solve optimization problems under uncertainty more efficiently and effectively, taking into account the range of possible outcomes and generating feasible solutions. This approach addresses uncertainty directly and can help us reduce complexity while producing accurate results.

Several decomposition algorithms exist to solve two-stage stochastic MIP problems faster. The most commonly used approaches are Benders decomposition, dual decomposition, and progressive hedging [56]. Each of these algorithms divides the original problem into subproblems, with each scenario representing a different problem. Benders decomposition divides the problem into a first-stage problem and a second-stage problem, where the second-stage problem becomes scenario-independent and can be solved separately. Dual decomposition splits up the problem by creating scenario-dependent first-stage decision variables and adds a constraint to prevent differences between the first-stage variables. With dual decomposition, the problem is split up into scenario-dependent subproblems, each with a first and second stage. Similarly, progressive hedging also introduces scenario-dependent first-stage variables, allowing the problem to be decomposed into smaller problems for each scenario. In progressive hedging, differences between first-stage decision variables are penalized in the objective function. More information on how these three methods work can be found in the paper by Roald et al. [56].

For this thesis, a progressive hedging approach is used to decompose the problem. In Equation 4.2 and Figure 1, the general mathematical description and a brief description of the algorithm are given. Here, all the functions and decision variables are the same as in equation 4.1, and s is realisation of all the decision variables for one specific scenario. The last two terms of the objective represent the penalty introduced due to deviations of the first-stage decision variables from the average value, $\bar{x}$, among all scenarios.

$$\min_{\boldsymbol{x}_s, \boldsymbol{y}_s} \quad \pi_s f^F(\boldsymbol{x}_s) + \pi_s f^S(\boldsymbol{x}_s, \boldsymbol{y}_s, \boldsymbol{\xi}_s) + \lambda_s^T(\boldsymbol{x}_s - \bar{\boldsymbol{x}}) + \frac{\rho}{2}||\boldsymbol{x}_s - \bar{\boldsymbol{x}}||^2 \tag{4.2a}$$

$$\text{s.t.} \quad \boldsymbol{h}^F(\boldsymbol{x}_s) = 0, \tag{4.2b}$$

$$\boldsymbol{g}^F(\boldsymbol{x}_s) \geq 0, \tag{4.2c}$$

$$\boldsymbol{h}^S(\boldsymbol{x}_s, \boldsymbol{y}_s, \boldsymbol{\xi}_s) = 0, \tag{4.2d}$$

$$\boldsymbol{g}^S(\boldsymbol{x}_s, \boldsymbol{y}_s, \boldsymbol{\xi}_s) \geq 0 \tag{4.2e}$$

Algorithm 1 Progressive Hedging

1: **Initialization**: Let $\nu \leftarrow 0$ and $w^{(t,\nu)}(\xi) \leftarrow 0, \forall \xi \in \Xi, t = 1, \ldots, T$. Compute for each $\xi \in \Xi$:

$$x^{(\nu+1)}(\xi) \in \text{arg}\min_x f_1(x_1) + \sum_{t=2}^{T} f_t\left(x^t; \overrightarrow{x}^{t-1}(\xi), \overrightarrow{\xi}^t\right)$$

2: **Iteration Update**: $\nu \leftarrow \nu + 1$

3: **Aggregation**: Compute for each $t = 1, \ldots, T-1$ and each $\mathcal{D} \in \mathcal{G}_t$:

$$\bar{x}^{(\nu)}(\mathcal{D}) \leftarrow \sum_{\xi \in \mathcal{D}^{-1}} \pi_\xi x^{(t,\nu)}(\xi) \; / \sum_{\xi \in \mathcal{D}^{-1}} \pi_\xi$$

4: **Price Update**: Compute for each $t = 1, \ldots, T-1$ and each $\xi \in \Xi$:

$$w^{(t,\nu)}(\xi) \leftarrow w^{(t,\nu-1)}(\xi) + \rho\left[x^{(t,\nu)}(\xi)) - \bar{x}^{(\nu)}(\mathcal{G}_t(\xi))\right]$$

5: **Decomposition**: Compute for each $\xi \in \Xi$:

$$x^{(\nu+1)}(\xi) \in \text{arg}\min_x f_1(x^1) + \sum_{t=2}^{T} f_t\left(x^t; \overrightarrow{x}^{t-1}(\xi), \overrightarrow{\xi}^t\right)$$
$$+ \sum_{t=1}^{T-1}\left[w^{(t,\nu)}(\xi)^T \cdot x^t + \rho \cdot \frac{1}{2}\|x^t - \bar{x}^{(\nu)}(\mathcal{G}_t(\xi))\|^2\right]$$

6: **Termination**: If a criterion is met, Stop. Otherwise, go to step 2.

4.3. Scenario generation and reduction

For stochastic programming, scenarios need to be created for the electricity prices and ship arrival times. As there are infinite combinations possible for both of these random variables, one of the most common ways to represent them is by taking a finite set of samples [56]. While a larger number of samples may provide more accurate identification of the problem, it also increases the problem's complexity. Therefore, an attempt should be made to represent uncertainty with the fewest amount of samples.

To create scenarios for the arrival times of ships, a quasi random sampling approach was taken. In a paper by Kolley et al. [46], different methods were used to find the normal distribution of the arrival times of ships up to 24 hours before arrival. Kolley found a standard deviation of the arrival times compared to the estimated arrival times of 3 hours. It was also assumed that the average of the arrival times is the same as the estimated arrival time. Instead of randomly taking samples from the distribution, the samples were drawn quasi-randomly using the Halton sampling technique. Halton sampling results in more uniformly distributed samples through the search space compared to random sampling. This ensures that the created scenarios are more distinct, resulting in more accurate results for stochastic optimization. All arrival time samples are rounded to the nearest hour, and a probability can be calculated for each hour, resulting in a probability of every ship.

In a paper by Crespo-Vazquez [6], different approaches to generate scenarios for electricity prices were explained. First, historical data is obtained and split up by day. Scenarios can be obtained by taking random samples or by clustering the electricity prices by day and taking the centroid of each cluster. Additionally, weight for each scenario can be assigned, equiprobabilistic, by using a frequentist approach or with Bayesian reasoning. Figure 4.3 shows the approaches.

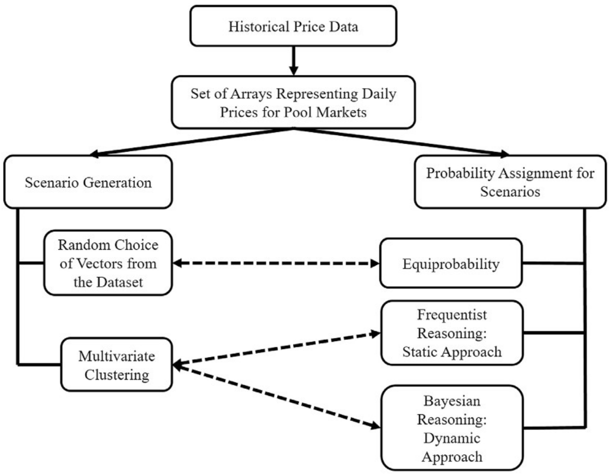


Figure 4.3: Scenario generation approaches for energy price

For this thesis, an approach similar to the clustering - frequentist approach proposed by Crespo-Vazquez in [6] and the approach in [65] is used. Crespo-Vazquez found that the dynamic approach gave the best results [6]. However, this approach was found to be too complex for this thesis. Therefore, a static approach was selected since it also significantly outperforms the approach where random samples are taken [6]. Historical electricity prices for the German day-ahead market were obtained from ENTSEO [8]. A k-means clustering algorithm was used to create clusters of days with similar electricity prices. From every cluster, the median day was taken to represent the entire cluster. The amount of clusters was selected based on the elbow method. Additionally, a weight of the cluster was obtained by normalizing the amount of days within the cluster. Figure 4.4 shows 3 clusters of electricity prices alongside the mean and standard deviation of the prices throughout a day.

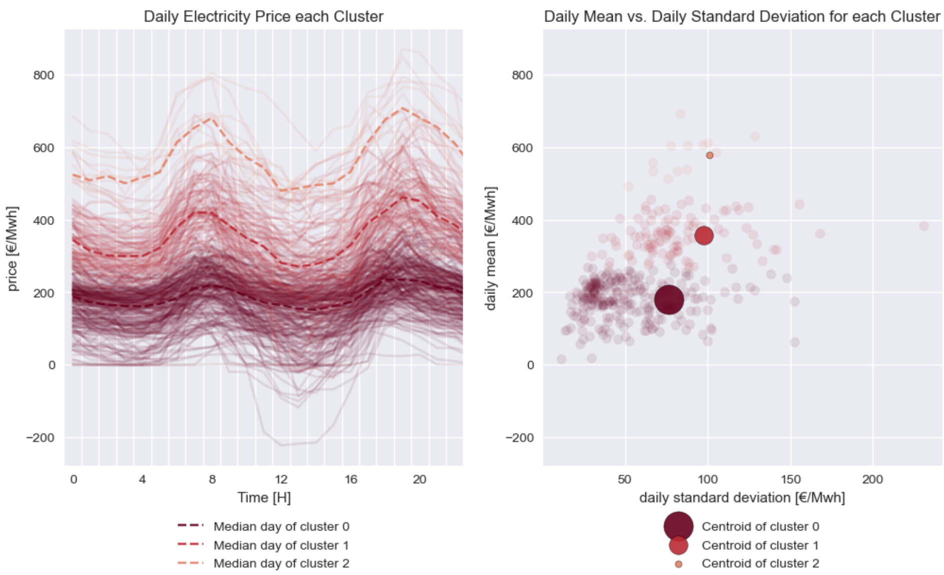


Figure 4.4: Clusters of daily electricity prices in 2022

After obtaining scenarios for the arrival times and electricity prices, a total set of scenarios can be created by taking the Cartesian product of the two sets. The probability of each scenario is obtained by multiplying the probability of the arrival time with the electricity prices. With the method described above, uncertainty can be accurately represented with fewer scenarios resulting in lower computation times for the optimization model.

5
Experiments & Results

In this chapter the results obtained from the optimization model discussed in 3 are presented. The computations were all conducted using the commercially available solver Gurobi v10.0.1, in combination with the Pyomo modeling language. For the stochastic decomposition, the mpi-sppy package was utilized [44]. The optimization model was run on an Intel i7-7700HQ processor with a 2.80 GHz clock speed and 8.00 GB of RAM.

All optimizations were solved using the progressive hedging algorithm, as described in section 4.2. Ten iterations and a penalty parameter of 8000 were employed for each scenario's solution to converge. A convergence threshold of 0.01 was set. For most of the experiments the convergence was lower 0.01, however not in every experiment the threshold was reached within 10 iterations. In all case the convergence metric was lower then 0.05. For all models, a mixed-integer programming optimality gap of 5 percent was used. The solve time for each individual scenario was limited to 300 seconds. Unless stated otherwise, each experiment was repeated ten times with different randomly generated parameters.

The chapter begins with explaining the setup of all the experiments conducted in section 5.1. This is followed by presenting the results of the experiemtns in section 5.2. Based on the experiments conducted the fourth and fifth research question outlined in 1.3 can be answered.

5.1. Experimental setup

In this section the validation and verification of the model to ensure its accuracy and relevance, as presented in section 5.1.1 and 5.1.2. The practicality of the model is evaluated by applying it to a real-world case study: the Altenwerder container terminal in Hamburg, as outlined in Section 5.1.3. This provides deeper insights into the model's actual application and performance in a realistic scenario. The evaluation of the impact of stochastic modeling is explained in Section 5.1.4. Subsequently, the evaluation of the impact of demand response is explained in Section 5.1.5.

5.1.1. Verification

To ensure that the model is functioning as intended, verification was conducted. The model has been built modularly, starting with a minimal viable problem formulated to determine a berth assignment schedule considering energy consumption. Additional modules were then added to increase complexity. The minimal viable problem consisted of a deterministic berth assignment problem. Subsequently, the energy consumption of quay cranes, yard cranes, AGVs, and reefers was sequentially incorporated into the model. Stochasticity was introduced by considering ship arrival times and electricity prices. Verification experiments were conducted after each additional module was implemented.

Verification involved conducting constraint verification and checking the model's behavior under different scenarios and conditions. For constraint verification, the right-hand side and left-hand side of each constraint were calculated and compared. The model's behavior was checked by changing a single parameter and observing if the results changed as expected. Special attention was given to checking edge cases.

5.1.2. Validation

To validate the model's results, a comparison is made with the model presented by Iris and Lam [33]. As explained in Section **??**, Iris and Lam's model accounts for energy consumption through On-shore Power Supply, Quay Cranes, Yard Cranes, and Reefers. It also considers the energy supply from the grid, solar panels, and a battery storage system. Different scenarios with varying solar production are considered in their model. Iris and Lam conducted an experiment to determine sensitivity to solar production, including a scenario without PV production. The results from this experiment are compared with those obtained from the model presented in this thesis.

Both Iris and Lam's model and the model presented in this thesis share similar implementations and should, therefore, yield comparable results. However, certain differences exist. The key disparities between Iris and Lam's model and this thesis are outlined below:

- Iris and Lam consider multiple scenarios of solar production. However, in the zero PV production experiment they conducted, the solar energy generated is zero in every scenario, resulting in the same results for every scenario.
- In the model presented in this thesis, uncertainty in ship arrival times and electricity prices is considered. Since Iris and Lam do not account for these uncertainties, the expected values of both parameters were used in the comparison.
- Iris and Lam's model includes a battery. However, if the solar panels do not produce power, the battery cannot deliver power to the terminal or the grid.
- Iris and Lam considered the potential for PV panels to return power to the grid. Since the PV production is zero, no power is returned in this case.
- Electricity consumption due to the setup of quay cranes was considered in Iris and Lam's model. However, as this constituted only 0.02 percent of the total energy consumption, it was not included in the thesis model.
- Iris and Lam modeled the electricity consumption of reefers based on the berthing of ships. They assumed a constant energy consumption for the reefers for every hour a ship was berthed. In this thesis, the energy demand of reefers depends on the heat transfer with the environment. For the validation, the heat transfer with the environment was set to zero, and instead, a constant heat transfer based on the berthing time of ships was considered.
- Since Iris and Lam did not account for energy consumption from AGV charging, it was also not consider in the thesis model for this comparison.
- Iris and Lam modeled the constraint related to the occupancy of the quay differently. They created an initial berthing schedule where ships were already assigned to one of several discrete berths. In this thesis, the quay occupancy was accounted for by assigning a length to every ship and the quay.

To compare the results of Iris and Lam with the model presented in this thesis, the same parameters were used wherever possible. However, due to minor differences in how ships are assigned a berth, some additional parameters related to ship and quay length had to be estimated. For the ships, it was assumed that the length for Feeder, Medium, and Jumbo ships is uniformly distributed. Similar to another paper by Iris and Lam [34], lengths of U(70,200), U(210,300), and U(300,400) were used for Feeder, Medium, and Jumbo ships, respectively. The quay length was estimated using the quay occupancy with a simple calculation, as shown in Equation 5.1. Literature suggests that the average quay utilization was 64 percent under normal workload conditions [19]. For this comparison, a quay utilization of 0.6 was used.

$$\sum_{i \in \mathbf{V}} l_i^{\text{ship}} \cdot eht_i = \eta^{\text{quay}} \cdot l^{\text{quay}} \cdot t^{\text{horizon}} \tag{5.1}$$

5.1.3. CTA Case study

To explore the potential for demand response, a case study was conducted on the HHLA Container Terminal Altenwerder (CTA) in Hamburg. Altenwerder is a state-of-the-art container terminal with a high degree of automation and operates in a climate-neutral manner. Due to these reasons, this terminal was selected for the case study. In this section, an overview is of the Container Terminal Altenwerder (CTA) and its operational characteristics.

The CTA is a large container terminal that, along with two other HHLA-owned container terminals in Hamburg, handled a combined throughput of 6.1 million TEU in 2022 [25]. A sail list from the CTA revealed that between April 10, 2023, and May 7, 2023, a total of 190 ships arrived at the CTA terminal, averaging 7 per day [26]. Containers can access the terminal via ships, trucks, or trains. The terminal employs a fleet of battery electric Automated Guided Vehicles (AGVs) to transport containers from the seaside to the yard, where Automated Stacking Cranes (ASCs) store them. Containers destined for the landside are picked up from the yard by trucks or terminal trucks, which move the containers to the rail terminal. Rail-mounted gantry cranes then pick up the containers and load them onto trains. An overview of the CTA terminal layout is presented in Figure 5.1. The travel distance of AGVs is estimated based on the terminal layout described by Zhang et al. [78]. According to the layout of the CTA, the average travel distance and time for AGVs are estimated to be 947 meters and 237 seconds, respectively. The CTA is currently expanding its fleet of Battery Electric AGVs and has installed 18 charging stations with a total capacity of 4 MW [27]. While HHLA is working on establishing On Shore Power (OPS) stations for container ships to recharge, such facilities are not yet available at the CTA terminal [9]. Further technical details of the terminal can be found on the HHLA website [24]. Table **??** provides a summary of all the technical data related to the CTA.

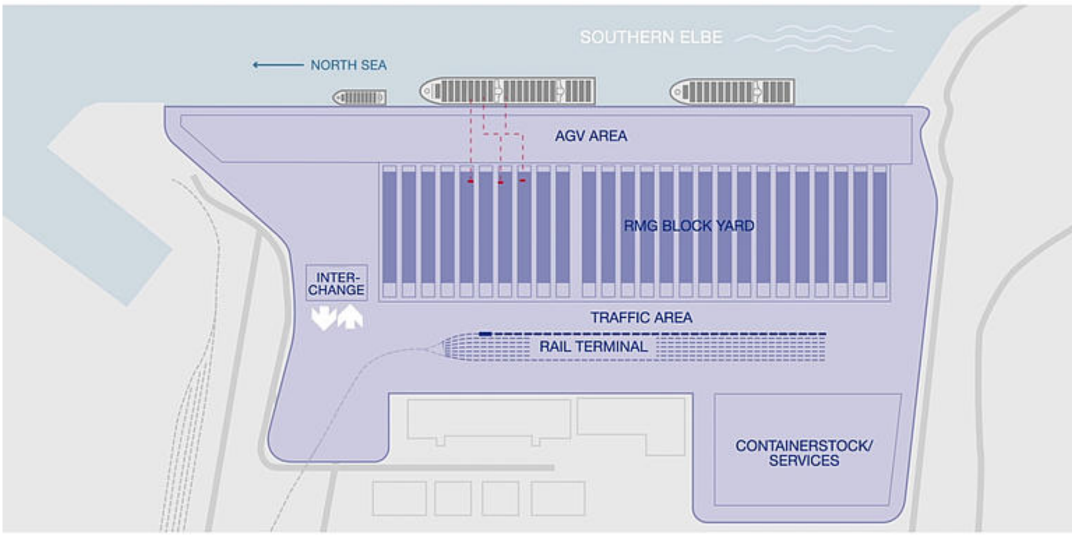


Figure 5.1: Layout of container terminal altenwerder in Hamburg [24]

Parameter	Value
Ships arriving daily	7
Length of quay wall	1400m
AGV travel distance	947m
AGV travel time	237s
Quay cranes	14
Battery electric AGVs	74
Automated yard blocks	26
Reefer connections	2200
Charging points	18
Charging capacity	4 MW
On Shore Power capacity	0 MW

Table 5.1: Technical data of Container Terminal Altenwerder [24]

The parameters for the three types of machinery considered in the model were determined based on the terminal data. He et al. conducted a study on the tradeoff between energy saving and time saving, and their research provides estimates for the energy consumption of a Quay Crane (QC) and Yard Crane (YC) as 8 kW and 2 kW per container move, respectively [20][21]. They also assumed that both the QC and YCs have a handling speed of 30 containers per hour. Furthermore, in another paper by He, the energy consumption of Automated Guided Vehicles (AGVs) was estimated per meter [22]. The average energy consumption for AGVs was found to be 0.00935 kW/m. Additionally, based on the AGV travel distance at the CTA, the handling rate is calculated to be 15 containers per hour.

Machinery type	k_m	h_m	$e_m^{machinery}$
Quay Crane	14	30	8 kW
Yard Crane	52	30	2 kW
AGV	74	15	9 kW

Table 5.2: Parameters of terminal machinery

Three types of ships were considered to arrive at the container terminal: Feeder, Medium, and Jumbo ships. Similar to Iris and Lam's study [33], it was assumed that 40 percent of the ships are feeders, 40 percent are Medium, and 20 percent are Jumbo ships. The length of the ships is distributed uniformly between 70 and 200 for Feeders, 210 and 300 for Medium ships, and 300 and 400 for Jumbo ships [34]. The container demand was also assumed to be distributed uniformly between 200 and 600 for Feeders, 600 and 1600 for Medium ships, and 1600 and 4500 for Jumbo ships [33]. The minimum and maximum handling rates considered in each of the patterns are calculated based on the minimum and maximum number of QC cranes that can be assigned to a ship class, as suggested by Iris and Lam. The estimated time of arrival of the ships is randomly generated between 0 and 24. According to Kolley et al. [46], the standard deviation of the estimated time of arrival is 3 hours, 24 hours prior to arrival. The estimated time of finishing is calculated by dividing the container demand by the minimum handling rate and adding the estimated time of arrival. If a ship is departing later than the estimated finishing time, a penalty is applied. This penalty is obtained by converting the penalty stated by Iris and Lam to euros, assuming an exchange rate of 0.63 euro/SDG [33]. Finally, a penalty of 20 percent of the late penalty is assumed with regards to changing the berthing schedule created on the previous day, similar to the approach used by Liu et al. [49]. An overview of all the ship parameters is provided in Table **??**.

Ship Class	Share	l_i	d_i	p_i^{min}, p_i^{max}	eat_i	eft_i	c_i^{late}
Feeder	0.4	U(70,200)	U(200,600)	[50,100]	U(0,24)	$\frac{d_i}{p_i^{min}} + eat_i$	630
Medium	0.4	U(210,300)	U(600,1600)	[100,200]	U(0,24)	$\frac{d_i}{p_i^{min}} + eat_i$	1260
Jumbo	0.2	U(300, 400)	U(1600,4500)	[200,300]	U(0,24)	$\frac{d_i}{p_i^{min}} + eat_i$	1890

Table 5.3: Ship parameters

For the energy consumption of reefer containers, it was assumed that all reefers are of the same type. According to a breakdown by van Duin et al. [7], frozen reefer containers are the most common type. The temperature range allowed for frozen products, such as meat and fish, is between -20 and -16 degrees Celsius [7]. The mass, specific heat, heat transfer coefficient, and area of a reefer container are based on the average values for a 40ft container as reported by Kanellos [37]. The cooling efficiency was estimated based on the ratio between cooling power and electrical power for a container with a temperature of -18 degrees Celsius [37]. Additionally, the maximum cooling power was also obtained from Kanellos's study. It was assumed that out of the 2200 available reefer connections, on average 1500 connections are used at the same time. An overview of all reefer parameters can be found in Table 5.4.

Parameter	Value
Reefer connections used	1500
Maximum cooling power	6.0 kWh/h
Allowed temperature range	[-20,-16] °C
Mass	24500 kg
Specific heat	2.76 Kj/ kg K
Heat transfer coefficient	0.4 W/m^2K
Area	135.26 m^2
Ambient temperature	11.6 °C
Cooling efficiency	0.95

Table 5.4: Reefer container parameters

In the CTA container terminal, there are 18 charging points available with a combined capacity of 4 MW. Information obtained from the HHLA website indicates that it takes approximately 1.5 hours to fully charge one AGV [28]. Consequently, the total charging time for the entire AGV fleet is calculated to be 6.2 hours. Assuming a charging speed of 4 MW over this duration, the total battery capacity required for all AGVs amounts to 24.7 MWh. Similar to Kanellos [37], a charging efficiency of 90 percent is employed. An overview of all AGV charging parameters can be found in Table 5.5.

Parameter	Value
Charging points	18
Charging capacity	4 MW
Fleet charging time	6.2 h
Battery capacity	24.7 MWh
Charging efficiency	0.95

Table 5.5: AGV charging parameters

Historical prices from the day-ahead market in Germany were obtained from the ENTSEO website [8] to determine the electricity prices. To account for energy surplus or shortage, a penalty equivalent to 20 percent of the day-ahead price was assumed, following the approach by Crespo-Vazquez et al. [6]. The maximum allowed imbalance was set to 10 MW.

5.1.4. Evaluation of stochastic modeling

To evaluate the impact that stochastic modeling has on the solution, the results should be compared with a deterministic solution. This allows for a trade-off between the added complexity and accuracy that a stochastic model brings. In Section 4.1, the mathematical formulation of a two-stage stochastic model with recourse was presented, as shown in Equation 5.2. In the formulation, x represents the first-stage decision variables, y_ξ represents the second-stage decision variables, and ξ represents the uncertain parameters.

$$
\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{y_\xi}} \quad & f^F(\boldsymbol{x}) + \mathbb{E}_P[f^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi})] && (5.2a)\\
\text{s.t.} \quad & \boldsymbol{h}^F(\boldsymbol{x}) = 0, && (5.2b)\\
& \boldsymbol{g}^F(\boldsymbol{x}) \geq 0, && (5.2c)\\
& \boldsymbol{h}^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi}) = 0, && (5.2d)\\
& \boldsymbol{g}^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi}) \geq 0 && (5.2e)
\end{aligned}
$$

The stochastic model can be simplified to what is known as the Expected Value (EV) problem. This problem transforms the original stochastic formulation into a deterministic one by replacing all uncertain parameters $\boldsymbol{\xi}$ with their corresponding expected value $\mathbb{E}_P[\boldsymbol{\xi}]$. In Chapter 2, it was explained that literature on demand response in container terminals often adopts a deterministic approach and solves the EV problem. The formulation of the EV problem is presented in Equation 5.3. The use of the EV solution can lead to a significant underestimation of costs since it does not account for stochasticity in the model. For the problem discussed in this thesis, the EV solution does not consider the costs associated with rescheduling and imbalance.

$$
\begin{aligned}
\min_{\mathbf{x},\boldsymbol{y}_{\bar{\xi}}} \quad & f(\boldsymbol{x},\boldsymbol{y}_{\bar{\xi}},\bar{\xi}) && (5.3a)\\
\text{where} \quad & \bar{\xi} = \mathbb{E}_P[\boldsymbol{\xi}] && (5.3b)
\end{aligned}
$$

To address this limitation and incorporate the rescheduling and imbalance costs, a reactive approach (RE) can be employed. In a reactive problem, the first-stage decision variables are fixed, and for each scenario, an optimization is conducted to minimize the second-stage costs. The mathematical formulation of the RE problem is provided in Equation 5.4.

$$
\begin{aligned}
\min_{\boldsymbol{x_0},\boldsymbol{y_\xi}} \quad & f^F(\boldsymbol{x_0}) + \mathbb{E}_P[f^S(\boldsymbol{x_0},\boldsymbol{y_\xi},\boldsymbol{\xi})] && (5.4a)\\
\text{where} \quad & \boldsymbol{x_0} : \text{fixed} && (5.4b)
\end{aligned}
$$

A special version of the RE problem is known as the Expected Expectation Value (EEV) problem. In the EEV problem, the first-stage decision variables are fixed based on the optimal solution obtained from the EV problem. The mathematical formulation of the EEV problem is presented in Equation 5.5. To quantify the impact of stochastic modeling, the Value of Stochastic Solution (VSS) can be calculated. The VSS is defined as the difference between the expected cost of the EEV problem and the expected cost of the Stochastic Problem (SP). This relation is expressed by Equation 5.13.

$$
\begin{aligned}
\min_{\bar{\boldsymbol{x}},\boldsymbol{y_\xi}} \quad & f^F(\bar{\boldsymbol{x}}) + \mathbb{E}_P[f^S(\bar{\boldsymbol{x}},\boldsymbol{y_\xi},\boldsymbol{\xi})] && (5.5a)\\
\text{where} \quad & \bar{\boldsymbol{x}} : \text{optimal } \boldsymbol{x} \text{ in EV} && (5.5b)
\end{aligned}
$$

$$
VSS = EEV - SP \tag{5.6}
$$

Similar to the VSS, the Expected Value of Perfect Information (EVPI) can be utilized to evaluate the impact of stochastic modeling. The EVPI can be calculated by taking the difference between the expected cost of the Stochastic Problem (SP) and the cost of the Wait and See solution (WS), as presented in Equation 5.14. The WS solution represents an ideal scenario where perfect information is available for decision-making. In the WS solution, each individual scenario is treated separately, allowing for different first-stage decisions for each scenario. However, it is important to note that the WS solution is unattainable in practice since perfect information does not exist. The objective of the WS solution is given by Equation 5.7.

$$\min_{\boldsymbol{x},\boldsymbol{y_\xi}} \quad \mathbb{E}_P[f(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi})] \tag{5.7}$$

$$EVPI = RP - WS \tag{5.8}$$

In summary, metrics like VSS and EVPI offer valuable insights into the benefits of stochastic modeling in decision-making. The WS and EEV solutions provide upper and lower bounds for evaluating the stochastic solution. To further explore stochastic modeling and its evaluation, the book by Birge and Louveaux, "Introduction to Stochastic Programming," serves as a comprehensive resource [5].

5.1.5. Evaluation of Demand Response

To assess the impact of demand response on the solution, different electricity pricing schemes are considered: No Price (NP), Constant Price (CP), and Real-Time Price (RTP) cases.

In the NP case, all energy-related costs in the objective function are disregarded. The objective function is simplified by removing the energy cost terms, resulting in equation 5.9.

$$\min_{\mathbf{V},\mathbf{T}} \sum_{w\in\mathbf{S}} \pi_w \bigg(\sum_{i\in\mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i\in\mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) \bigg) \tag{5.9}$$

In the CP case, the electricity price $c^d a_{t,w}$ in the objective function is replaced with a constant price $\bar{c}^d a_w$ for each hour. The objective function is modified accordingly, resulting in equation 5.10.

$$\begin{aligned} \min_{\mathbf{V},\mathbf{T}} \sum_{w\in\mathbf{S}} \pi_w \bigg(& \sum_{i\in\mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i\in\mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) + \\ & \sum_{t\in\mathbf{T}} \bar{c}_w^{\text{da}} P_t^{\text{da}} + \sum_{t\in\mathbf{T}} \bar{c}_w^{\text{da}} (c^{\text{shor}} P_{t,w}^{\text{shor}} - c^{\text{sur}} P_{t,w}^{\text{sur}}) \bigg) \end{aligned} \tag{5.10}$$

The mathematical formulation presented in Section 3.2 remains the same for the RTP case. However, for the CP and NP cases, minor adjustments need to be made. Specifically, Constraint 3.22 and Constraint 3.24 are replaced with Constraint 5.11 and Constraint 5.12, respectively. These changes ensure that the energy consumed by operations, such as charging and cooling, matches the energy demand for each time period without considering different prices. Constraints 5.11 and 5.12 prevent unnecessary rescheduling of charging and cooling times that would occur under the assumption of a constant or no price.

$$\eta^{charge} \cdot E^{charge} t, w = \sum i \in V \sum_{p\in P_i} e_m \cdot u_{i,p,m} \cdot H_{i,p,t,w} \qquad m = AGV,\ \forall t \in T,\ \forall w \in S \tag{5.11}$$

$$ua \cdot (ta - (tc^{min} + tc^{max})/2) = \eta_{reefer} \cdot E_{t,w}^{reefer} \qquad \forall t \in T,\ \forall w \in S \tag{5.12}$$

By enforcing these constraints, unnecessary rescheduling of charging and cooling times is avoided, as the timing of consumption becomes irrelevant in the CP and NP cases.

Overall, the evaluation of demand response involves comparing the results obtained from the NP, CP, and RTP cases, taking into account the different pricing schemes and their impact on the solution.

5.1.6. Evaluation of On-shore power supply

Currently, the CTA container terminal does not offer the option for ships to utilize an On-shore Power Supply (OPS). However, considering the ongoing investigation by the terminal operator, HHLA, regarding the installation of OPS in other container terminals in Hamburg, it is worthwhile to evaluate the potential impact of OPS on the electricity consumption of the terminal.

Since OPS is not yet widely implemented, obtaining specific data on its usage is challenging. As discussed in Section 2.4, the energy consumption of ships can be categorized into critical and time-shiftable components. However, no breakdown of the share of energy demand from ships that falls under the critical category was found. As a result, it is assumed that the entire energy consumption of ships is critical, leading to a constant demand throughout the duration of a ship's berthing period. Furthermore, it is assumed that all ships have the capability to utilize OPS, and no constraints are imposed on the number of available ”charging stations” for ships.

By assessing the impact of OPS on the electricity consumption of the CTA container terminal, valuable insights can be gained, aiding the decision-making process regarding the potential implementation of OPS in the future.

5.2. Results

This section presents the results of the conducted experiments. It begins with a validation experiment in subsection 5.2.1 to assess the performance of the developed model. Subsequently, the impact of stochastic modeling is analyzed in subsection 5.2.2. The following subsection, 5.2.3, presents the findings of an experiment investigating the effect of demand response. The subsequent subsection, 5.2.4, explores the price sensitivity of the demand response experiment by repeating it with different electricity prices. Finally, the impact of introducing on-shore power supply in the terminal is examined in section 5.2.5.

5.2.1. Validation

The results of a validation experiment comparing the model presented in this study with the model developed by Iris and Lam are summarized in Table **??**. Two pricing strategies were considered: a constant energy price for each hour of the day, and a real-time energy price that varies based on the wholesale electricity market. The experiment was conducted by running the models 10 times with different randomly generated arrival times for ships. In the first five runs, 30 ships were considered, while in the remaining runs, 40 ships were expected to arrive within the two-day time window.

	Iris & Lam (Zero PV production)		Thesis model	
	Total cost [€]		Total cost [€]	
#	Real-time price	Constant price	Real-time price	Constant price
1	108788.1	119311.4	104387.0	117257.4
2	104460.2	112578.6	83132.7	98409.2
3	101185.3	121967.3	91191.9	102404.0
4	97015.2	109504.1	83677.0	100286.8
5	110036.9	128185.7	75326.9	93376.9
Avg.	**104297.1**	**118309.4**	**87543.1**	**102346.9**
6	132014.2	157487.6	106498.1	137411.4
7	121328.8	151907.5	99464.1	121513.5
8	147648.2	164447.0	112440.5	130757.9
9	131308.0	155608.0	105591.5	125700.4
10	127688.2	154309.1	109421.1	133906.4
Avg.	**131997.5**	**156751.8**	**106683.0**	**129857.9**

Table 5.6: Validation experiment

A comparison of the total costs obtained from Iris and Lam's model and the thesis model reveals notable differences. On average, the costs calculated by Iris and Lam were approximately 15-20 percent higher than the costs obtained in this study.

Furthermore, the impact of pricing schemes can be analyzed. Both Iris and Lam's model and the thesis model demonstrated cost reductions when utilizing real-time pricing compared to constant pricing. Iris and Lam achieved cost reductions of 12 percent and 16 percent for 30-ship and 40-ship alternatives, respectively. Similarly, the thesis model achieved cost reductions of 14 percent and 18 percent for the same alternatives.

Additionally, the cost difference between 30-ship and 40-ship alternatives was examined. Iris and Lam's model experienced a 27 percent increase in the objective function for the real-time price alternative and a 32 percent increase for the constant price alternative. In contrast, the thesis model demonstrated a 22 percent increase for the real-time price alternative and a 27 percent increase for the constant price alternative.

These validation results provide insights into the performance and accuracy of the developed model, indicating its ability to capture cost dynamics and generate comparable outcomes to an existing model.

5.2.2. Stochastic modeling

This section presents the results of the stochastic problem (SP) and compares them with the solutions obtained from the expected value problem (EV), reactive problem (RE), expectation of the expected value problem (EEV), and wait and see problem (WS). The problem was solved 10 times for all problem formulations.

Table 5.7 provides a comparison between the EV and SP problems. As discussed in 5.1, the EV problem underestimates the total operational cost by considering only the First Stage Cost (FSC), which combines the late and day-ahead energy costs. The remaining costs, namely reschedule and imbalance, are grouped as the Second Stage Cost (SSC).

	EV	SP	
#	FSC [€]	FSC [€]	SSC [€]
1	36685.3	39086.8	11051.8
2	41680.7	42223.5	4825.6
3	45963.7	47097.0	10362.0
4	34575.3	35757.0	4071.9
5	50004.6	52365.7	10172.6
6	45651.0	48725.9	4078.5
7	47160.2	49402.4	11751.8
8	33573.2	37112.1	2802.2
9	44801.1	48264.2	6291.7
10	37797.4	41539.6	11176.6
Avg	**41789.3**	**44157.4**	**7658.5**

Note: EV (Expected value problem), SP (Stochastic problem), FSC (First stage cost), SSC (Second stage cost),

Table 5.7: Cost comparison between EV and SP

The comparison reveals that the first stage costs of the EV and SP are similar. However, when the second stage costs are included, the total cost of the SP is €10,026.6 higher than that of the EV.
To incorporate the second stage costs, the reactive problem (RE) is formulated by making assumptions about the first stage decision variables. Two reactive strategies, RE and RE+, are defined to determine the energy consumption for each hour and the start time for each ship. In the RE strategy, it is assumed that no day-ahead prediction of energy consumption is available, leading to all energy being purchased

in the second stage based on the imbalance price. The start time of operations is assumed to be equal to the estimated arrival time. In the RE+ strategy, the daily average energy consumption (estimated at 8.5 MWh for the CTA case) is purchased on the day-ahead market for each hour, while the start time of operations remains the same as in the RE scenario. The EEV strategy utilizes the solution of the EV problem for the day-ahead energy consumption and start time.

Table 5.8 displays the costs for the four strategies (RE, RE+, EEV, and SP) used to incorporate uncertainty in the model. Additionally, the WS strategy is included to demonstrate the hypothetical maximum cost reduction. However, the WS solution is not practically feasible as it assumes a perfect forecast. The cost reduction gap with respect to the RE solution is determined for each strategy. By employing the EEV strategy, a cost reduction of 16.6 percent can be achieved. The stochastic problem presented in this thesis further increases the cost reduction to 20.6 percent. The hypothetical maximum reduction achievable is 32.4 percent.

	RE	RE+	EEV	SP	WS
#	Total cost [€]	Total cost [€]	Total cost [€]	Total cost [€]	Total cost [€]
1	62863.8	58775.9	53217.3	50138.7	38999.6
2	62074.0	57967.5	53056.8	47049.1	42296.7
3	69925.5	63784.6	59770.4	57459.1	47054.6
4	53117.1	51103.7	40004.2	39828.8	35364.0
5	81891.7	74881.7	67645.8	62538.3	52268.0
6	67430.5	61454.6	53747.0	52804.4	48830.5
7	75826.3	69324.2	62984.9	61154.2	49513.6
8	48113.5	45913.3	41666.9	39914.3	37006.6
9	71876.7	65269.8	56203.4	54556.0	48370.4
10	59377.4	55685.1	55818.4	52716.3	41260.9
Avg	**65249.7**	**60416.1**	**54411.5**	**51815.9**	**44096.5**
Gap (%)	**0.0**	**-7.4**	**-16.6**	**-20.6**	**-32.4**

Note: RE (Reactive problem), EEV (Excpectation of the expected value problem), SP (Stochastic problem), WS (Wait-and-see problem), Gab (%) = $(x - Avg_{RE}) * 100/Avg_{RE}$

Table 5.8: Influence of stochastics

Based on the differences between the EEV and SP solutions, the Value of the Stochastic Solution (VSS) is calculated using Equation 5.13. Similarly, the Expected Value of Perfect Information (EVPI) is computed using Equation 5.14, which represents the difference between the SP and WS solutions.

$$VSS = EEV - SP = 54992.1 - 53185.9 = 1806.2€ \tag{5.13}$$

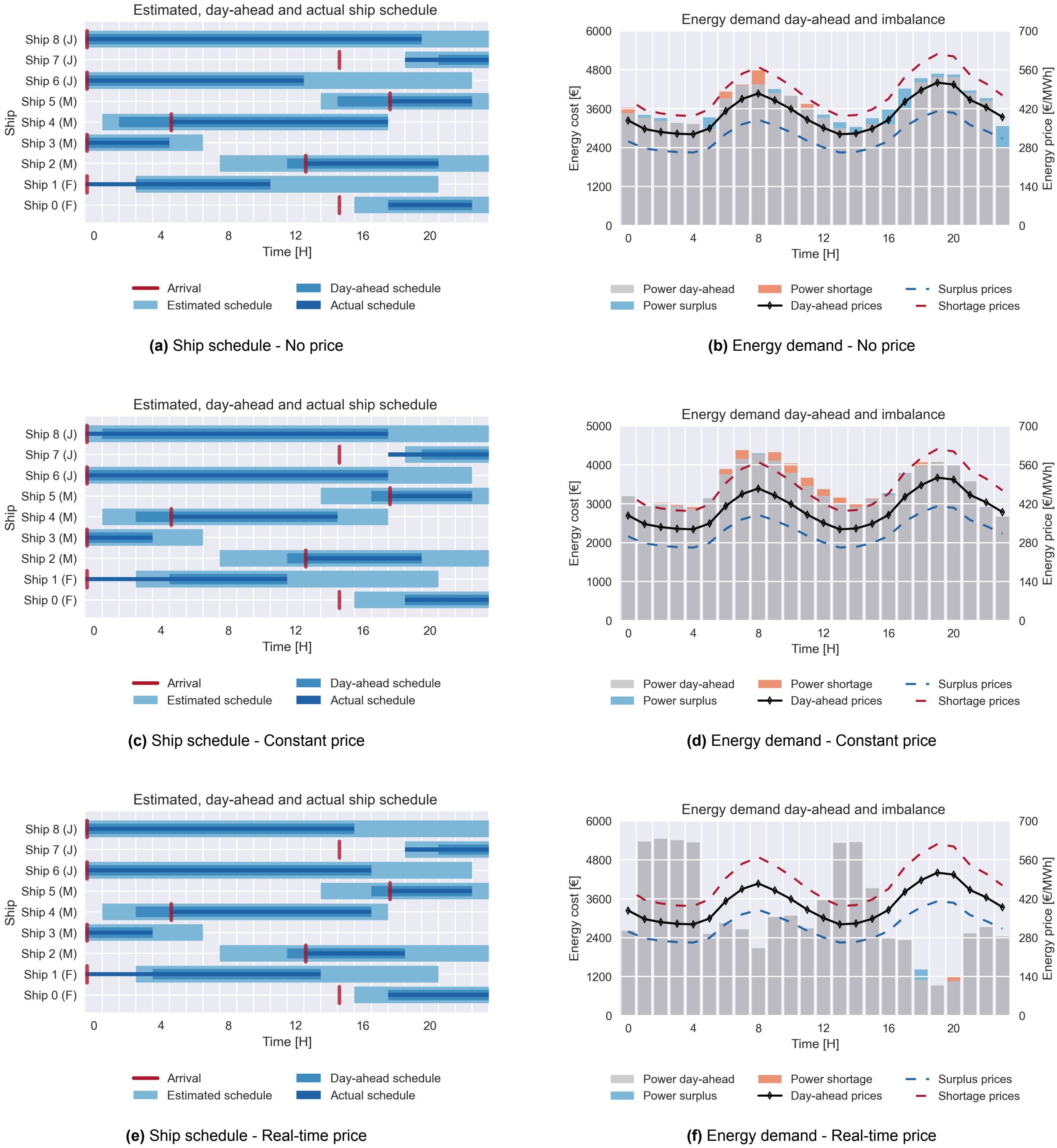
$$EVPI = SP - WS = 53185.9 - 44096.5 = 9089.4€ \tag{5.14}$$

These results demonstrate the value and benefits of incorporating stochastic modeling in decision-making processes, allowing for cost reductions and providing insights into the potential value of perfect information in uncertain environments.

5.2.3. Demand response

In this section, three different pricing strategies, namely No Price (NP), Constant Price (CP), and Real-Time Price (RTP), are compared. Price scenarios were created using the electricity prices in Germany for 2022, and ten instances were run for each pricing strategy.

Figure 5.2 illustrates the ship schedule and energy consumption for the second instance in the fourth scenario. By plotting the ship schedule and energy consumption, a visual comparison can be made between the different pricing strategies, including the decisions made in the first and second stage.



(a) Ship schedule - No price

(b) Energy demand - No price

(c) Ship schedule - Constant price

(d) Energy demand - Constant price

(e) Ship schedule - Real-time price

(f) Energy demand - Real-time price

Figure 5.2: Ship schedule and hourly energy consumption for different pricing strategies

For the NP alternative, power imbalances can be observed for most hours, resulting in higher energy costs. When the cost of electricity is taken into account in the CP alternative, these imbalances are significantly reduced, leading to lower energy costs. Once real-time prices are considered in the optimization (RTP scenario), the energy consumption pattern also changes, with reduced consumption during times of high prices. Some differences in the berthing schedule can be observed between the different alternatives, although they are minor. Most of the differences are noticeable between the RTP scenario and the other two scenarios. For example, in the RTP scenario, Ship 1 departs later to take advantage of lower prices in the afternoon, while Ship 9 departs earlier to finish just before the evening peak price.

Table 5.9 presents the results of the different pricing strategies, including No Price, Constant Price, and Real-Time Price. The costs are divided into energy-related costs and schedule-related costs. It can be observed that introducing a constant price scheme reduces the total cost by 5.9 percent. With real-time prices, the cost further decreases by 13.2 percent.

	No price			Constant price			Real-time price		
#	EC [€]	SC [€]	TC [€]	EC [€]	SC [€]	TC [€]	EC [€]	SC [€]	TC [€]
1	44628.1	13482.0	58110.1	43325.8	13692.0	57017.8	38798.7	11340.0	50138.7
2	49746.6	6804.0	56550.6	47013.8	6602.4	53616.2	42317.8	4731.2	47049.1
3	53979.6	11390.4	65370.0	50921.5	10735.2	61656.7	47429.5	10029.6	57459.1
4	45266.7	3931.2	49197.9	39856.1	4989.6	44845.7	35544.8	4284.0	39828.8
5	57095.3	11793.6	68888.9	55677.2	11844.0	67521.2	52357.5	10180.8	62538.3
6	55265.5	3376.8	58642.3	52559.4	4737.6	57297.0	48559.9	4244.5	52804.4
7	55561.2	10533.6	66094.8	52899.1	9626.4	62525.5	48999.4	12154.8	61154.2
8	46231.0	4284.0	50515.0	40303.2	3780.0	44083.2	35991.5	3922.8	39914.3
9	54584.0	8618.4	63202.4	51742.4	6442.8	58185.2	47626.0	6930.0	54556.0
10	50439.0	9651.6	60090.6	45624.5	8794.8	54419.3	41401.5	11314.8	52716.3
Avg	**51279.7**	**8386.6**	**59666.3**	**47992.3**	**8124.5**	**56116.8**	**43902.6**	**7913.3**	**51815.9**
Gap (%)	**0.0**	**0.0**	**0.0**	**-6.4**	**-3.1**	**-5.9**	**-14.4**	**-5.6**	**-13.2**

Note: EC (Energy cost), SC (Schedule cost), TC (Total cost), Gab (%) = $(x - Avg_{NP}) * 100/Avg_{NP}$

Table 5.9: Comparison of different pricing strategies with 2022 prices

Figure 5.3 displays the average energy demand across all instances for the NP and RTP schemes. A negative correlation between energy demand and electricity price is observed in the real-time case. The average demand increases at night and in the early afternoon when prices are lowest. To quantify this correlation, the Pearson correlation coefficient is calculated between energy demand and electricity price. Table 5.10 presents the Pearson coefficient for NP, CP, and RTP. No correlation exists between price and demand in the case of NP and CP pricing schemes. However, when RTP is considered, the Pearson correlation coefficient becomes -0.85, indicating a strong negative correlation.

Furthermore, increased volatility in electricity demand for RTP can be observed in Figure 5.3. Table 5.11 shows the Peak-to-Average Ratio (PAR) calculated for all different pricing schemes. The NP and CP schemes have PAR values of 1.17 and 1.19, respectively. In contrast, the RTP scheme exhibits a significantly higher PAR of 2.05.

Similarly, other decision variables can be compared between different pricing schemes. Figure 5.4 illustrates the number of berthed ships, the handling rate of ship loading/unloading, the rate of AGV charging, and the rate of reefer cooling. Each of these variables responds to price signals, with a higher difference between NP and RTP indicating a greater responsiveness to price changes. To compare the sensitivity of each variable to price changes, the standard deviation of the difference between the NP and RTP schemes is computed. Each standard deviation is then normalized by dividing it by the mean. The Flexibility Coefficient (FC), calculated using Equation 5.15, quantifies the degree of flexibility for each variable (X).

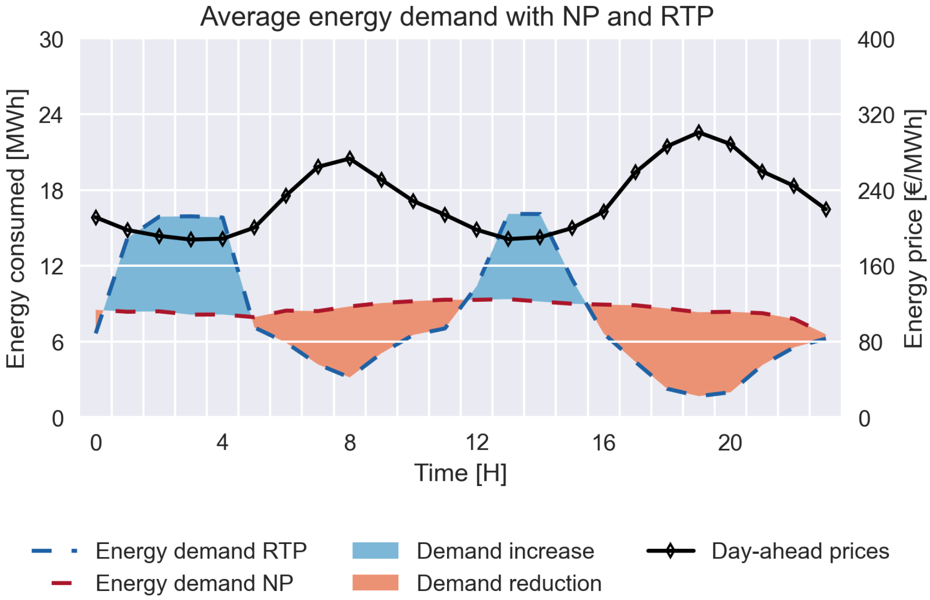


Figure 5.3: Average energy demand with No pricing and Real-time pricing

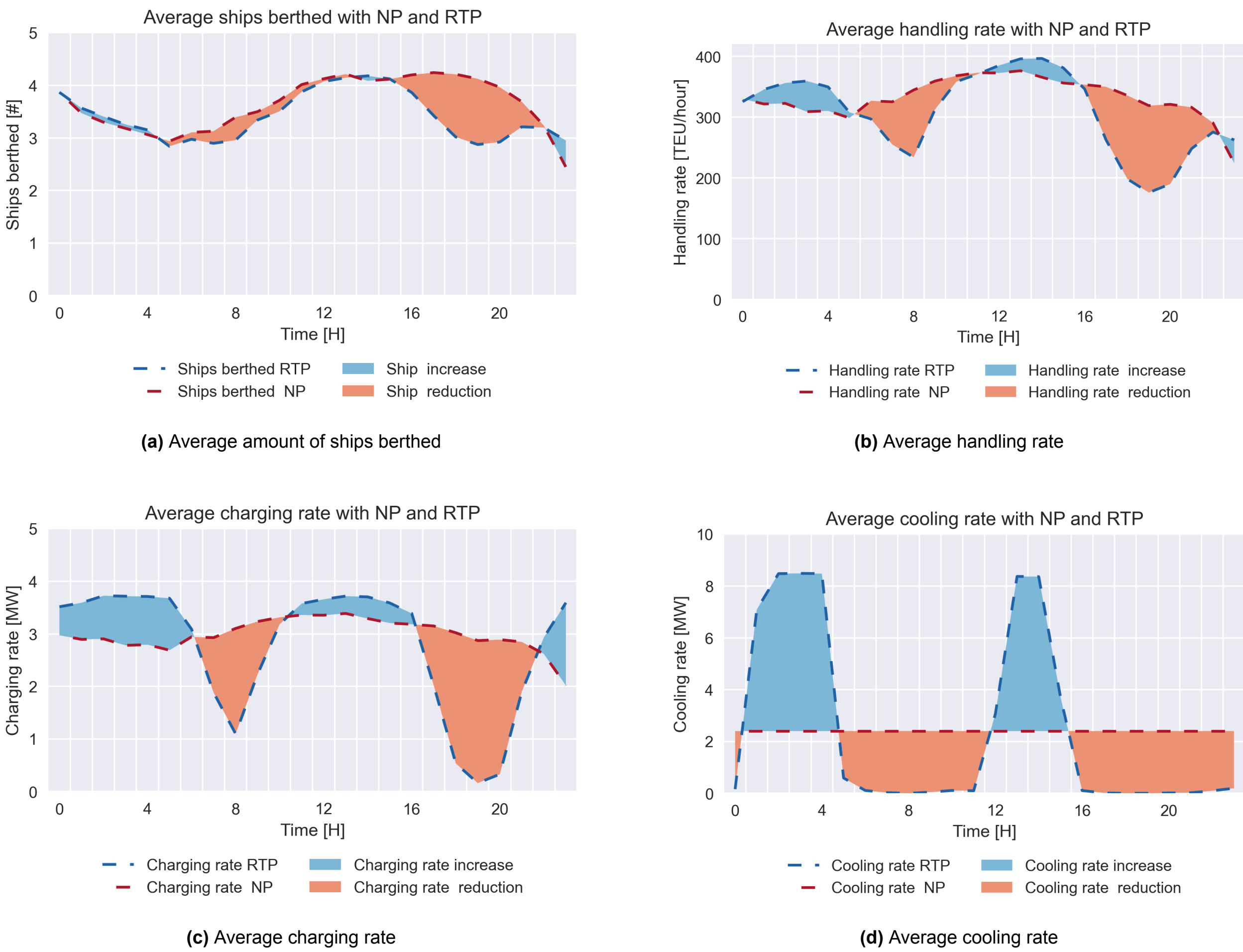
#	No Price	Constant Price	Real-Time Price
1	0.15	0.21	-0.79
2	-0.35	-0.08	-0.87
3	-0.16	-0.35	-0.84
4	0.23	0.14	-0.86
5	-0.07	-0.04	-0.80
6	-0.17	-0.12	-0.86
7	0.09	0.05	-0.84
8	-0.19	-0.40	-0.87
9	-0.29	-0.29	-0.88
10	0.09	0.03	-0.86
Avg	**-0.07**	**-0.08**	**-0.85**

Table 5.10: Pearson Correlation Coefficient (r) for Different Pricing Strategies

#	No Price	Constant Price	Real-Time Price
1	1.35	1.37	2.24
2	1.21	1.15	2.06
3	1.10	1.10	1.90
4	1.34	1.35	2.44
5	1.04	1.05	1.77
6	1.07	1.09	1.87
7	1.07	1.11	1.85
8	1.30	1.35	2.33
9	1.08	1.11	1.89
10	1.19	1.18	2.11
Avg	**1.17**	**1.19**	**2.05**

Table 5.11: Peak to Average Ratio (PAR) for Different Pricing Strategies

$$\text{FC} = \frac{\sigma(X_{NP} - X_{RTP})}{\bar{X}_{NP}} \tag{5.15}$$



(a) Average amount of ships berthed

(b) Average handling rate

(c) Average charging rate

(d) Average cooling rate

Figure 5.4: Comparison No pricing and Real-time pricing for different variables

In Table 5.12 the flexibility coefficient is given for the variables mentioned above. Here it can be observed that the cooling rate is the most flexible, with a normalised standard deviation of 1.48. This implies that the rate at which reefers are cooled can be adjusted more readily in response to price changes. Following this, the AGV charging rate also demonstrates notable flexibility. The handling rate and the number of ships berthed exhibit relatively lower levels of flexibility compared to the other variables, and other therefore more constraint by the operational planning.

Variable	FC [-]
Ships berthed	0.12
Handling rate	0.18
Charging rate	0.41
Cooling rate	1.48

Table 5.12: Flexibility coefficient (FC) for different variables

These results highlight the impact of different pricing strategies on various decision variables and demonstrate the effectiveness of demand response mechanisms in optimizing costs and adapting operations based on real-time price.

5.2.4. Price sensitivity

In light of the ongoing energy crisis in Europe, the electricity prices in 2022 were significantly higher compared to previous years. To assess the impact of demand response under different price scenarios, a sensitivity analysis was conducted. Figure 5.5 illustrates the electricity prices in the Netherlands from 2016 to 2022. It can be observed that there was a notable increase in day-ahead electricity prices between 2020 and 2022. This upward trend, coupled with the rising standard deviation of energy prices, signifies increased volatility in the energy market.

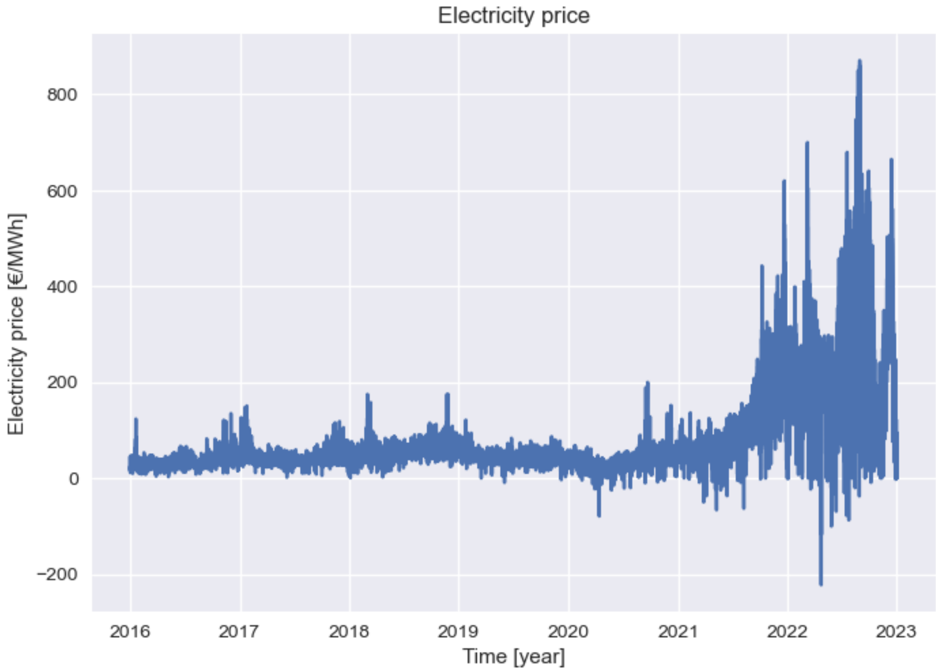


Figure 5.5: Historical electricity prices for the day-ahead market in the Netherlands

To evaluate the influence of prices, the experiments described in Subsection 5.2.3 were repeated using the price data from 2019. The results are presented in Table 5.14. Since the energy prices were lower in 2019, the energy-related costs exhibit a significant decrease compared to the higher prices of 2022. When comparing the gap between the constant price and real-time price schemes, a total cost reduction of 1.3 percent and 12 percent is observed, respectively.

To further investigate the impact of rising electricity prices, the cost based on the real-time price scheme was calculated for each year from 2016 to 2022. For each year, ten instances were simulated, and the average cost of all instances, as well as the cost increase compared to 2016, are shown in Table 5.14. It can be seen that due to the upward trend in electricity prices, the energy costs have increased by more than 800 percent since 2016. Consequently, the total costs have also risen significantly. Based on the simulations conducted in this study, no clear relationship can be observed between the scheduling costs and the rising electricity prices.

In summary, the sensitivity analysis highlights the considerable impact of electricity prices on the energy-related costs and the overall cost of operations. The results underscore the importance of incorporating demand response strategies to mitigate the effects of fluctuating electricity prices and improve cost efficiency in port operations.

#	No price			Constant price			Real-time price		
	EC [€]	SC [€]	TC [€]	EC [€]	SC [€]	TC [€]	EC [€]	SC [€]	TC [€]
1	5880.4	11844.0	17724.4	5719.5	10180.8	15900.3	4818.0	11491.2	16309.2
2	6420.6	7106.4	13527.0	6236.1	7812.0	14048.1	5283.5	3628.8	8912.3
3	7079.7	8013.6	15093.3	6715.2	10827.6	17542.8	5882.2	8693.5	14575.7
4	5896.8	4384.8	10281.6	5322.6	3024.0	8346.6	4416.5	3880.8	8297.3
5	7389.1	9374.4	16763.5	7287.6	11877.6	19165.2	6540.4	11852.4	18392.8
6	7127.7	4435.2	11562.9	6873.5	4183.2	11056.7	6056.7	3074.4	9131.1
7	7144.6	10836.0	17980.6	6939.1	12322.8	19261.9	6099.3	9618.0	15717.3
8	6042.9	4284.0	10326.9	5294.0	3376.8	8670.8	4319.7	3780.0	8099.7
9	7127.2	7761.6	14888.8	6744.7	5594.4	12339.1	5971.8	7761.6	13733.4
10	6617.9	9651.6	16269.5	5987.5	10155.6	16143.1	5131.2	8744.4	13875.6
Avg	**6672.7**	**7769.2**	**14441.8**	**6312.0**	**7935.5**	**14247.4**	**5451.9**	**7252.5**	**12704.4**
Gap (%)	**0.0**	**0.0**	**0.0**	**-5.4**	**2.1**	**-1.3**	**-18.3**	**-6.7**	**-12.0**

Note: EC (Energy cost), SC (Schedule cost), TC (Total cost), Gab (%) = $(x - Avg_{NP}) * 100/Avg_{NP}$

Table 5.13: Comparison of different pricing strategies with 2019 prices

Year	Average energy cost		Average schedule cost		Average total cost	
	€	%	€	%	€	%
2016	5124.8	100.0	7646.5	100.0	12771.3	100.0
2017	6537.3	127.6	7208.2	94.3	13745.6	107.6
2018	7604.0	148.4	7174.4	93.8	14778.4	115.7
2019	5451.9	106.4	7252.5	94.8	12704.4	99.5
2020	4418.7	86.2	7232.4	94.6	11651.1	91.2
2021	29074.0	567.3	7279.4	95.2	36353.5	284.6
2022	43902.6	856.7	7913.3	103.5	51815.9	405.7

Table 5.14: Average cost per year between 2016-2022 with Real-time prices

5.2.5. On-shore power supply

An experiment was conducted to assess the potential impact of implementing On-Shore Power Supply (OPS) on a large scale. Three alternatives were formulated to evaluate the effect of OPS on energy consumption. Based on a study that investigated container ships with a capacity of 65,000 TEUs, an average hourly demand of 2 MWh/h was reported [79]. For each alternative, a different average hourly demand was assumed: 0 MWh/h, 1 MWh/h, and 2 MWh/h. Ten optimizations were performed for each alternative, with different randomly generated schedules.

Figure 5.6 presents the average energy demand for all three alternatives. It can be observed that the introduction of OPS leads to a significant increase in the energy consumption of a container terminal. In the case where no power demand is assumed (0 MWh/h), the total daily consumption is 194 MWh. However, if an average power demand of 2 MWh/h is assumed for each ship, the total daily consumption rises to 329 MWh.

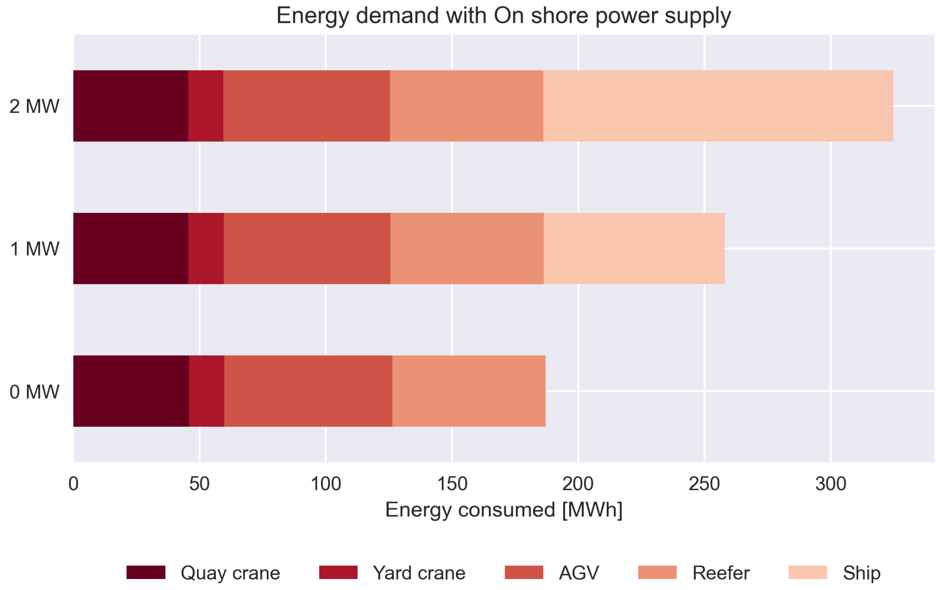


Figure 5.6: Energy demand with the introduction of on-shore power supply

6 Discussion

The Discussion chapter serves as a critical analysis and interpretation of the results presented in Chapter 5.2. This chapter delves into a comprehensive examination of the findings and their implications, aiming to provide a deeper understanding of the research outcomes. Section 6.1 focuses on the interpretation of the results, where key insights, trends, and patterns are identified and discussed. Furthermore, in Section **??**, the research contribution of this thesis is explored, highlighting the practical implications and potential applications of the findings. The limitations encountered during the research process are addressed in Section 6.3. Lastly, Section 6.4 presents potential avenues for future research, suggesting areas that could benefit from further investigation and advancement.

6.1. Interpretation

This section aims to provide an interpretation of the results presented in Chapter 5.2. The findings from each experiment will be discussed in their respective subsections, allowing for a comprehensive analysis of the outcomes.

6.1.1. Validation

When comparing the results of the Iris and Lam model with the model presented in this thesis, a difference of 15-20 percent in the total cost was observed. This cost difference can be attributed to the disparity in objective functions. In the Iris and Lam model, two terms are used to calculate the energy cost. One term calculates the energy cost for the base scenario, while an additional term calculates the energy cost for each of the other four scenarios, weighted by their expected occurrence (5 percent each). The variation between the scenarios is due to the photovoltaic (PV) production. In the zero PV production experiment, all scenarios are effectively the same. On the other hand, the thesis model utilizes only the base scenario, without considering the energy cost of alternative scenarios. Therefore, it is expected that a 20 percent energy cost would be observed ($4 \times 5 = 20$ percent), which aligns with the results obtained in this thesis model.

Regarding the comparison between real-time and constant price alternatives, it can be concluded that both models exhibit similar responses to energy prices. However, there is a notable difference between the 30-ship and 40-ship cases, indicating different scaling behaviors. This discrepancy can be explained by the way both models handle berth assignment. Iris and Lam create a pre-determined schedule based on ships expected to use the same berth, but it is unknown whether the schedule for the 40-ship alternative allows for more available berths compared to the 30-ship alternative. In the thesis model, the length of the quay is scaled according to the expected number of arriving ships.

In conclusion, the validation experiment demonstrated that the model behaved as anticipated based on the literature. Adjusting the results of the Iris and Lam model based on differences in the objective yields similar outcomes. Both models exhibit consistent responses to changes in electricity prices, but they differ slightly in their scaling behaviors when the number of ships increases. Overall, the results of the validation experiment indicate similar behavior between the two models.

6.1.2. Stochastic modeling

The results in Section 5.2.2 reveal that simply using expected values (EV) for electricity prices and ship arrival times leads to a significant underestimation of costs.

Similar to other studies, this thesis assumes an additional cost of 20 percent for rescheduling and imbalances. In the renewable energy (RE) scenario, where all energy is considered an imbalance, it is logical that the total cost is 20 percent higher. If a higher value were used for rescheduling and imbalances, a larger difference between the RE and standard planning (SP) solutions could be expected.

The additional cost reduction for the SP compared to the EV solution is lower than expected. Two reasons were identified for this minimal impact. Firstly, examining the energy price scenarios as shown in Section 4.3, it can be observed that all scenarios are temporally aligned, with peaks and troughs occurring simultaneously. This implies that operations are shifted to the same times in every scenario. Despite significant differences in the size of the peaks and troughs and the mean price, distinct solutions are not generated. Secondly, the ship arrival time windows were broad enough to mitigate uncertainty caused by late arrivals. If a ship arrived late, it was often still possible to complete handling the ship before the estimated finish time, thereby avoiding late fees. Since starting the handling of a ship earlier in another scenario would not lead to reduced late costs, especially considering the incurred rescheduling costs, the optimal solutions for each individual scenario are similar. As a result, only a modest increase in cost is observed due to the introduction of uncertainty.

In summary, the impact of stochastic modeling on costs is substantial, highlighting the limitations of using expected values alone. The introduction of uncertainty and considering a range of scenarios leads to a more accurate assessment of costs, particularly in terms of rescheduling and imbalances.

6.1.3. Demand response

The results clearly demonstrate that implementing a demand response program can lead to a significant reduction in operational costs. Even considering a constant electricity price alone yields a substantial benefit, with a 5.9 percent cost reduction. When real-time prices are taken into account, this benefit increases further to a 13.2 percent cost reduction. It can be concluded that there is potential for demand response in container terminals.

Interpreting the influence of energy-related costs on scheduling costs is challenging. In some instances, both the constant price and real-time price schemes resulted in lower scheduling costs compared to the no-price scheme, while in other instances, the opposite was observed. On average, scheduling costs decreased in 2022 for both the constant and real-time price schemes. However, in 2019, a small cost increase was observed for scheduling costs. In all cases, the absolute cost reduction or increase was small, always lower than 400 euros. To draw more conclusive findings, it would be beneficial to repeat the experiments more then ten times and with better lower convergence threshold between the scenarios.

An unexpected result is that the real-time pricing (RTP) strategy led to higher peak loads. Generally, it is not desirable to have these peak loads. Since the peak electricity cost is not considered in this model, there is no penalty to incentivize reducing peak consumption.

The flexibility of the cooling rate of reefer containers was found to be greater than anticipated. When estimating the heat loss of reefers, factors such as variations in ambient temperature or solar irradiance were not included. Additionally, the heat loss was assumed to be independent of the temperature of the reefer container, resulting in a constant heat loss throughout the day. Treating all reefers as one large cold storage would cause them to turn on simultaneously, leading to high peak loads generated by the reefers, which is undesirable. Modeling each reefer container independently, considering accurate heat losses, would provide a more realistic assessment of reefer flexibility.

6.1.4. Price Sensitivity

The price sensitivity experiment revealed that the potential for demand response is not strongly correlated with electricity prices. It is expected that demand response will have a lower impact on costs when electricity prices are lower. However, when comparing the electricity prices of 2019 and 2022, an eight-fold increase can be observed, while the cost reduction from the no-price scenario to the real-time price scenario only decreased from 13.2 percent to 12.0 percent.
Increasing energy prices do not significantly affect scheduling costs. It was expected that as energy costs increase, scheduling costs would also slightly increase. However, a different tradeoff was observed, where higher scheduling costs were not necessarily accompanied by much lower energy costs.

6.1.5. On-shore Power Supply

The results of the on-shore power supply (OPS) experiment clearly demonstrate the significant impact of implementing OPS on a container terminal's electricity demand. However, practical considerations must be taken into account, particularly regarding the availability of capacity on the electricity grid in the port, as additional capacity may not be readily accessible. These findings underscore the substantial influence of OPS implementation on a terminal's energy requirements, emphasizing the importance of considering energy consumption patterns and optimizing scheduling strategies in conjunction with OPS to achieve efficient resource utilization and minimize environmental impact.

6.2. Implication

The insights garnered from this research bear significant implications for the operations and management of container terminals. By incorporating electricity prices into operational planning, the study demonstrates the potential for substantial cost reductions, ranging from 12-13.2 percent. It becomes apparent that the balance between minimizing electricity costs and additional operational expenses leans towards reducing electricity costs. Failing to account for electricity demand in operational research can lead to inaccurate portrayals of actual operational costs experienced by a terminal.

The findings of this thesis align with existing literature. Iris and Lam identified cost reductions between CP and RTP of 12-19 percent when neither solar panels nor battery storage were factored in, and reductions of 18.5-21 percent when considering these sources, albeit with uncertainty in solar production. Mao reported cost savings of 5-6 percent between CP and RTP, considering the heating system as well. Pu found a cost reduction between NP and a time of use pricing scheme of between 5-19 percent. This thesis' cost reduction result of 12-13.2 percent between NP and RTP (or 7.8 - 10.3 percent between CP and RTP) aligns with those found in previous studies. Unlike those studies, this thesis modeled a higher quantity of flexible loads but did not factor in potential cost savings associated with shifting on-shore power supply, which may become more prevalent in the future. Additionally, considering uncertainty in arrival times and electricity prices resulted in a modest gain from demand response.

This thesis provides an overview of different methods for controlling electricity demand. This groundwork can be employed by other researchers to investigate each potential source more deeply, analyzing how electricity demand can be managed and the operational implications thereof. Some of these sources, such as modulating the cooling rate of reefers or the lifting cycle of quay cranes, have been studied to a certain extent. As evidenced in this thesis, numerous unexplored opportunities (even beyond those presented here) exist to decrease energy consumption and costs, aspects that have largely been overlooked in the scientific literature.

As noted in Section 2, most research into energy consumption at container terminals is centered on port loads, in tandem with the deployment of energy storage technologies or renewable energy infrastructure, such as large battery packs, solar power plants, or wind turbines. The flexibility of loads is seldom considered. The findings presented in this thesis suggest that research into energy management systems or microgrids in future ports should not solely focus on the introduction of new technologies. More efficient control of existing loads can significantly reduce energy-related costs. Importantly, these reductions can be achieved without significant investments into storage or renewable generation—

improvements in terminal operations software alone could lead to substantial savings.

Another practical implication of this thesis is that future research employing a similar methodology should consider accounting for uncertainty within the optimization process. By incorporating a sufficient number of distinct scenarios, significant cost savings can be achieved. When stochasticity is taken into account, a less computationally intensive approach, such as the expectation of the expected value problem, can provide results that are close to those obtained with a two-stage stochastic problem.

6.3. Limitations

This study provides valuable insights into the potential for demand response in container terminals. However, to fully appreciate the accuracy of these findings, it is crucial to understand the limitations of the model.

As discussed in chapter 2, our understanding of energy consumption within container terminals is limited. It is challenging to determine precisely how much energy is used and from which sources. There is a lack of publicly accessible data detailing the breakdown of energy consumption within terminals. Because of this it is necessary to make certain assumptions in any study exploring energy consumption.

Furthermore, container terminals represent highly complex systems, and modeling their operations carries inherent complexities. Numerous interconnected planning problems exist within a terminal, as mentioned in section 3.1.1. This thesis examined the aspects of these planning problems that have the most significant impact on energy consumption. Yet, to more accurately evaluate a terminal's flexibility potential, all operational costs should be considered. This research primarily focused on the operational costs related to ship scheduling. A more comprehensive trade-off analysis, including all operational costs and energy costs, would provide a more accurate depiction of the potential for demand response.

Another consideration in assessing the accuracy of our results involves the time-step used in the model. For this study, average energy consumption was measured over one hour, a decision driven primarily by computational constraints. This approach may have overlooked potential demand response sources that operate on the scale of minutes or even seconds.

Lastly, this study didn't fully account for the electricity costs associated with peak loads. As outlined in chapter 2, peak loads can significantly contribute to overall electricity costs. As shown in section 2.3, the peak demand of a group of eight quay cranes can reach around 20 MW, which is similar to the overall hourly peak demand of the HHLA container terminal described in section 5.2.3. However, these peak loads are typically brief, often lasting only a few seconds, and are therefore not reflected in hourly averages. Therefore, including peak loads in the model would not be possible, as the model only account for hourly loads.

6.4. Recomendations

Based on the findings of this thesis, several recommendations for future research can be made.

Firstly, enhancements to the model presented in this thesis can be considered. In particular, alongside modeling the energy consumption of every load, an addition to consider is the peak power of each load. By accurately modeling this, an additional objective could be integrated to account for the peak load of the container terminals. This would provide a more precise estimation of energy-related costs.

Secondly, improvements could be made to the modeling of reefer energy consumption. Taking into account precise weather conditions, treating individual reefers rather than one large reefer park as a single entity, and constraining the peak load of reefers may lead to a more accurate consumption pattern.

Moreover, there’s a notable need for further research into the simulation of energy consumption within container terminals. Currently, understanding of how specific operations impact energy consumption is limited, with many values found in the literature based on assumptions. Precise simulations of energy usage within a container terminal, combined with validation using real-life data, are crucial. This could forge a more robust link between the operational decisions made and the resulting energy demand.

Lastly, conducting energy price-aware optimization of the most common operational research problems within container terminals is recommended. This would help to identify additional opportunities for cost savings and efficiency improvements.

7 Conclusion

This thesis investigated the potential for demand response within a container terminal. The central research question for this study was:

What is the potential of demand response for reducing the energy and operational costs of a container terminal?

In this thesis, it was demonstrated that a cost reduction of 12-13 percent can be achieved when implementing a real-time price demand response program compared to a situation where energy cost are not considered. With a energy aware optimization the energy-related costs decrease while the other operational costs remain the same.

Sub-Questions:

1. What demand flexibility exists in a container terminal?

   The primary sources of energy consumption in an electrified terminal were identified as vessels, quay cranes, yard cranes, automated guided vehicles, refrigerated containers, buildings, and lighting. Among these, all except lighting can be utilized for demand response to some extent. It was discovered that adjusting the berthing schedule could alter the consumption of vessels, quay cranes, and yard cranes. Similarly, flexible loads on the ship, handling rates, lifting speed, and the charging rate of automated guided vehicles can influence the energy consumption. Moreover, the demand of refrigerated containers and buildings can be varied by adjusting the heating/cooling rate of the (HV)AC system.

2. Which demand response programs would be suitable for a container terminal to participate in?

   Price-based demand response programs, such as real-time pricing, were identified as having the greatest potential for container terminals. Given the challenge of accurately forecasting energy consumption in a terminal, price-based demand response programs allow for consumption adjustment without upfront commitment, therefore requiring less precise forecasting.

3. How can the energy consumption of terminal operations be modeled and analyzed, given uncertain electricity demand and supply?

   Ship arrival times and electricity prices were identified as the most significant sources of uncertainty for both supply and demand. Due to the sequential nature of electricity markets and operational planning in container terminals, a two-stage optimization model was determined as the best method to represent this uncertainty. The day-ahead costs were calculated in the first stage, and real-time costs were calculated based on expected values in the second stage. A decomposition method like progressive hedging can be used to solve the stochastic model more rapidly.

4. What is the impact of demand response in a container terminal on peak energy consumption and energy consumption throughout the day?

   When considering a constant energy price, no correlation was found between price and consumption. However, with a real-time pricing strategy, a strong negative correlation was observed with a Pearson correlation coefficient of -0.85 . Additionally, the introduction of real-time prices increased peak energy consumption, with the peak to average ratio rising from 1.17 to 2.05.

5. How do different electricity prices influence the potential for demand response?

   It was found that the potential cost reduction from demand response was not strongly correlated with the electricity prices. with an eight increase in the energy prices resulting the cost reduction only increased from 12.0 to 13.2 percent.

To summarize, the implementation of demand response strategies presents a promising approach to managing electricity demands in container terminals, potentially leading to significant reductions in operational costs. The findings of this study provide a strong foundation and highlight the need for future research in this field.

References

[1] M. H. Albadi and E. F. El-Saadany. “Demand Response in Electricity Markets: An Overview”. In: *2007 IEEE Power Engineering Society General Meeting*. 2007 IEEE Power Engineering Society General Meeting. ISSN: 1932-5517. June 2007, pp. 1–5. DOI: 10.1109/PES.2007.385728.

[2] Nur Najihah Abu Bakar et al. “A Review of the Conceptualization and Operational Management of Seaport Microgrids on the Shore and Seaside”. In: *Energies* 14.23 (Jan. 2021). Number: 23 Publisher: Multidisciplinary Digital Publishing Institute, p. 7941. ISSN: 1996-1073. DOI: 10.3390/en14237941. URL: https://www.mdpi.com/1996-1073/14/23/7941 (visited on 01/12/2023).

[3] Christian Bierwirth and Frank Meisel. “A survey of berth allocation and quay crane scheduling problems in container terminals”. In: *European Journal of Operational Research* 202.3 (May 2010), pp. 615–627. ISSN: 03772217. DOI: 10.1016/j.ejor.2009.05.031. URL: https://linkinghub.elsevier.com/retrieve/pii/S0377221709003579 (visited on 05/06/2023).

[4] Nor Baizura Binti Ahamad et al. “Microgrids Technologies in Future Seaports”. In: *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe). June 2018, pp. 1–6. DOI: 10.1109/EEEIC.2018.8494428.

[5] John R. Birge and François Louveaux. *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. New York, NY: Springer, 2011. ISBN: 978-1-4614-0236-7 978-1-4614-0237-4. DOI: 10.1007/978-1-4614-0237-4. URL: https://link.springer.com/10.1007/978-1-4614-0237-4 (visited on 06/12/2023).

[6] Jose L. Crespo-Vazquez et al. “A machine learning based stochastic optimization framework for a wind and storage power plant participating in energy pool market”. In: *Applied Energy* 232 (Dec. 2018), pp. 341–357. ISSN: 03062619. DOI: 10.1016/j.apenergy.2018.09.195. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261918315150 (visited on 04/12/2023).

[7] J. H. R. (Ron) van Duin et al. “Cooling down: A simulation approach to reduce energy peaks of reefers at terminals”. In: *Journal of Cleaner Production* 193 (Aug. 20, 2018), pp. 72–86. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2018.04.258. URL: https://www.sciencedirect.com/science/article/pii/S0959652618313003 (visited on 01/10/2023).

[8] ENTSO-E. *ENTSO-E Transparency Platform*. URL: https://transparency.entsoe.eu/ (visited on 05/29/2023).

[9] The Maritime Executive. *First Shore Power Capability for Containerships Being Built in Hamburg*. The Maritime Executive. July 20, 2022. URL: https://maritime-executive.com/article/first-shore-power-capability-for-containerships-being-built-in-hamburg (visited on 05/29/2023).

[10] Sidun Fang et al. “Toward Future Green Maritime Transportation: An Overview of Seaport Microgrids and All-Electric Ships”. In: *IEEE Transactions on Vehicular Technology* 69.1 (Jan. 2020). Conference Name: IEEE Transactions on Vehicular Technology, pp. 207–219. ISSN: 1939-9359. DOI: 10.1109/TVT.2019.2950538.

[11] Harry Geerlings, Robert Heij, and Ron van Duin. “Opportunities for peak shaving the energy demand of ship-to-shore quay cranes at container terminals”. In: *Journal of Shipping and Trade* 3.1 (Feb. 26, 2018), p. 3. ISSN: 2364-4575. DOI: 10.1186/s41072-018-0029-y. URL: https://doi.org/10.1186/s41072-018-0029-y (visited on 02/01/2023).

[12] Stavros G. Gennitsaris and Fotis D. Kanellos. “Emission-Aware and Cost-Effective Distributed Demand Response System for Extensively Electrified Large Ports”. In: *IEEE Transactions on Power Systems* 34.6 (Nov. 2019). Conference Name: IEEE Transactions on Power Systems, pp. 4341–4351. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2019.2919949.

[13] Mihalis M Golias. “A bi-objective berth allocation formulation to account for vessel handling time uncertainty”. In: *Maritime Economics & Logistics* 13.4 (Dec. 1, 2011), pp. 419–441. ISSN: 1479-294X. DOI: 10.1057/mel.2011.21. URL: https://doi.org/10.1057/mel.2011.21 (visited on 05/07/2023).

[14] GREENCRANES and TEN-T EA. *GREEN TECHNOLOGIES AND ECO-EFFICIENT ALTERNATIVES FOR CRANES AND OPERATIONS AT PORT CONTAINER TERMINALS - PDF Free Download*. 2. Feb. 14, 2013, p. 142. URL: https://docplayer.net/53240318-Green-technologies-and-eco-efficient-alternatives-for-cranes-and-operations-at-port-container-terminals.html.

[15] Nico Grundmeier et al. “A simulation based approach to forecast a demand load curve for a container terminal using battery powered vehicles”. In: *2014 International Joint Conference on Neural Networks (IJCNN)*. 2014 International Joint Conference on Neural Networks (IJCNN). ISSN: 2161-4407. July 2014, pp. 1711–1718. DOI: 10.1109/IJCNN.2014.6889838.

[16] Salman Habib, Muhammad Kamran, and Umar Rashid. “Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks – A review”. In: *Journal of Power Sources* 277 (Mar. 1, 2015), pp. 205–214. ISSN: 0378-7753. DOI: 10.1016/j.jpowsour.2014.12.020. URL: https://www.sciencedirect.com/science/article/pii/S0378775314020370 (visited on 02/01/2023).

[17] J Han and M A Piette. “Solutions for Summer Electric Power Shortages: Demand Response and its Applications in Air Conditioning and Refrigerating Systems”. In: *Refrigeration, Air Conditioning, & Electric Power Machinery* 29.1 (Jan. 2008), pp. 1–4.

[18] Christine Harnischmacher et al. “Two-sided sustainability: Simulating battery degradation in vehicle to grid applications within autonomous electric port transportation”. In: *Journal of Cleaner Production* 384 (Jan. 15, 2023), p. 135598. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2022.135598. URL: https://www.sciencedirect.com/science/article/pii/S0959652622051721 (visited on 01/05/2023).

[19] Sönke Hartmann, Jennifer Pohlmann, and Axel Schoenknecht. “Simulation of Container Ship Arrivals and Quay Occupation”. In: *Operations Research/ Computer Science Interfaces Series*. Vol. 49. Journal Abbreviation: Operations Research/ Computer Science Interfaces Series. Feb. 26, 2011, pp. 135–154. DOI: 10.1007/978-1-4419-8408-1_8.

[20] Junliang He. “Berth allocation and quay crane assignment in a container terminal for the trade-off between time-saving and energy-saving”. In: *Advanced Engineering Informatics* 30.3 (Aug. 1, 2016). Publisher: Elsevier Ltd, pp. 390–405. ISSN: 14740346. DOI: 10.1016/J.AEI.2016.04.006. (Visited on 11/22/2022).

[21] Junliang He, Youfang Huang, and Wei Yan. “Yard crane scheduling in a container terminal for the trade-off between efficiency and energy consumption”. In: *Advanced Engineering Informatics* 29.1 (2015). Publisher: Elsevier Ltd, pp. 59–75. ISSN: 14740346. DOI: 10.1016/J.AEI.2014.09.003. (Visited on 11/22/2022).

[22] Junliang He et al. “Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption”. In: *Expert Systems with Applications* 42.5 (Apr. 2015), pp. 2464–2487. ISSN: 09574174. DOI: 10.1016/j.eswa.2014.11.016. URL: https://linkinghub.elsevier.com/retrieve/pii/S0957417414007027 (visited on 03/24/2023).

[23] Kyaw Hein et al. “Robustly coordinated operational scheduling of a grid-connected seaport microgrid under uncertainties”. In: *IET Generation, Transmission & Distribution* 15.2 (2021). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1049/gtd2.12025, pp. 347–358. ISSN: 1751-8695. DOI: 10.1049/gtd2.12025. URL: https://onlinelibrary.wiley.com/doi/abs/10.1049/gtd2.12025 (visited on 02/12/2023).

[24] HHLA. *Container Terminal Altenwerder (CTA)*. HHLA Hamburger Hafen und Logistik AG. URL: https://hhla.de/en/company/subsidiaries/container-terminal-altenwerder-cta (visited on 05/29/2023).

[25] HHLA. *HHLA Annual Report 2022*. HHLA. 2022. URL: https://report.hhla.de/annual-report-2022/services/downloads.html (visited on 05/29/2023).

[26] HHLA. *HHLA COAST Report*. URL: https://coast.hhla.de/report?id=Standard-Report-Segelliste (visited on 05/29/2023).

[27] HHLA. *Innovation: FRESH*. HHLA Hamburger Hafen und Logistik AG. URL: https://hhla.de/en/innovation/fresh (visited on 05/29/2023).

[28] HHLA. *Sustainability for container handling: AGV charging infrastructure completed*. HHLA Hamburger Hafen und Logistik AG. Sept. 9, 2022. URL: https://hhla.de/en/media/news/detail-view/cta-agv-charging-infrastructure-completed (visited on 05/29/2023).

[29] Stefanie Holly et al. "Flexibility management and provision of balancing services with battery-electric automated guided vehicles in the Hamburg container terminal Altenwerder". In: *Energy Informatics* 3.1 (Oct. 1, 2020). Publisher: Springer Nature, pp. 1–20. ISSN: 25208942. DOI: 10.1186/S42162-020-00129-1/FIGURES/11. URL: https://energyinformatics.springeropen.com/articles/10.1186/s42162-020-00129-1 (visited on 11/16/2022).

[30] N. Ihle et al. "Software components for demand side integration at a container terminal". In: *Computer Science - Research and Development* 31.1 (2016), pp. 25–31. ISSN: 1865-2034. DOI: 10.1007/s00450-014-0276-6.

[31] IMO. *Fourth Greenhouse Gas Study 2020*. 2020. URL: https://www.imo.org/en/OurWork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx (visited on 02/02/2023).

[32] Çağatay Iris and Jasmine Siu Lee Lam. "A review of energy efficiency in ports: Operational strategies, technologies and energy management systems". In: *Renewable and Sustainable Energy Reviews* 112 (Sept. 1, 2019). Publisher: Pergamon, pp. 170–182. ISSN: 1364-0321. DOI: 10.1016/J.RSER.2019.04.069. (Visited on 11/18/2022).

[33] Çağatay Iris and Jasmine Siu Lee Lam. "Optimal energy management and operations planning in seaports with smart grid while harnessing renewable energy under uncertainty". In: *Omega* 103 (Sept. 1, 2021), p. 102445. ISSN: 0305-0483. DOI: 10.1016/j.omega.2021.102445. URL: https://www.sciencedirect.com/science/article/pii/S0305048321000542 (visited on 01/05/2023).

[34] Çağatay Iris and Jasmine Siu Lee Lam. "Recoverable robustness in weekly berth and quay crane planning". In: *Transportation Research Part B: Methodological* 122 (Apr. 2019), pp. 365–389. ISSN: 01912615. DOI: 10.1016/j.trb.2019.02.013. URL: https://linkinghub.elsevier.com/retrieve/pii/S0191261518302686 (visited on 03/10/2023).

[35] A. Rezaee Jordehi. "Optimisation of demand response in electric power systems, a review". In: *Renewable and Sustainable Energy Reviews* 103 (Apr. 1, 2019), pp. 308–319. ISSN: 1364-0321. DOI: 10.1016/j.rser.2018.12.054. URL: https://www.sciencedirect.com/science/article/pii/S1364032118308566 (visited on 01/26/2023).

[36] Fotios D. Kanellos. "Multiagent-System-Based Operation Scheduling of Large Ports' Power Systems With Emissions Limitation". In: *IEEE Systems Journal* 13.2 (June 2019). Conference Name: IEEE Systems Journal, pp. 1831–1840. ISSN: 1937-9234. DOI: 10.1109/JSYST.2018.2850970.

[37] Fotis D. Kanellos. "Real-Time Control Based on Multi-Agent Systems for the Operation of Large Ports as Prosumer Microgrids". In: *IEEE Access* 5 (2017). Conference Name: IEEE Access, pp. 9439–9452. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2017.2706091.

[38] Fotis D. Kanellos, Eleftherios-Stefanis M. Volanis, and Nikos D. Hatziargyriou. "Power Management Method for Large Ports With Multi-Agent Systems". In: *IEEE Transactions on Smart Grid* 10.2 (Mar. 2019). Conference Name: IEEE Transactions on Smart Grid, pp. 1259–1268. ISSN: 1949-3061. DOI: 10.1109/TSG.2017.2762001.

[39] Jeffery Karafa et al. "The berth allocation problem with stochastic vessel handling times". In: *The International Journal of Advanced Manufacturing Technology* 65.1 (Mar. 1, 2013), pp. 473–484. ISSN: 1433-3015. DOI: 10.1007/s00170-012-4186-0. URL: https://doi.org/10.1007/s00170-012-4186-0 (visited on 05/07/2023).

[40] M. Kermani et al. "Optimization of Energy Consumption in STS Group Cranes by Using Hybrid Energy Storage Systems Based on PSO Algorithm". In: *2019 IEEE Industry Applications Society Annual Meeting*. 2019 IEEE Industry Applications Society Annual Meeting. ISSN: 2576-702X. Sept. 2019, pp. 1–5. DOI: 10.1109/IAS.2019.8912455.

[41] M. Kermani et al. "Optimization of Peak Load Shaving in STS Group Cranes Based on PSO Algorithm". In: *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe). June 2018, pp. 1–5. DOI: 10.1109/EEEIC.2018.8494467.

[42] M. Kermani et al. "Power Balancing in STS group Cranes with Flywheel Energy Storage based on DSM Strategy". In: *2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*. 2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON). Nov. 2018, pp. 1–5. DOI: 10.1109/RTUCON.2018.8659876.

[43] Mostafa Kermani et al. "A Comprehensive Technoeconomic Solution for Demand Control in Ports: Energy Storage Systems Integration". In: *IEEE Transactions on Industry Applications* 58.2 (Mar. 2022). Conference Name: IEEE Transactions on Industry Applications, pp. 1592–1601. ISSN: 1939-9367. DOI: 10.1109/TIA.2022.3145769.

[44] Bernard Knueven et al. *A Parallel Hub-and-Spoke System for Large-Scale Scenario-Based Optimization Under Uncertainty – Optimization Online*. Nov. 2, 2020. URL: https://optimization-online.org/2020/11/8088/ (visited on 05/26/2023).

[45] Mitja Kolenc et al. "Virtual power plant architecture using OpenADR 2.0b for dynamic charging of automated guided vehicles". In: *International Journal of Electrical Power & Energy Systems* 104 (Jan. 1, 2019), pp. 370–382. ISSN: 0142-0615. DOI: 10.1016/j.ijepes.2018.07.032. URL: https://www.sciencedirect.com/science/article/pii/S0142061517311560 (visited on 01/05/2023).

[46] Lorenz Kolley et al. "Robust berth scheduling using machine learning for vessel arrival time prediction". In: *Flexible Services and Manufacturing Journal* 35.1 (Mar. 1, 2023), pp. 29–69. ISSN: 1936-6590. DOI: 10.1007/s10696-022-09462-x. URL: https://doi.org/10.1007/s10696-022-09462-x (visited on 03/10/2023).

[47] Benjamin Kroposki. "Integrating high levels of variable renewable energy into electric power systems". In: *Journal of Modern Power Systems and Clean Energy* 5 (2017). DOI: 10.1007/s40565-017-0339-3. URL: https://doi.org/10.1007/s40565-017-0339-3 (visited on 11/15/2022).

[48] Jana Ksciuk et al. "Uncertainty in maritime ship routing and scheduling: A Literature review". In: *European Journal of Operational Research* 308.2 (July 16, 2023), pp. 499–524. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2022.08.006. URL: https://www.sciencedirect.com/science/article/pii/S037722172200649X (visited on 06/22/2023).

[49] Changchun Liu, Xi Xiang, and Li Zheng. "A two-stage robust optimization approach for the berth allocation problem under uncertainty". In: *Flexible Services and Manufacturing Journal* 32.2 (June 1, 2020), pp. 425–452. ISSN: 1936-6590. DOI: 10.1007/s10696-019-09343-w. URL: https://doi.org/10.1007/s10696-019-09343-w (visited on 05/08/2023).

[50] Anjia Mao et al. "Optimal scheduling for seaport integrated energy system considering flexible berth allocation". In: *Applied Energy* 308 (Feb. 15, 2022), p. 118386. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.118386. URL: https://www.sciencedirect.com/science/article/pii/S030626192101624X (visited on 01/05/2023).

[51] Lexuan Meng et al. "Microgrid supervisory controllers and energy management systems: A literature review". In: *Renewable and Sustainable Energy Reviews* 60 (July 1, 2016), pp. 1263–1273. ISSN: 1364-0321. DOI: 10.1016/j.rser.2016.03.003. URL: https://www.sciencedirect.com/science/article/pii/S1364032116002380 (visited on 02/01/2023).

[52] Sarthak Mohanty et al. "Demand side management of electric vehicles in smart grids: A survey on strategies, challenges, modeling, and optimization". In: *Energy Reports* 8 (Nov. 1, 2022), pp. 12466–12490. ISSN: 2352-4847. DOI: 10.1016/j.egyr.2022.09.023. URL: https://www.sciencedirect.com/science/article/pii/S2352484722017462 (visited on 02/01/2023).

[53] Peter Palensky and Dietmar Dietrich. "Demand side management: Demand response, intelligent energy systems, and smart loads". In: *IEEE Transactions on Industrial Informatics* 7.3 (Aug. 2011), pp. 381–388. ISSN: 15513203. DOI: 10.1109/TII.2011.2158841. (Visited on 11/21/2022).

[54] Rui Pei et al. “Robust Multi-Layer Energy Management and Control Methodologies for Reefer Container Park in Port Terminal”. In: *Energies* 14.15 (Jan. 2021). Number: 15 Publisher: Multidisciplinary Digital Publishing Institute, p. 4456. ISSN: 1996-1073. DOI: 10.3390/en14154456. URL: https://www.mdpi.com/1996-1073/14/15/4456 (visited on 01/12/2023).

[55] Yue Pu et al. “Optimal Operation Strategy of Port Integrated Energy System Considering Demand Response”. In: *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)*. 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2). Oct. 2020, pp. 518–523. DOI: 10.1109/EI250167.2020.9346904.

[56] Line A. Roald et al. “Power systems optimization under uncertainty: A review of methods and applications”. In: *Electric Power Systems Research* 214 (Jan. 2023), p. 108725. ISSN: 03787796. DOI: 10.1016/j.epsr.2022.108725. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378779622007842 (visited on 05/06/2023).

[57] Filipe Rodrigues and Agostinho Agra. “Berth allocation and quay crane assignment/scheduling problem under uncertainty: A survey”. In: *European Journal of Operational Research* 303.2 (Dec. 1, 2022), pp. 501–524. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2021.12.040. URL: https://www.sciencedirect.com/science/article/pii/S0377221721010961 (visited on 12/05/2022).

[58] Anthony Roy et al. “Design, Sizing, and Energy Management of Microgrids in Harbor Areas: A Review”. In: *Energies* 13.20 (Jan. 2020). Number: 20 Publisher: Multidisciplinary Digital Publishing Institute, p. 5314. ISSN: 1996-1073. DOI: 10.3390/en13205314. URL: https://www.mdpi.com/1996-1073/13/20/5314 (visited on 04/17/2023).

[59] Muhammad Sadiq et al. “Future Greener Seaports: A Review of New Infrastructure, Challenges, and Energy Efficiency Measures”. In: *IEEE Access* 9 (2021). Publisher: Institute of Electrical and Electronics Engineers Inc., pp. 75568–75587. ISSN: 21693536. DOI: 10.1109/ACCESS.2021.3081430. (Visited on 11/18/2022).

[60] Tariq Samad, Edward Koch, and Petr Stluka. “Automated Demand Response for Smart Buildings and Microgrids: The State of the Practice and Research Challenges”. In: *Proceedings of the IEEE* 104.4 (Apr. 2016). Conference Name: Proceedings of the IEEE, pp. 726–744. ISSN: 1558-2256. DOI: 10.1109/JPROC.2016.2520639.

[61] J. Schmidt et al. “Demand side integration for electric transport vehicles”. In: *International Journal of Energy Sector Management* 9.4 (2015), pp. 471–495. ISSN: 1750-6220. DOI: 10.1108/IJESM-11-2014-0002.

[62] Johannes Schmidt, Matthias Eisel, and Lutz M. Kolbe. “Assessing the potential of different charging strategies for electric vehicle fleets in closed transport systems”. In: *Energy Policy* 74 (Nov. 1, 2014), pp. 179–189. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2014.08.008. URL: https://www.sciencedirect.com/science/article/pii/S0301421514004613 (visited on 01/05/2023).

[63] Felix Schütze et al. “Integration of Renewable Energies at Maritime Container Terminals”. In: *Dynamics in Logistics*. Ed. by Michael Freitag et al. Lecture Notes in Logistics. Cham: Springer International Publishing, 2022, pp. 156–167. ISBN: 978-3-031-05359-7. DOI: 10.1007/978-3-031-05359-7_13.

[64] Marcelo Eduardo Vieira Segatto et al. “14 - Telecommunication Technologies for Smart Grids: Total Cost Optimization”. In: *Advances in Renewable Energies and Power Technologies*. Ed. by Imene Yahyaoui. Elsevier, Jan. 1, 2018, pp. 451–478. ISBN: 978-0-12-813185-5. DOI: 10.1016/B978-0-12-813185-5.00007-3. URL: https://www.sciencedirect.com/science/article/pii/B9780128131855000073 (visited on 02/01/2023).

[65] C. Silva et al. “Demand response performance and uncertainty: A systematic literature review”. In: *Energy Strategy Reviews* 41 (May 1, 2022), p. 100857. ISSN: 2211-467X. DOI: 10.1016/j.esr.2022.100857. URL: https://www.sciencedirect.com/science/article/pii/S2211467X22000566 (visited on 04/21/2023).

[66] Meng Song. *Planning and Operation of Demand-Side Flexibility*. 2019. ISBN: 978-91-7873-333-0.

[67] Liang Tao et al. "A ROADMAP TOWARDS SMART GRID ENABLED HARBOUR TERMINALS". In: 2014. URL: https://www.semanticscholar.org/paper/A-ROADMAP-TOWARDS-SMART-GRID-ENABLED-HARBOUR-Tao-Guo/e4a30d66ccf1a93562f0a532e9efbc89969aaf80 (visited on 01/31/2023).

[68] Tennet. *Balancing markets*. TenneT. URL: https://www.tennet.eu/markets/market-news/balancing-markets (visited on 04/21/2023).

[69] Tennet. *Dutch Ancillary Services*. TenneT. URL: https://www.tennet.eu/markets/dutch-ancillary-services (visited on 04/21/2023).

[70] Tennet. *Market roles*. TenneT. URL: https://www.tennet.eu/market-roles (visited on 04/21/2023).

[71] Tennet. *Market types*. TenneT. URL: https://www.tennet.eu/market-types (visited on 04/21/2023).

[72] Moslem Uddin et al. "A review on peak load shaving strategies". In: *Renewable and Sustainable Energy Reviews* 82 (Feb. 1, 2018), pp. 3323–3332. ISSN: 1364-0321. DOI: 10.1016/j.rser.2017.10.056. URL: https://www.sciencedirect.com/science/article/pii/S1364032117314272 (visited on 02/01/2023).

[73] R. A. Verzijlbergh. "The Power of Electric Vehicles - Exploring the Value of Flexible Electricity Demand in a Multi-actor Context". In: (2013). Publisher: Next Generation Infrastructures Foundation. URL: https://repository.tudelft.nl/islandora/object/uuid%5C%3A47c8faa7-94de-40fe-8be7-fccec6ee07bb (visited on 05/06/2023).

[74] R.A. Verzijlbergh and Z. Lukszo. "Conceptual model of a cold storage warehouse with PV generation in a smart grid setting". In: *2013 10th IEEE INTERNATIONAL CONFERENCE ON NETWORKING, SENSING AND CONTROL (ICNSC)*. 2013 10th IEEE INTERNATIONAL CONFERENCE ON NETWORKING, SENSING AND CONTROL (ICNSC). Apr. 2013, pp. 889–894. DOI: 10.1109/ICNSC.2013.6548855.

[75] Wenyuan Wang et al. "A two-stage framework for the optimal design of a hybrid renewable energy system for port application". In: *Ocean Engineering* 191 (Nov. 1, 2019), p. 106555. ISSN: 0029-8018. DOI: 10.1016/j.oceaneng.2019.106555. URL: https://www.sciencedirect.com/science/article/pii/S0029801819306894 (visited on 01/10/2023).

[76] G. Wilmsmeier et al. "Energy Consumption and Efficiency: Emerging Challenges from Reefer Trade in South American Container Terminals". In: 2014. URL: https://www.semanticscholar.org/paper/Energy-Consumption-and-Efficiency%5C%3A-Emerging-from-in-Wilmsmeier-Froese/bb57fdbb6c15b6ac38b2dd733ab37629dcf1412d (visited on 02/02/2023).

[77] Jong-Kyun Woo, Daniel S. H. Moon, and Jasmine Siu Lee Lam. "The impact of environmental policy on ports and the associated economic opportunities". In: *Transportation Research Part A: Policy and Practice* 110 (Apr. 1, 2018), pp. 234–242. ISSN: 0965-8564. DOI: 10.1016/j.tra.2017.09.001. URL: https://www.sciencedirect.com/science/article/pii/S0965856417305487 (visited on 02/02/2023).

[78] Xiaoju Zhang et al. "Comparing the Efficiency of Two Types of Yard Layout in Container Terminals". In: *Sustainability* 15.9 (Jan. 2023). Number: 9 Publisher: Multidisciplinary Digital Publishing Institute, p. 7195. ISSN: 2071-1050. DOI: 10.3390/su15097195. URL: https://www.mdpi.com/2071-1050/15/9/7195 (visited on 05/10/2023).

[79] Θεόδωρος Γ Παπούτσογλου and Theodoros G. Papoutsoglou. "A Cold Ironing Study on Modern Ports, Implementation and Benefits Thriving for Worldwide Ports". Accepted: 2012-11-20T10:37:30Z. bachelorThesis. Oct. 1, 2012. DOI: 10.26240/heal.ntua.12134. URL: https://dspace.lib.ntua.gr/xmlui/handle/123456789/6970 (visited on 05/24/2023).

A

Research paper

Graphical Abstract

Optimal energy management and operations planning for a container terminal, with uncertain supply and demand

Jasper Stoter, Xinyu Tang, Milos Cvetkovic, Peter Palensky, Henk Polinder, Frederik Schulte

Highlights

Optimal energy management and operations planning for a container terminal, with uncertain supply and demand

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- Consider the impact of DR on an entire terminal solely in the context of operational flexibility
- Consider uncertainty in both the electricity demand and supply

Optimal energy management and operations planning for a container terminal, with uncertain supply and demand

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Abstract

Amidst the ongoing energy crisis in Europe, escalating energy costs pose a significant impact on operational costs for container terminal operators. This paper investigates the potential of demand response as a viable strategy to reduce energy-related costs. By modifying operational planning, energy consumption could be deferred from peak to off-peak hours, resulting in cost savings. We propose a two-stage stochastic mixed-integer programming model to optimize operations planning, incorporating energy-related costs. Both energy demand and supply uncertainties are accounted for, exploring various scenarios for vessel arrival times and electricity prices. The model was decomposed using a progressive hedging algorithm. Operational aspects considered in this model include vessel arrival scheduling, temperature control of refrigerated containers, and the allocation of handling capacity across quay cranes, yard cranes, and automated guided vehicles. A case study of the Alterwerder container terminal in Hamburg was conducted to test the model. Preliminary results suggest potential cost savings of 5.9 % with a constant electricity price incorporated in the operational planning. This saving increases to 13.2 % when considering varying electricity prices based on wholesale market rates. These findings underscore the substantial potential of demand response strategies in the context of container terminal operations.

Keywords: Demand Response, Container Terminal, Load flexibility, Energy Consumption

1. Introduction

Due to the energy crisis in Europe that began in the summer of 2021, electricity prices have soared. Between 2019 and 2022, the average yearly electricity price has increased from 38 €/MWh to 235 €/MWh, representing an increase of 518 percent (ENTSO-E). This price surge has resulted in higher operational costs for container terminal operators, particularly those with a high level of electrification, who have been significantly impacted by the rising electricity prices. Unfortunately, there is a limited understanding among terminal operators regarding energy consumption patterns (Wilmsmeier et al., 2014).

One effective approach to reduce energy costs is by implementing energy efficiency measures to decrease overall energy consumption. Alternatively, demand response measures can be employed. Demand response (DR) programs aim to shift consumption from high-price periods to lower-price periods. By implementing demand response programs, container terminals can effectively lower energy costs by reducing overall energy consumption and strategically shifting consumption from high-price periods to lower-price periods.

The logistics process within a port are uncertain, leading to complex operational planning and a unpredictable energy demand. Energy consumption fluctuates significantly throughout the day, depending on the scheduling (Bakar et al., 2021). Terminal operators currently possesses limited knowledge about energy consumption patterns (Wilmsmeier et al., 2014) . Unlike other industries, container terminals lack continuous and recurring production cycles (Grundmeier et al., 2014). Instead, daily processes are highly dynamic due to their dependence on the number of containers and ships arriving (Grundmeier et al., 2014). This dynamic nature makes forecasting electricity demand challenging (Grundmeier et al., 2014).

Simultaneously, the supply of electricity is uncertain due to the increasing utilization of variable renewable energy sources, such as solar and wind power. The availability of renewable energy depends on weather conditions, causing significant variability throughout the day. Maintaining a balance between load and generation at all timescales poses technical challenges when integrating uncertain generation from variable renewable energy sources (VRES) into the grid (Kroposki, 2017).

This study aims to investigate the relationship between operational planning and energy consumption. We optimize the planning of operations within a container terminal, considering the associated energy costs. This optimization takes into account the cost of purchasing electricity from the wholesale market and the cost of imbalances resulting from inaccurate consumption predictions. We enhance the planning process by directly incorporating these energy costs into the objective function, using both a constant price throughout the day and varying prices per hour. To address the uncertainty of electricity demand and supply, we consider multiple scenarios of ship arrival times and electricity prices. We examine the impact of this uncertainty by comparing the solutions to deterministic modeling approaches.

This paper contributes to the field in two ways:

1. We quantify the effect of demand flexibility on terminal operations using an existing terminal as a case study.
2. We consider uncertainty in both energy supply and demand.

For our case study, we focus on the HHLA Container Terminal Altenwerder (CTA) in Hamburg, Germany. Altenwerder is a state-of-the-art container terminal with a high degree of electrification. Additionally, CTA is the world's first container handling facility to be certified as climate neutral (HHLA, c).

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 defines the problem and Section 4 gives the mathematical formulation of the problem. Section 5 discusses the methodology. The numerical results and their implications are presented in Section 6. Based on these results, managerial insights are provided in Section 7. Finally, Section 8 presents the conclusions.

2. Related works

Energy consumption in ports has not been widely studied in the literature. In a review paper by Iris and Lam (2019b), an overview is provided on operational strategies, technologies, and energy management systems aimed at increasing energy efficiency in ports. The authors emphasize the need for future research in operational strategies that incorporate energy-aware planning of operations, particularly in integrated planning problems. Additionally, the importance of an energy management system for balancing energy demand with supply is highlighted. However, this task is challenging due to fluctuating energy supply from renewable sources and the difficulty in predicting energy demand resulting from the high operational complexity. Similarly, a review by Bakar et al. (2021) emphasizes the growing significance of energy management in future ports.

A review was conducted on energy-aware planning problems within container terminals, with a focus on demand response for integrated planning problems involving multiple energy loads. Several studies were found that focus on demand response using a single load. In a study by van Duin et al. (2018) demand response of reefers is considered to lower the peak load. Geerlings et al. (2018) and Kermani et al. (2018) investigate strategies to reduce the peak loads of Quay cranes. These two loads account for the majority of peak demand in container terminals. Another intriguing application of demand response is the use of Vehicle-to-Grid (V2G) charging for Automated Guided Vehicles (AGVs) within the terminal. Schmidt et al. (2015) explore various business cases for V2G charging with AGVs, and Harnischmacher et al. (2023) further investigate the use of AGVs for frequency containment reserves. As the trend towards electrification continues within terminals, ships become a significant electric load through on-shore power supply. Yu et al. (2022) perform a multi-objective optimization considering energy-related costs and emissions for berth allocation and quay crane assignment (BACAP) problems. Similarly, He (2016) quantify the impact of energy-aware planning on operational costs by comparing optimization results of energy-saving strategy with a constant electricity price with a time-saving strategy with no electricity related cost. He also quantified the effect that energy-aware planning has on the yard crane and automated guided vehicle scheduling has on the operational cost in (He et al., 2015a) and (He et al., 2015b).

Literature specifically focusing on energy-aware integrated planning problems involving multiple energy loads is scarce. Table 1 provides an overview of the most relevant literature, categorized based on the pricing schemes considered for price-based demand response programs. Table 2 adds all the sources of energy demand and supply considered in these studies.

Kanellos et al. have conducted multiple studies on demand response in container terminals ((Kanellos, 2019); (Kanellos et al., 2019); (Kanellos, 2017); (Gennitsaris and Kanellos, 2019)), developing a multi-agent system where different loads communicate with each other. Mao et al. (2022) focus on loads within an integrated energy system encompassing electricity, heat, and cooling demands, employing mixed-integer programming optimization. Pu et al. (2020) also address an integrated energy system but estimate the

		Uncertainty		Pricing scheme			
Reference	Focus	D	S	NP	CP	TOU	RTP
Gennitsaris and Kanellos (2019)	Demand response					√	
Iris and Lam (2021)	Smart grid		√		√	√	√
Kanellos (2019)	Demand response					√	
Kanellos (2017)	Demand response			√			
Kanellos et al. (2019)	Demand response					√	
Mao et al. (2022)	Integrated energy system				√		√
Pu et al. (2020)	Integrated energy system			√		√	
This paper	Demand response	√	√	√	√		√

Uncertainty: D (Electricity demand), S (Electricity supply)
Pricing scheme: NP (No price), CP (Constant price), TOU (Time-of-use price), RTP (Real-time price)

Table 1: Area of Focus and Pricing Scheme

total amount of fixed, reducible, and shiftable loads. In a study by Iris and Lam (2021), an integrated operations planning and energy management problem is solved using stochastic mixed-integer optimization.

When proposing energy-aware operational planning, authors often stress the importance of considering the stochastic nature of both electricity demand and supply. However, only one study identified in the literature partly utilized a stochastic modeling approach, specifically Iris and Lam (2021), which considered multiple scenarios of solar energy production to account for stochastic electricity supply. In the study of Iris and Lam no uncertainty in the operations, nor the energy demand was considered.

	Demand							Supply				
Reference	SH	QC	YC	AGV	RE	ESS	Other	EG	WT	PV	ESS	Other
Gennitsaris and Kanellos (2019)	√				√			√	√			
Iris and Lam (2021)	√	√	√		√	√		√		√	√	
Kanellos (2019)	√			√	√			√				
Kanellos (2017)				√	√			√	√			
Kanellos et al. (2019)	√			√	√			√				
Mao et al. (2022)	√				√	√	√	√	√	√	√	√
Pu et al. (2020)						√	√	√				√
This paper	√	√	√	√	√			√				

Demand: SH (Ship), QC (Quay crane), YC (Yard crane), AGV (Automated guided vehicle), RE (Reefer), ESS (Energy storage system)
Supply: EG (Electricity grid), WT (Wind turbine), PV (Photovoltaic panel), ESS (Energy storage system)

Table 2: Demand and Supply

3. Problem description

This study builds upon the work of Iris and Lam (2021) and proposes an optimization model to assess the potential of demand response in a container terminal. On the demand side, the energy consumption of vessels, quay cranes (QCs), yard cranes (YCs), reefers, and automated guided vehicles (AGVs) is considered. On the supply side, the energy is purchased from the electricity grid. This study takes into account the uncertainty in both the demand and supply of energy. Different pricing schemes, namely no price, constant price, and real-time price, are considered to quantify the impact that demand response has on the operations in the terminal. Figure 1 provides an overview of the considered loads within the terminal. Various aspects from different operational research problems are included to accurately represent the operations within the terminal. Additionally Figure 1 shows, the energy and information flows between all the loads and the electricity grid are depicted. The information flows are controlled by the terminal operation system, while the electricity flows are coordinated by the energy management system. The terminal operation and energy management systems exchange information to match the operational and electricity aspects.

This problem contains several sources of uncertainty, both in the supply and demand of electricity. Notably, the prices of electricity and the arrival times of ships are the most significant uncertainties when optimizing

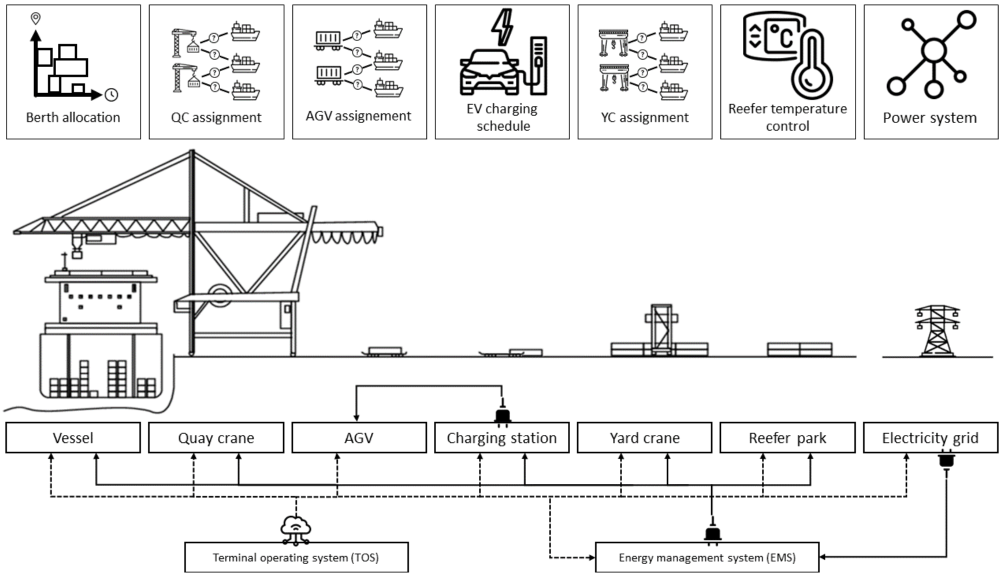


Figure 1: Overview of operational planning problems, energy flows and information flows

a container terminal's operational planning. We use a two-stage optimization problem to take this uncertainty into account. The first stage, known as the "here-and-now" decision, takes place before the values of the uncertain parameters are known. These decisions are taken one day ahead of the when the operations are performed. The second stage, the "wait-and-see" decision, is a response to the realization of these uncertain parameters. These decisions are made in real-time just before performing the operations. In equation 1 the mathematical formulation of a two-stage stochastic optimization with recourse is given. In this equation $\boldsymbol{\xi}$ is the realisation of the uncertain parameters, $\mathbb{E}_P$ is the expected value of all realisations of $\boldsymbol{\xi}$, $\boldsymbol{x}$ are the first stage decision variables and $\boldsymbol{y_\xi}$ the second stage decision variables.

$$
\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{y_\xi}} \quad & f^F(\boldsymbol{x}) + \mathbb{E}_P[f^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi})] && \text{(1a)}\\
\text{s.t.} \quad & \boldsymbol{h}^F(\boldsymbol{x}) = 0, && \text{(1b)}\\
& \boldsymbol{g}^F(\boldsymbol{x}) \geq 0, && \text{(1c)}\\
& \boldsymbol{h}^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi}) = 0, && \text{(1d)}\\
& \boldsymbol{g}^S(\boldsymbol{x},\boldsymbol{y_\xi},\boldsymbol{\xi}) \geq 0 && \text{(1e)}
\end{aligned}
$$

In this model, a time step of one hour is considered. Electricity prices from the day ahead market are obtained every hour. Additionally, the energy demand of different loads is averaged over a hour assuming a constant consumption within the hour.

In the model, N Vessels arrive in the terminal over H hours. For every vessel a start time S and finish time F are decided upon. Each vessel has a specific container demand d of containers that need to be handled between those times. Instead of assigning a ship to a specific berth, like is consumary in berth assignment problems, a simplification is made were a ship is allowed to berth if there is available space on the quay. Once berthed a number of QCs, YCs and AGVs are assigned to the ship for every hour to load and unload the containers. A handling rate p is determined based on the minimum of the assigned handling capacity of QCs, YCs and AGVs.

In the yard, all reefer containers are modelled as one large cold storage tank, with heat transfer to the ambient. Specific bounds are set in between the temperature is allowed to fluctuate. The amount of reefers present in the yard is assumed to be constant.

There are five electric loads considered. The energy consumption of Ships through On-shore power supply. The consumption is present for every hour that a ship is berthed and assumed constant for every hour. The energy consumption of the QCs and YCs which depends on the handling rate. The energy consumption of AGVs happens through the charging of the battery. All AGVs are modelled as one large battery that is deplated based on the handling rate of the AGVs. The reefers consume energy through required for cooling.

For every hour the amount of energy consumed is equal to the amount of energy supplied from the grid. The required energy P is purchased from the day ahead market.

The second stage objective is based on the expected value of all the different scenarios. Different weights are assigned to every scenario based on the likelihood of occurrence. The uncertainty of the arrival times and electricity prices are considered to be independent from each other.

Within this problem the arrival times of vessels and the day-ahead electricity price are considered uncertain. Different scenarios are created to represent this uncertainty, each with their own probability. One day before a baseline schedule is created were the expected start time S_i^{da} for every vessel and the expected energy consumption P_t^{da} for every hour are decided upon. Then for every scenario changes to the baseline schedule are made.

The objective is to minimize the ship lateness cost and energy-related cost. Additionally, deviations from the baseline schedule are minimized by considering rescheduling cost and power imbalance cost.

4. Mathematical model

in this section, a mixed integer linear programming mode is formulated for the problem described above. In tables 3, 4 and 5 an overview is given of all the sets, parameters and decision variables used in the model.

Sets	**Description**
V	Set of vessels to be served, $i \in 1, 2, \ldots, N$, where N is the number of vessels to be served.
T	Set of time periods $t \in 0, 1, \ldots, H-1$, where H is 48 hours.
P_i	Set of possible handling rate p that can be assigned to a ship $i \in V$.
M	Types of machinery present in the terminal $m \in \{QC, YC, AGV\}$.
S	Set of scenarios $w \in S$.

Table 3: Sets

The objective function consists of schedule and energy-related cost. The initial two components of the objective function in Equation 2 serve to minimize the total cost of lateness for all ships ($\sum_{i \in \mathbf{V}} c^{\text{late}} i L i, w$) and the cost associated with deviations from the baseline schedule ($\sum_{i \in \mathbf{V}} c^{\text{resch}} c^{\text{late}} i (S^{\text{late}} i, w + S^{\text{early}} i, w)$). The subsequent two elements aim to minimize the cost connected to energy purchase on the day-ahead market ($\sum t \in \mathbf{T} c^{\text{da}} t, w P^{\text{da}} t$) and the cost associated with power imbalances in both shortage and surplus ($\sum t \in \mathbf{T} c^{\text{da}} t, w (c^{\text{shor}} P^{\text{shor}} t, w - c^{\text{sur}} P^{\text{sur}} t, w)$). These costs are calculated for each scenario and the weighted average of all scenarios is minimized.

$$\min_{\mathbf{V},\mathbf{T}} \sum_{w \in \mathbf{S}} \pi_w \Bigg(\sum_{i \in \mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i \in \mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) + \sum_{t \in \mathbf{T}} c_{t,w}^{\text{da}} P_t^{\text{da}} + \sum_{t \in \mathbf{T}} c_{t,w}^{\text{da}} (c^{\text{shor}} P_{t,w}^{\text{shor}} - c^{\text{sur}} P_{t,w}^{\text{sur}}) \Bigg) \tag{2}$$

Parameters	Description
k_m	Amount of machinery $m \in M$ available .
h_m	Handling rate of machinery m in containers per hour .
d_i	The total demand of containers to be handled (loaded + unloaded) for ship $i \in V$.
$u_{p,m}$	The amount of machinery of type m used in pattern p
$l^{ship}i$	The quay length that ship i takes up.
l^{total}	The total length of the quay.
eat_i	Expected arrival time of vessel $i \in V$.
eft_i	Expected berthing finishing time of vessel $i \in V$.
$a_{i,w}$	Actual arrival time of vessel $i \in V$ in scenario $w \in S$.
e^{ship}	energy consumption of a ship for on shore power for one hour.
$e_m^{machinery}$	Energy consumption of machinery m for operating for one hour
e^{charge}	Energy consumpted by one charger.
$e^{charge,max}$	Maxiumum Energy consumpted by all chargers.
b^{min}	Minimum AGV battery level.
b^{max}	Maximum AGV battery level.
η^{charge}	Charging efficiency.
e^{reefer}	Energy consumption of one reefer connection
$e^{reefer,max}$	Maxiumum energy consumption of all reefer connection
tc^{min}	Minimum reefer temperature.
tc^{max}	Maximum reefer temperature.
η^{reefer}	Cooling efficiency.
ta_t	Ambient temperature at time t
mc^p	Specific heat capacity of a reefer.
u^a	Heat transfer coefficient of a reefer.
c_t^{da}	Day electricity price at time t
c_i^{late}	Penalty cost of exceeding the expected finishing time (EFT) for vessel $i \in V$ for one hour.
$c_i^{reschedule}$	cost of changing the initial schedule by one hour.
c^{sur}	cost of having a surplus of energy.
c^{shor}	cost of having a shortage of energy.
M	A large positive number.
ρ_w	Probability of scenario w occurring

Table 4: Parameters

Decision variables	Description
$S_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing start time of vessel $i \in V$
$S_{i,w} \in \mathbb{Z}^+$	Berthing start time of vessel $i \in V$ in scenario $w \in S$
$S_{i,w}^{early} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives ahead of schedule in scenario $w \in S$
$S_{i,w}^{late} \in \mathbb{Z}^+$	Time the vessel $i \in V$ arrives behind schedule in scenario $w \in S$
$F_i^{DA} \in \mathbb{Z}^+$	Scheduled berthing end time (time when handling ends) of vessel $i \in V$
$F_{i,w} \in \mathbb{Z}^+$	Berthing end time (time when handling ends) of vessel $i \in V$ in scenario $w \in S$
$L_{i,w} \in \mathbb{Z}^+$	Lateness of operations for ship $i \in V$ in scenario $w \in S$
$A_{i,t,w} \in \mathbb{B}$	1 if vessel $i \in V$ is assigned at to a berth in period t in scenario $w \in S$, 0 otherwise
$H_{i,p,t,w} \in \mathbb{B}$	1 if pattern p of quay cranes, yard cranes and agvs is assigned to serve vessel $i \in V$ at time period t in scenario $w \in S$, 0 otherwise
$B_{t,w}^{level} \in \mathbb{R}^+$	Battery level at time t in scenario $w \in S$
$TC_{t,w}^{temp} \in \mathbb{R}$	Reefer temperature at time t in scenario $w \in S$
$E_{t,w}^{charge} \in \mathbb{R}^+$	Energy consumed to charge AGVs at time t in scenario $w \in S$
$E_{t,w}^{reefer} \in \mathbb{R}$	Energy consumed to cool the reefers at time t in scenario $w \in S$
$P_{t,w} \in \mathbb{R}^+$	Power used from the utility grid at time t in scenario $w \in S$
$P_t^{da} \in \mathbb{R}^+$	Power purchased at the day ahead market at time t
$P_t^{sur} \in \mathbb{R}^+$	Power surplus at time t
$P_t^{shor} \in \mathbb{R}^+$	Power shortage at time t
$IM_t^{state} \in \mathbb{B}$	Imbalance state, 1 if there is a surplus and 0 if there is a deficit

Table 5: Decision Variables

The model is subject to the following set of constraints. Constraint 3 ensures the energy consumed by the ships, quay cranes (QCs), yard cranes (YCs), automated guided vehicle (AGV) charging, and reefer cooling, matches the power drawn from the grid.

$$\begin{aligned}&\sum_{i \in V} e_{ship}\ A_{i,t} + \sum_{i \in V} \sum_{p \in P_i} u_{p,'QC'}\ H_{i,p,t}\ e_{'QC'} + \\ &\sum_{i \in V} \sum_{p \in P_i} u_{p,'YC'}\ H_{i,p,t}\ e_{'YC'} + E_t^{reefer} + E_t^{charge} = P_t\end{aligned} \tag{3}$$

Constraints 4 - 12 are associated with the berth assignment of ships and the handling capacity assignment. For example, Constraint 4 guarantees that the start time of vessel operation is either equal to or later than its expected arrival time. Constraint 5 defines the lateness time, which is the time a ship departs after the expected departure time. To ensure that the ships are berthed during every hour between the berthing start time and end time, Constraints 6, 8, and 7 are introduced. Constraint 9 prevents overcrowding of the berth by ensuring that the length of all berthed vessels is shorter than the quay length. A handling rate is assigned to every ship for every hour it is berthed. This is accomplished by Constraints 10 and 11. Constraint 12 guarantees that the machinery capacity is not exceeded for QCs, YCs, and AGVs.

$$S_{i,w} \geq a_{i,w} \qquad \forall i \in V, \forall w \in S \tag{4}$$

$$L_{i,w} \geq F_{i,w} - eft_i \qquad \forall i \in V, \forall w \in S \tag{5}$$

$$\sum_{t \in T} A_{i,t,w} = F_{i,w} - S_{i,w} \qquad \forall i \in V, \forall w \in S \tag{6}$$

$$(t+1)A_{i,t,w} \leq F_{i,w} \qquad \forall i \in V, t \in T, \forall w \in S \tag{7}$$

$$tA_{i,t,w} + t_{max}(1 - A_{i,t,w}) \geq S_i \qquad \forall i \in V, t \in T, \forall w \in S \tag{8}$$

$$\sum_{i \in V} A_{i,t,w} l_i^{ship} \leq l_{total} \qquad \forall t \in T, \forall w \in S \tag{9}$$

$$\sum_{p \in \Pi_i} H_{i,p,t,w} = A_{i,t,w} \qquad \forall i \in V, t \in T, \forall w \in S \tag{10}$$

$$\sum_{p \in \Pi_i} pH_{i,p,t,w} \geq d_i \qquad \forall i \in V, t \in T, \forall w \in S \tag{11}$$

$$\sum_{i \in V} \sum_{p \in P_i} u_{p,m} H_{i,p,t,w} \leq k_m \qquad \forall t \in T, m \in M, \forall w \in S \tag{12}$$

A day-ahead schedule is formulated for both the arrivals of the ships and power consumption. Constraint 13 establishes the day-ahead start time of the ships, which remains consistent across all scenarios. The difference between the start time and day-ahead start time is equivalent to the deviation of start time. Similarly, Constraint 16 defines this for the day-ahead energy consumption. It is impossible to have a surplus and a deficit in energy consumption simultaneously. A binary variable IM^state_t is used to keep track of whether there is a surplus or shortage, with Constraints 14 and 15 capturing this dynamic.

$$S^{late}i, w - S^{early}i, w = S_i, w - S_i^{da} \qquad \forall i \in V, \forall w \in S \tag{13}$$

$$P^{shor}t, w - P^{sur}t, w = P_t, w - P_t^{da} \qquad \forall t \in T, \forall w \in S \tag{14}$$

$$P^{sur}t, w \leq M \cdot IM^{state}t, w \qquad \forall t \in T, \forall w \in S \tag{15}$$

$$P^{shor}t, w \leq M \cdot (1 - IM^{state}t, w) \qquad \forall t \in T, \forall w \in S \tag{16}$$

Constraint 17 - **??** concern the operation of AGVs and regulate their charging and discharging procedures. The total power used to charge the AGVs is constraint based on the number of charging stations and the number of AGVs available for charging. These restrictions are described by Constraints 17 and 18. Constraint 19 ensures that the battery level always remains within the minimum and maximum allowed levels. The state of battery charge should fluctuate based on the amount of energy charged and discharged. This principle is captured by Constraints 20 and 21 for time periods 1 to H and for time period zero respectively. Constraint 22 asserts that the battery level at the start of the day should be equivalent to the level at the end of the day, thereby preventing overcharging. It also ensures that over one day, the amount of energy consumed equals the energy charged. To prevent the complete discharge of the battery, the energy consumed in every time period should be less than the energy stored in the battery. This principle is enforced by Constraints **??** and **??** for each time period.

$$E_{t,w}^{charge} \leq e^{charge,max} \qquad \forall t \in T, \forall w \in S \tag{17}$$

$$\begin{aligned} & E_{t,w}^{charge} \leq (k_m - \sum_{i \in V} \sum_{p \in P_i} u_{i,p,m} \cdot H_{i,p,t}) \cdot e_{charge} \\ & m = \{AGV\},\ \forall t \in T,\ \forall w \in S \end{aligned} \tag{18}$$

$$b^{min} \leq B_{t,w} \leq b^{max} \qquad \forall t \in T,\ \forall w \in S \tag{19}$$

$$\begin{aligned} & B_{t,w} = B_{t-1,w} + \eta_{charge} \cdot E_{t,w}^{charge} - \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m,w} \cdot H_{i,p,t,w} \\ & m = \{AGV\},\ \forall t \in T,\ \forall w \in S \end{aligned} \tag{20}$$

$$\begin{aligned} & B_{t,w} = b_{min} + \eta_{charge} \cdot E_{t,w}^{charge} - \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m,t} \cdot H_{i,p,t,w} \\ & m = \{AGV\},\ t = \{0\},\ \forall w \in S \end{aligned} \tag{21}$$

$$\begin{aligned} & \sum_{t \in T} \eta^{charge} \cdot E_{t,w}^{charge} = \sum_{t \in T} \sum_{i \in V} \sum_{p \in P_i} e_m \cdot u_{i,p,m} \cdot H_{i,p,t,w} \\ & m = \{AGV\},\ \forall w \in S \end{aligned} \tag{22}$$

The following five constraints ensure the proper operation of the reefers. The temperature of the reefers, represented by TC_t, should always be within the minimum and maximum temperature levels to ensure the quality of the stored goods, as indicated by Constraint 23. The energy consumed by the reefers at any time should not exceed the rated power of all the reefer connections, as dictated by Constraint 24. The reefers lose heat to the environment through convection. This heat loss depends on the temperature difference between the container and the environment, both of which are assumed to be constant for every hour. Constraint 25 is the cooling balance constraint, which stipulates that the temperature change of the reefer container depends on the heat loss and the cooling energy supplied. Constraint 27 is the reefer energy constraint, which ensures that the total energy lost through heat transfer equals the total energy consumed by cooling.

$$tc^{min} \leq TC_{t,w} \leq tc^{max} \qquad \forall t \in T, \forall w \in S \tag{23}$$

$$E^{reefer}_{t,w} \leq e^{reefer,max} \qquad \forall t \in T, \forall w \in S \tag{24}$$

$$\begin{aligned} & mc_p \cdot (TC_{t,w} - TC_{t-1,w}) = ua \cdot (ta - (tc^{min} + tc^{max})/2) - \\ & \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad \forall t \in T, \forall w \in S \end{aligned} \tag{25}$$

$$\begin{aligned} & mc_p \cdot (TC_{t,w} - tc_{max}) = ua \cdot (ta - (tc^{min} + tc^{max})/2) - \\ & \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad t = \{0\}, \forall w \in S \end{aligned} \tag{26}$$

$$\sum_{t \in T} ua \cdot (ta - (tc^{min} + tc^{max})/2) = \sum_{t \in T} \eta_{reefer} \cdot E^{reefer}_{t,w} \qquad \forall w \in S \tag{27}$$

These constraints together manage the energy consumption of ships, quay cranes, yard cranes, automated guided vehicles, and reefer containers, while adhering to the constraints based on the operational planning.

5. Solution procedure

In this section it is explained how the solutions are obtained. First the stochastic decomposition method, progressive hedging is explained. Second it is explained how the scenarios can be obtained.

5.1. Stochastic decomposition with Progressive Hedging

Optimization problems under uncertainty are notoriously complex to solve, both in theory and practice. A practical method to tackle these problems involves the use of decomposition strategies in stochastic programming models. This process breaks down the overarching issue into manageable subproblems, simplifying the overall optimization process and reducing computational complexity. Efficient and effective solutions to optimization problems under uncertainty are thus feasible, thanks to these strategies, which accommodate a spectrum of potential outcomes.

To handle this complexity efficiently, we chose to implement the progressive hedging algorithm, a notable decomposition method. This algorithm splits the problem into smaller subproblems, each representing a different scenario. In the Algorithm 1 the pseudo-code of the algorithm is given.

Algorithm 1 Progressive Hedging

1: **Initialization**: Let $\nu \leftarrow 0$ and $w^{(t,\nu)}(\xi) \leftarrow 0, \forall \xi \in \Xi, t = 1, \ldots, T$. Compute for each $\xi \in \Xi$:

$$x^{(\nu+1)}(\xi) \in \arg\min_{x} f_1(x_1) + \sum_{t=2}^{T} f_t\left(x^t; \overrightarrow{x}^{t-1}(\xi), \overrightarrow{\xi}^{t}\right)$$

2: **Iteration Update**: $\nu \leftarrow \nu + 1$

3: **Aggregation**: Compute for each $t = 1, \ldots, T-1$ and each $\mathcal{D} \in \mathcal{G}_t$:

$$\bar{x}^{(\nu)}(\mathcal{D}) \leftarrow \sum_{\xi \in \mathcal{D}^{-1}} \pi_\xi x^{(t,\nu)}(\xi) \ / \sum_{\xi \in \mathcal{D}^{-1}} \pi_\xi$$

4: **Price Update**: Compute for each $t = 1, \ldots, T-1$ and each $\xi \in \Xi$:

$$w^{(t,\nu)}(\xi) \leftarrow w^{(t,\nu-1)}(\xi) + \rho\left[x^{(t,\nu)}(\xi)) - \bar{x}^{(\nu)}(\mathcal{G}_t(\xi))\right]$$

5: **Decomposition**: Compute for each $\xi \in \Xi$:

$$x^{(\nu+1)}(\xi) \in \arg\min_{x} f_1(x^1) + \sum_{t=2}^{T} f_t\left(x^t; \overrightarrow{x}^{t-1}(\xi), \overrightarrow{\xi}^{t}\right) + \sum_{t=1}^{T-1}\left[w^{(t,\nu)}(\xi)^T \cdot x^t + \rho \cdot \frac{1}{2}\|x^t - \bar{x}^{(\nu)}(\mathcal{G}_t(\xi))\|^2\right]$$

6: **Termination**: If a criterion is met, Stop. Otherwise, go to step 2.

5.2. Scenario generation

In stochastic programming for electricity prices and ship arrival times, generating and reducing scenarios accurately is crucial. For efficiency and accuracy, a balance between sample size and complexity is sought, with a preference for the least number of samples (Roald et al., 2023).

For ship arrival times, a quasi-random sampling technique, specifically Halton sampling, was utilized, to get distinct scenarios. The arrival distribution was obtained from a paper by Kolley et al. (2023). This method promotes uniform distribution and distinct scenarios, leading to more accurate optimization results. The arrival times were rounded to the nearest hour, with corresponding probabilities for each hour.

In terms of electricity price scenarios, an approach similar to the Crespo-Vazquez et al. (2018) clustering - frequentist method was used . Using historical data from the German day-ahead market, a k-means clustering algorithm was implemented to group days with similar prices. The median day represented each cluster, with cluster weights derived from normalizing the number of days in each cluster.

Upon obtaining the individual scenarios for both the arrival times and electricity prices, the total set of scenarios was generated using the Cartesian product of the two sets. The associated probability for each scenario was the product of the probabilities of arrival time and electricity prices. This method led to a reduced, yet accurate representation of uncertainty and lesser computational times for the optimization model.

6. Experimental Study

In this section the results obtained from the optimization experiments are presented. The computations were all conducted using the commercially available solver Gurobi v10.0.1, in combination with the Pyomo modeling language. For the stochastic decomposition, the mpi-sppy package was utilized (Knueven et al., 2020). The optimization model was run on an Intel i7-7700HQ processor with a 2.80 GHz clock speed and 8.00 GB of RAM.

All optimizations were solved using the progressive hedging algorithm. Ten iterations and a penalty parameter of 8000 were employed for each scenario's solution to converge. A convergence threshold of 0.01 was set. For most of the experiments the convergence was lower 0.01, however not in every experiment the threshold was reached within 10 iterations. In all case the convergence metric was lower than 0.05. For all models, a mixed-integer programming optimality gap of 5 percent was used. The solve time for each individual scenario was limited to 300 seconds.

To find what potential for demand response is present a case study of the HHLA Container Terminal Altenwerder (CTA) in Hamburg. Altenwerder is a state-of-the-art container terminal with a high degree of automation. Additionally, it is operating climate neutral. Due to these reasons this terminal was selected for a case study.

6.1. Model parameters

In this section, the parameters used in the study are presented. A sailing list from the CTA revealed that between April 10, 2023, and May 7, 2023, 190 ships arrived at the CTA terminal, averaging 7 per day (HHLA, b). The terminal utilizes 14 quay cranes (QCs), 74 battery electric automated guided vehicles (AGVs), and 52 yard cranes (YCs) for container handling (HHLA, a). Containers are delivered and dispatched via ship, truck, or train. No onshore power facilities are currently present at the CTA terminal. The length of the quay at CTA was found to be 1400 meters (HHLA, a). Based on the container layout, it is estimated that the AGVs travel an average distance of 947 meters in 237 seconds to move a container (Zhang et al., 2023). Currently, there are 18 charging stations with a combined capacity of 4 MW for these AGVs (HHLA, c).

The energy consumption for QCs and YCs to move one container is estimated to be 8 kWh and 2 kWh, respectively (He, 2016; He et al., 2015a). Additionally, the handling speed of both QCs and YCs is set to 30 containers per hour (He, 2016; He et al., 2015a). The average energy consumption of AGVs per meter is 0.00935 kW/m (He et al., 2015b). By multiplying the energy consumption per meter with the average travel distance, the energy consumption for AGVs is estimated to be 9 kW per container move. Furthermore, based on the travel time, the handling rate for the AGVs is calculated to be 15 containers per hour.

Three types of ships are assumed to arrive at the container terminal: feeder, medium, and jumbo ships. Following the work of Iris and Lam, it is assumed that 40 percent of ships are feeders, 40 percent are medium-sized, and 20 percent are jumbo ships (Iris and Lam, 2021). The ship lengths are distributed uniformly in the ranges [70, 200] for feeders, [210, 300] for medium ships, and [300, 400] for jumbo ships (Iris and Lam, 2019a). The container demand is also assumed to be uniformly distributed in the ranges [200, 600] for feeders, [600, 1600] for medium ships, and [1600, 4500] for jumbo ships (Iris and Lam, 2021). Based on the number of QCs, YCs, and AGVs assigned to fulfill the demand, the ship unloading rate varies. The handling rate is defined as the minimum of the handling speed multiplied by the number of QCs, YCs, and AGVs assigned. For feeders, the handling rate can be one of 30, 45, 60, for medium ships 60, 75, 90, 105, 120, and for jumbo ships 120, 135, 150, 165, 180.

The estimated time of arrival for each ship is distributed uniformly in the range [0, 24], and it is different for every ship. The standard deviation of the estimated time of arrival is 3 hours, 24 hours prior to arrival (Kolley et al., 2023). The estimated time of finishing is calculated by dividing the container demand by the minimum handling rate and adding the estimated time of arrival. If a ship departs later than the estimated finishing time, a penalty is applied. This penalty is obtained by converting the penalty stated by Iris and Lam to euros, assuming an exchange rate of 0.63 euro/SDG, resulting in penalties of 630 euros, 1260 euros, and 1890 euros for feeder, medium, and jumbo ships, respectively Iris and Lam (2021). Additionally, a penalty of 20 percent of the late penalty is assumed with regards to changing the berthing schedule created on the previous day, similar to the approach used by Liu et al. Liu et al. (2020).

For the energy consumption of reefer containers, it is assumed that all reefers are of the same type. According to a breakdown by van Duin et al. (2018), frozen reefer containers are the most common type (van Duin et al., 2018). The temperature range allowed for frozen products like meat and fish is between -20 and -16 degrees Celsius (van Duin et al., 2018). The mass, specific heat, heat transfer coefficient, and area of a reefer container are based on the average values for a 40ft container from Kanellos and are 24500 kg, 2.76 kJ/kg K, 0.4 W/m^2 K, and 135.26 m^2, respectively Kanellos (2017). A cooling efficiency of 0.95 is used, similar to Kanellos Kanellos (2017). The maximum cooling power is also obtained from Kanellos. At the CTA terminal, there are 2200 reefer connections, of which it is assumed that an average of 1500 are used simultaneously HHLA (a).

According to the HHLA website, it takes 1.5 hours to charge one AGV HHLA (2022). Based on the charging rate and the number of AGVs, it can be calculated that all AGVs together can store 24.7 MWh of electricity. A charging efficiency of 90 percent, similar to Kanellos, is assumed Kanellos (2017).

Historical electricity prices from the day-ahead market in Germany were obtained from the ENTSO-E (n.d.) website. A penalty of 20 percent of the day-ahead price was assumed for having an energy surplus or shortage, following the approach of Crespo-Vazquez et al. (2018). The maximum allowed imbalance was set to 10 MW.

6.2. The impact of stochastic modeling

In this study a two-stage stochastic problem has been formulated in equation 1. For this uncertainty in the arrival times of ships and electricity prices are considered. To find the impact that stochastic modeling has on the results, a comparison is made between the stochastic problem (SP) and several reactive approaches. For these reactive approach the first stage variables of the stochastic problem are fixed to some specific values. In the problem described in Section 3 the first stage variables are the start time of operations, S_i^{da}, and the energy purchased on the day-ahead market, P_t^{da} . Three reactive approaches are formulated, RE, RE+ and EEV. For the RE and RE+ approach S_i^{da} is set to the estimated arrival time eat_i, and P_t^{da} is set to 0 and the average daily consumption $\bar{P}^{da}$ for the RE and RE+ approach respectively. For the expectation of the expected value problem (EEV) S_i^{da} and P_t^{da} are set to the solutions that can be obtained by solving the expected value problem. The mathematical formulation of the reactive approach is given in equation 28

$$\min_{\boldsymbol{x_0},\boldsymbol{y_\xi}} \quad f^F(\boldsymbol{x_0}) + \mathbb{E}_P[f^S(\boldsymbol{x_0}, \boldsymbol{y_\xi}, \boldsymbol{\xi})] \tag{28a}$$

$$\text{where} \quad \boldsymbol{x_0} : \text{fixed} \tag{28b}$$

For comparison the results of the stochastic model can be compared with the wait-and-see solution (WS). This solution gives a lower bound to the problem in case a perfect forecast of the first stage decision variables is known. the wait and see solution is however not achievable in practice, since no perfect forecast exists.

In Table 6 the total cost for the RE, RE+, EEV, SP and WS approaches is given. The optimization was done ten different times for each appraoch, using different random seeds. For every approach the cost reduction with regards to the RE approach is calculated. By employing the EEV strategy, a cost reduction of 16.6 percent can be achieved. The stochastic problem presented in this paper further increases the cost reduction to 20.6 percent. The hypothetical maximum reduction achievable is 32.4 percent.

#	RE	RE+	EEV	SP	WS
	Total cost [€]	Total cost [€]	Total cost [€]	Total cost [€]	Total cost [€]
1	62863.8	58775.9	53217.3	50138.7	38999.6
2	62074.0	57967.5	53056.8	47049.1	42296.7
3	69925.5	63784.6	59770.4	57459.1	47054.6
4	53117.1	51103.7	40004.2	39828.8	35364.0
5	81891.7	74881.7	67645.8	62538.3	52268.0
6	67430.5	61454.6	53747.0	52804.4	48830.5
7	75826.3	69324.2	62984.9	61154.2	49513.6
8	48113.5	45913.3	41666.9	39914.3	37006.6
9	71876.7	65269.8	56203.4	54556.0	48370.4
10	59377.4	55685.1	55818.4	52716.3	41260.9
Avg	**65249.7**	**60416.1**	**54411.5**	**51815.9**	**44096.5**
Gap (%)	**0.0**	**-7.4**	**-16.6**	**-20.6**	**-32.4**

Note: RE (Reactive problem), EEV (Excpectation of the expected value problem), SP (Stochastic problem), WS (Wait-and-see problem), gap (%) = $(x - Avg_{RE}) * 100/Avg_{RE}$

Table 6: Influence of stochastics modelling

Based on the differences between the EEV and SP solutions, the Value of the Stochastic Solution (VSS) is calculated using Equation 29. Similarly, the Expected Value of Perfect Information (EVPI) is computed using Equation 30, which represents the difference between the SP and WS solutions.

$$VSS = EEV - SP = 54992.1 - 53185.9 = 1806.2 \tag{29}$$

$$EVPI = SP - WS = 53185.9 - 44096.5 = 9089.4 \tag{30}$$

6.3. The impact of demand response

To assess the impact of demand response on the solution, different electricity pricing schemes are considered: No Price (NP), Constant Price (CP), and Real-Time Price (RTP) cases.

In the NP case, all energy-related costs in the objective function are disregarded. The objective function is simplified by removing the energy cost terms, resulting in equation 31.

$$\min_{\mathbf{V},\mathbf{T}} \sum_{w\in\mathbf{S}} \pi_w \left(\sum_{i\in\mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i\in\mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) \right) \tag{31}$$

In the CP case, the electricity price $c^d a_{t,w}$ in the objective function is replaced with a constant price $\bar{c}^d a_w$ for each hour. The objective function is modified accordingly, resulting in equation 32.

$$\begin{aligned} \min_{\mathbf{V},\mathbf{T}} \sum_{w\in\mathbf{S}} \pi_w \Bigg(& \sum_{i\in\mathbf{V}} c_i^{\text{late}} L_{i,w} + \sum_{i\in\mathbf{V}} c^{\text{resch}} c_i^{\text{late}} (S_{i,w}^{\text{late}} + S_{i,w}^{\text{early}}) + \\ & \sum_{t\in\mathbf{T}} \bar{c}_w^{\text{da}} P_t^{\text{da}} + \sum_{t\in\mathbf{T}} \bar{c}_w^{\text{da}} (c^{\text{shor}} P_{t,w}^{\text{shor}} - c^{\text{sur}} P_{t,w}^{\text{sur}}) \Bigg) \end{aligned} \tag{32}$$

The mathematical formulation presented in Section 3 remains the same for the RTP case. However, for the CP and NP cases, minor adjustments need to be made. Specifically, Constraint 22 and Constraint 24 are replaced with Constraint 33 and Constraint 34, respectively. These changes ensure that the energy consumed by operations, such as charging and cooling, matches the energy demand for each time period without considering different prices. Constraints 33 and 34 prevent unnecessary rescheduling of charging and cooling times that would occur under the assumption of a constant or no price.

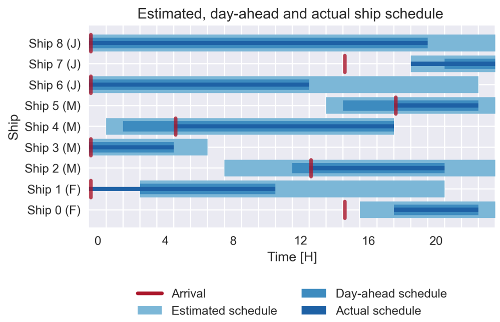
$$\begin{aligned} & \eta^{charge} \cdot E^{charge} t, w = \sum i \in V \sum_{p\in P_i} e_m \cdot u_{i,p,m} \cdot H_{i,p,t,w} \\ & m = AGV, \ \forall t \in T, \ \forall w \in S \end{aligned} \tag{33}$$

$$ua \cdot (ta - (tc^{min} + tc^{max})/2) = \eta_{reefer} \cdot E_{t,w}^{reefer} \qquad \forall t \in T, \ \forall w \in S \tag{34}$$

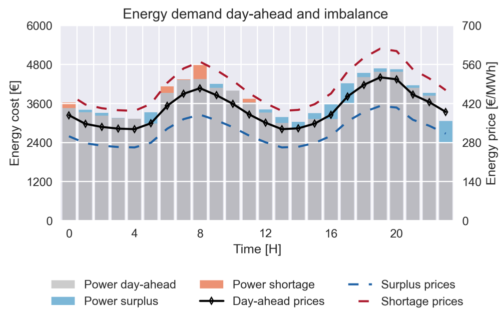
By enforcing these constraints, unnecessary rescheduling of charging and cooling times is avoided, as the timing of consumption becomes irrelevant in the CP and NP cases.

Ten optimizations were performed for all three pricing schemes. For the optimization electricity prices of Germany in 2022 were used.

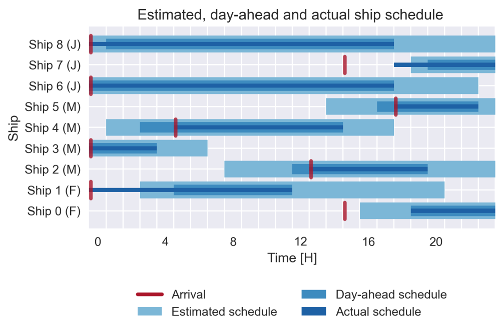
Figure 2 illustrates the ship schedule and energy consumption for the second instance in the fourth scenario. By plotting the ship schedule and



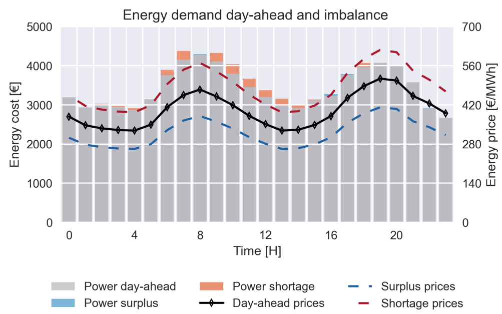
(a) Ship schedule - No price



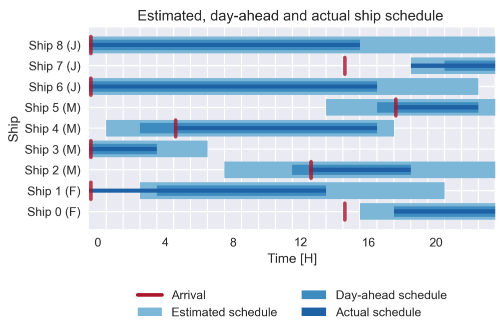
(b) Energy demand - No price



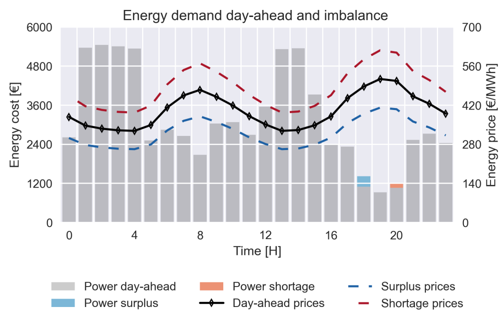
(c) Ship schedule - Constant price



(d) Energy demand - Constant price



(e) Ship schedule - Real-time price



(f) Energy demand - Real-time price

Figure 2: Ship schedule and hourly energy consumption for different pricing strategies

energy consumption, a visual comparison can be made between the different pricing strategies, including the decisions made in the first stage and how they changed in the second.

For the NP alternative, power imbalances can be observed for most hours, resulting in higher energy costs. When the cost of electricity is taken into account in the CP alternative, these imbalances are significantly reduced, leading to lower energy costs. Once real-time prices are considered in the optimization (RTP scenario), the energy consumption pattern also changes, with reduced consumption during times of high prices. Some differences in the berthing schedule can be observed between the different alternatives, although they are minor. Most of the differences are noticeable between the RTP scenario and the other two scenarios. For example, in the RTP scenario, Ship 1 departs later to take advantage of lower prices in the afternoon, while Ship 9 departs earlier to finish just before the evening peak price.

Table 7 presents the results of different pricing strategies, including No Price, Constant Price, and Real-Time Price. The costs are divided into energy-related costs and schedule-related costs. By considering a constant price or a real-time price of electricity, the energy-related costs decrease by 6.4 percent and 14.4 percent, respectively. It appears that scheduling costs also slightly decrease. However, the absolute difference in scheduling costs between the no price and real-time price is small, at 400 euros. No definitive conclusions can be drawn regarding the impact of energy-aware optimization on scheduling costs. However, it can be concluded that it will not have a significant impact. By considering energy prices, the total operational cost of the terminal is reduced by 5.9 percent and 13.2 percent for the constant and real-time pricing schemes, respectively.

Figure 3 displays the average energy demand across all instances for the NP and RTP schemes. A negative correlation between energy demand and electricity price is observed in the real-time case. The average demand increases at night and in the early afternoon when prices are lowest. To quantify this correlation, the Pearson correlation coefficient is calculated between energy demand and electricity price. The average Pearson coefficient for NP, CP, and RTP was calculated. For the NP and CP pricing schemes a correlation of 0.09 and 0.03 was found, so no correlation exists between price and demand. However, when RTP is considered, the Pearson correlation coefficient becomes -0.85, indicating a strong negative correlation.

Furthermore, increased volatility in electricity demand for RTP can be

#	No price EC [€]	SC [€]	TC [€]	Constant price EC [€]	SC [€]	TC [€]	Real-time price EC [€]	SC [€]	TC [€]
1	44628.1	13482.0	58110.1	43325.8	13692.0	57017.8	38798.7	11340.0	50138.7
2	49746.6	6804.0	56550.6	47013.8	6602.4	53616.2	42317.8	4731.2	47049.1
3	53979.6	11390.4	65370.0	50921.5	10735.2	61656.7	47429.5	10029.6	57459.1
4	45266.7	3931.2	49197.9	39856.1	4989.6	44845.7	35544.8	4284.0	39828.8
5	57095.3	11793.6	68888.9	55677.2	11844.0	67521.2	52357.5	10180.8	62538.3
6	55265.5	3376.8	58642.3	52559.4	4737.6	57297.0	48559.9	4244.5	52804.4
7	55561.2	10533.6	66094.8	52899.1	9626.4	62525.5	48999.4	12154.8	61154.2
8	46231.0	4284.0	50515.0	40303.2	3780.0	44083.2	35991.5	3922.8	39914.3
9	54584.0	8618.4	63202.4	51742.4	6442.8	58185.2	47626.0	6930.0	54556.0
10	50439.0	9651.6	60090.6	45624.5	8794.8	54419.3	41401.5	11314.8	52716.3
Avg	**51279.7**	**8386.6**	**59666.3**	**47992.3**	**8124.5**	**56116.8**	**43902.6**	**7913.3**	**51815.9**
Gap (%)	**0.0**	**0.0**	**0.0**	**-6.4**	**-3.1**	**-5.9**	**-14.4**	**-5.6**	**-13.2**

Note: EC (Energy cost), SC (Schedule cost), TC (Total cost), gap (%) = $(x - Avg_{NP}) * 100/Avg_{NP}$

Table 7: Comparison of different pricing strategies with 2022 prices

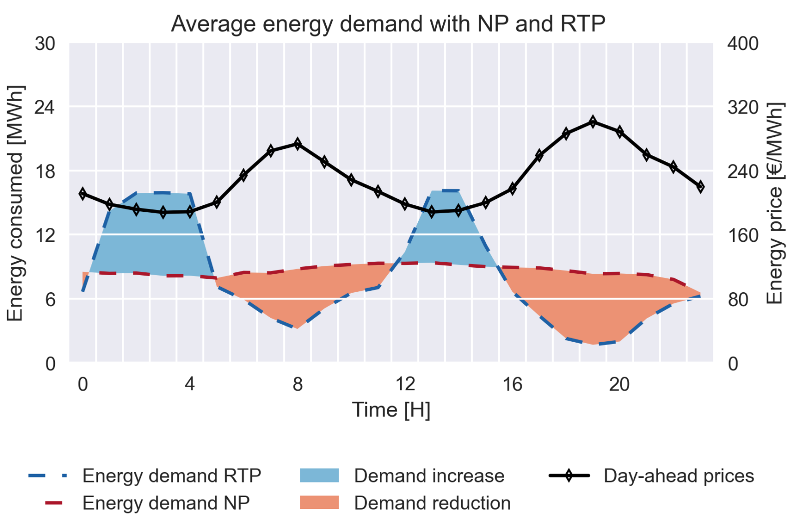


Figure 3: Average energy demand with No pricing and Real-time pricing

observed in Figure 3. The Peak-to-Average Ratio (PAR) calculated for all different pricing schemes. The NP and CP schemes have PAR values of 1.17 and 1.19, respectively. In contrast, the RTP scheme exhibits a significantly higher PAR of 2.05. This shows that in Case of RTP the consumption is more concentrated.

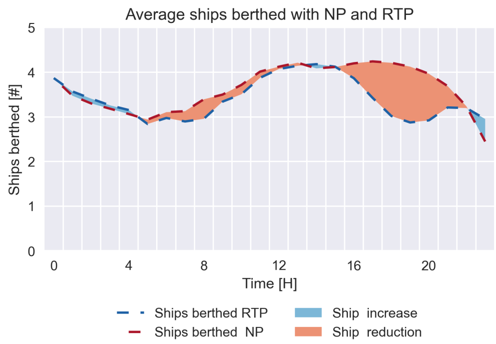
Similarly to the energy demand, other decision variables can be compared between different pricing schemes. Figure 4 illustrates the number of berthed ships, the handling rate of ship loading/unloading, the rate of AGV charging, and the rate of reefer cooling. Each of these variables responds to price signals, with a higher difference between NP and RTP indicating a greater responsiveness to price changes. To compare the sensitivity of each variable to price changes, the standard deviation of the difference between the NP and RTP schemes is computed. Each standard deviation is then normalized by dividing it by the mean. The Flexibility Coefficient (FC), calculated using Equation 35, quantifies the degree of flexibility for each variable (X). When comparing the flexibility coefficient for the variables above it can be observed that the cooling rate is the most flexible, with a normalised standard deviation of 1.48. This implies that the rate at which reefers are cooled can be adjusted more readily in response to price changes. Following this, the AGV charging rate also demonstrates notable flexibility. The handling rate and the number of ships berthed exhibit relatively lower levels of flexibility compared to the other variables, and other therefore more constraint by the operational planning.

$$\text{FC} = \frac{\sigma(X_{NP} - X_{RTP})}{\bar{X}_{NP}} \tag{35}$$

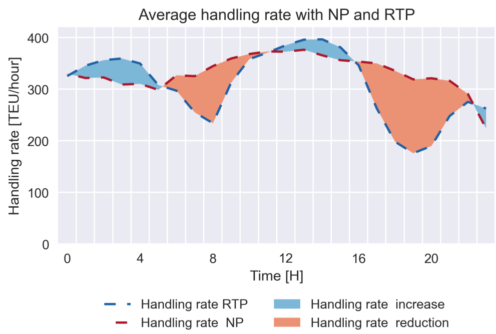
7. Managerial Insights

The research conducted in this thesis provides valuable managerial insights for the operations and management of container terminals. By considering the implications energy-aware optimization of the operations , the following key insights emerge:

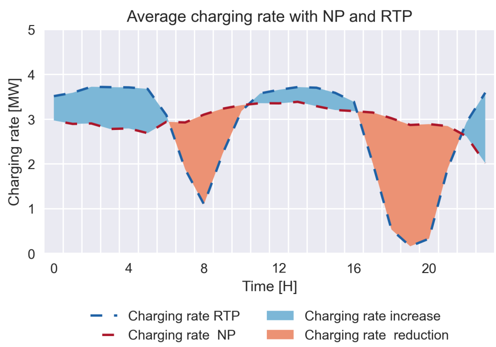
- Properly accounting for uncertainty in the demand and supply of energy is crucial when optimizing energy consumption and operational planning in container terminals. Failing to consider this uncertainty



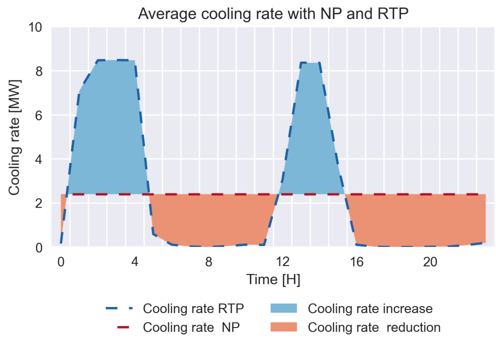
(a) Average amount of ships berthed



(b) Average handling rate



(c) Average charging rate



(d) Average cooling rate

Figure 4: Comparison No pricing and Real-time pricing for different variables

can result in up to 20 percent higher costs, on average, due to the need for subsequent operational plan changes.

- Implementing an energy-aware optimization approach based on hourly varying electricity prices can lead to significant cost reductions in container terminals, with potential savings ranging from 13.2 percent of the operational costs.

- There is no significant trade-off between energy-related costs and scheduling costs. The inclusion of energy-related costs has minimal to no impact on the scheduling costs. Instead, the optimization focuses on minimizing energy consumption within the existing constraints imposed by the terminal's logistical operations.

- By considering real-time prices the peak energy demand increases. This study fails to accurately incorporate what effect this will have on the peak-related electricity cost.

- The control of reefer energy consumption has the most potential to alter the overall energy consumption pattern, followed by adjusting the charging times of Automated Guided Vehicles (AGVs). Modifying the handling rate of ship (un)loading and adjusting ship arrival and departure times have some potential to influence energy consumption throughout the day, although their impact is smaller compared to reefers and AGVs.

- Efficient control of existing loads can significantly reduce energy-related costs without necessitating substantial investments in storage or renewable energy infrastructure.

These insights highlight the potential for cost savings and operational improvements by considering electricity demand and implementing efficient control measures. By adopting these insights, container terminals can optimize their operations, reduce energy-related expenses, and make informed decisions that align with their sustainability goals.

8. Conclusions

This paper presents an integrated energy-aware optimization approach for the operations of a container terminal, with a specific focus on identifying the existing flexibility within an operational terminal. A case study was conducted at the HHLA Container Terminal Alternwerder to examine the practical implications. The optimization process considered uncertainty in ship arrival times and electricity prices to evaluate their impact on the results. Various pricing strategies were analyzed to assess the potential benefits of demand response.

Future research endeavors should aim to enhance the current model in several aspects. These include refining the modeling of peak power for individual loads, conducting a more detailed analysis of reefer energy consumption. Additionally, exploring energy price-aware optimization for common operational challenges in container terminals could unveil additional opportunities for cost savings and efficiency improvements. To better understand the practical implications of demand response, simulations of the operation can be conducted in which energy consumption is taken into account. Ultimately, this research underscores the crucial role of energy-conscious operational planning in reducing operational costs and enhancing performance within container terminals.

References

Bakar, N.N.A., Guerrero, J.M., Vasquez, J.C., Bazmohammadi, N., Yu, Y., Abusorrah, A., Al-Turki, Y.A., 2021. A review of the conceptualization and operational management of seaport microgrids on the shore and seaside. Energies 14, 7941. URL: https://www.mdpi.com/1996-1073/14/23/7941, doi:10.3390/en14237941. number: 23 Publisher: Multidisciplinary Digital Publishing Institute.

Crespo-Vazquez, J.L., Carrillo, C., Diaz-Dorado, E., Martinez-Lorenzo, J.A., Noor-E-Alam, M., 2018. A machine learning based stochastic optimization framework for a wind and storage power plant participating in energy pool market. Applied Energy 232, 341–357. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261918315150, doi:10.1016/j.apenergy.2018.09.195.

van Duin, J.H.R.R., Geerlings, H.H., Verbraeck, A.A., Nafde, T.T., 2018. Cooling down: A simulation approach to reduce energy peaks of reefers at terminals. Journal of Cleaner Production 193, 72–86. URL:

https://www.sciencedirect.com/science/article/pii/S0959652618313003, doi:10.1016/j.jclepro.2018.04.258.

ENTSO-E, . ENTSO-e transparency platform. URL: https://transparency.entsoe.eu/.

Geerlings, H., Heij, R., van Duin, R., 2018. Opportunities for peak shaving the energy demand of ship-to-shore quay cranes at container terminals. Journal of Shipping and Trade 3, 3. URL: https://doi.org/10.1186/s41072-018-0029-y, doi:10.1186/s41072-018-0029-y.

Gennitsaris, S.G., Kanellos, F.D., 2019. Emission-aware and cost-effective distributed demand response system for extensively electrified large ports. IEEE Transactions on Power Systems 34, 4341–4351. doi:10.1109/TPWRS.2019.2919949. conference Name: IEEE Transactions on Power Systems.

Grundmeier, N., Hahn, A., Ihle, N., Runge, S., Meyer-Barlag, C., 2014. A simulation based approach to forecast a demand load curve for a container terminal using battery powered vehicles, pp. 1711–1718. doi:10.1109/IJCNN.2014.6889838. ISSN: 2161-4407.

Harnischmacher, C., Markefke, L., Brendel, A.B., Kolbe, L., 2023. Two-sided sustainability: Simulating battery degradation in vehicle to grid applications within autonomous electric port transportation. Journal of Cleaner Production 384, 135598. URL: https://www.sciencedirect.com/science/article/pii/S0959652622051721, doi:10.1016/j.jclepro.2022.135598.

He, J., 2016. Berth allocation and quay crane assignment in a container terminal for the trade-off between time-saving and energy-saving. Advanced Engineering Informatics 30, 390–405. doi:10.1016/J.AEI.2016.04.006. publisher: Elsevier Ltd.

He, J., Huang, Y., Yan, W., 2015a. Yard crane scheduling in a container terminal for the trade-off between efficiency and energy consumption. Advanced Engineering Informatics 29, 59–75. doi:10.1016/J.AEI.2014.09.003. publisher: Elsevier Ltd.

He, J., Huang, Y., Yan, W., Wang, S., 2015b. Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption. Expert Systems with Applications 42, 2464–2487. URL: https://linkinghub.elsevier.com/retrieve/pii/S0957417414007027, doi:10.1016/j.eswa.2014.11.016.

HHLA, a. Container terminal altenwerder (CTA). URL: https://hhla.de/en/company/subsidiaries/container-terminal-altenwerder-cta.

HHLA, b. HHLA COAST report. URL: https://coast.hhla.de/report?id=Standard-Report-Segelliste.

HHLA, c. Innovation: FRESH. URL: https://hhla.de/en/innovation/fresh.

HHLA, 2022. Sustainability for container handling: AGV charging infrastructure completed. URL: https://hhla.de/en/media/news/detail-view/cta-agv-charging-infrastructure-comple

Iris, , Lam, J.S.L., 2019a. Recoverable robustness in weekly berth and quay crane planning. Transportation Research Part B: Methodological 122, 365–389. URL: https://linkinghub.elsevier.com/retrieve/pii/S0191261518302686, doi:10.1016/j.trb.2019.02.013.

Iris, , Lam, J.S.L., 2019b. A review of energy efficiency in ports: Operational strategies, technologies and energy management systems. Renewable and Sustainable Energy Reviews 112, 170–182. doi:10.1016/J.RSER.2019.04.069. publisher: Pergamon.

Iris, , Lam, J.S.L., 2021. Optimal energy management and operations planning in seaports with smart grid while harnessing renewable energy under uncertainty. Omega 103, 102445. URL: https://www.sciencedirect.com/science/article/pii/S0305048321000542, doi:10.1016/j.omega.2021.102445.

Kanellos, F.D., 2017. Real-time control based on multi-agent systems for the operation of large ports as prosumer microgrids. IEEE Access 5, 9439–9452. doi:10.1109/ACCESS.2017.2706091. conference Name: IEEE Access.

Kanellos, F.D., 2019. Multiagent-system-based operation scheduling of large ports' power systems with emissions limitation. IEEE Systems Journal 13, 1831–1840. doi:10.1109/JSYST.2018.2850970. conference Name: IEEE Systems Journal.

Kanellos, F.D., Volanis, E.S.M., Hatziargyriou, N.D., 2019. Power management method for large ports with multi-agent systems. IEEE Transactions on Smart Grid 10, 1259–1268. doi:10.1109/TSG.2017.2762001. conference Name: IEEE Transactions on Smart Grid.

Kermani, M., Parise, G., Martirano, L., Parise, L., Chavdarian, B., 2018. Optimization of peak load shaving in STS group cranes based on PSO algorithm, pp. 1–5. doi:10.1109/EEEIC.2018.8494467.

Knueven, B., Muir, C., Watson, J.P., Mildebrath, D.T., Siirola, J.D., Woodruff, D.L., 2020. A parallel hub-and-spoke system for large-scale scenario-based optimization under uncertainty – optimization online. URL: https://optimization-online.org/2020/11/8088/.

Kolley, L., Rückert, N., Kastner, M., Jahn, C., Fischer, K., 2023. Robust berth scheduling using machine learning for vessel arrival time prediction. Flexible Services and Manufacturing Journal 35, 29–69. URL: https://doi.org/10.1007/s10696-022-09462-x, doi:10.1007/s10696-022-09462-x.

Kroposki, B., 2017. Integrating high levels of variable renewable energy into electric power systems. Journal of Modern Power Systems and Clean Energy 5. URL: https://doi.org/10.1007/s40565-017-0339-3, doi:10.1007/s40565-017-0339-3.

Liu, C., Xiang, X., Zheng, L., 2020. A two-stage robust optimization approach for the berth allocation problem under uncertainty. Flexible Services and Manufacturing Journal 32, 425–452. URL: https://doi.org/10.1007/s10696-019-09343-w, doi:10.1007/s10696-019-09343-w.

Mao, A., Yu, T., Ding, Z., Fang, S., Guo, J., Sheng, Q., 2022. Optimal scheduling for seaport integrated energy system considering flexible berth allocation. Applied Energy 308, 118386. URL:

https://www.sciencedirect.com/science/article/pii/S030626192101624X, doi:10.1016/j.apenergy.2021.118386.

Pu, Y., Chen, W., Zhang, R., Liu, H., 2020. Optimal operation strategy of port integrated energy system considering demand response, pp. 518–523. doi:10.1109/EI250167.2020.9346904.

Roald, L.A., Pozo, D., Papavasiliou, A., Molzahn, D.K., Kazempour, J., Conejo, A., 2023. Power systems optimization under uncertainty: A review of methods and applications. Electric Power Systems Research 214, 108725. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378779622007842, doi:10.1016/j.epsr.2022.108725.

Schmidt, J., Lauven, L.P., Ihle, N., Kolbe, L., 2015. Demand side integration for electric transport vehicles. International Journal of Energy Sector Management 9, 471–495. doi:10.1108/IJESM-11-2014-0002.

Wilmsmeier, G., Froese, J., Zotz, A., Meyer, A., 2014. Energy consumption and efficiency: Emerging challenges from reefer trade in south american container terminals. URL: https://www.semanticscholar.org/paper/Energy-Consumption-and-Efficiency%3A-Emerg

Yu, J., Voß, S., Song, X., 2022. Multi-objective optimization of daily use of shore side electricity integrated with quayside operation. Journal of Cleaner Production 351, 131406. URL: https://www.sciencedirect.com/science/article/pii/S0959652622010277, doi:10.1016/j.jclepro.2022.131406.

Zhang, X., Gu, Y., Yang, Y., Liu, B., 2023. Comparing the efficiency of two types of yard layout in container terminals. Sustainability 15, 7195. URL: https://www.mdpi.com/2071-1050/15/9/7195, doi:10.3390/su15097195. number: 9 Publisher: Multidisciplinary Digital Publishing Institute.

B
Method literature review

The appendix describes the method used to conduct the literature research. Several database, search terms were used to find relevant scientific literature. The literature found was categorised to be able to make generalised conclusions.

B.1. Search method

Initially databases of scientific literature, such as Science Direct, IEEE and Scopus were used to find literature. Based on this literature forward and backward snowballing was used to find related articles. No filters were applied while searching the databases. Originally the search was confined to demand response in container terminal, which didn't generate a lot of results. Therefore the search area was expanded to included demand side management (DSM) in general. The search words were the for the literature research were the following:

- Demand side management
- Demand side flexibility
- Demand flexibility
- Demand response
- Container terminal
- Port
- electricity price
- Micro grid
- Smart grid
- Real-time pricing
- Time-of-use
- critical peak pricing

These words were organised in a query with the use of Boolean operators. The first four words are synonyms for DSM, which was combined with either the word container terminal or port. One common application of DSM was alongside micro grid or smart grids. Therefore an additional search query was created to find those papers which did use DSM but did not explicitly mention it. Finally different types of DSM (see section **??**) were searched for. In the table **??** the exact search query along side the database used and the date of search is shown.

B.2. Classification of literature

The literature found was classified to create some structure. Three fields of research were found working on DSM in container terminals. Research is being conducted in the introduction of an energy management system in a container terminal, to manage the electricity demand. Furthermore peak shaving within container terminals is field that is being researched. Lastly the application of vehicle-to-grid charging of an electric vehicle fleet is being researched.

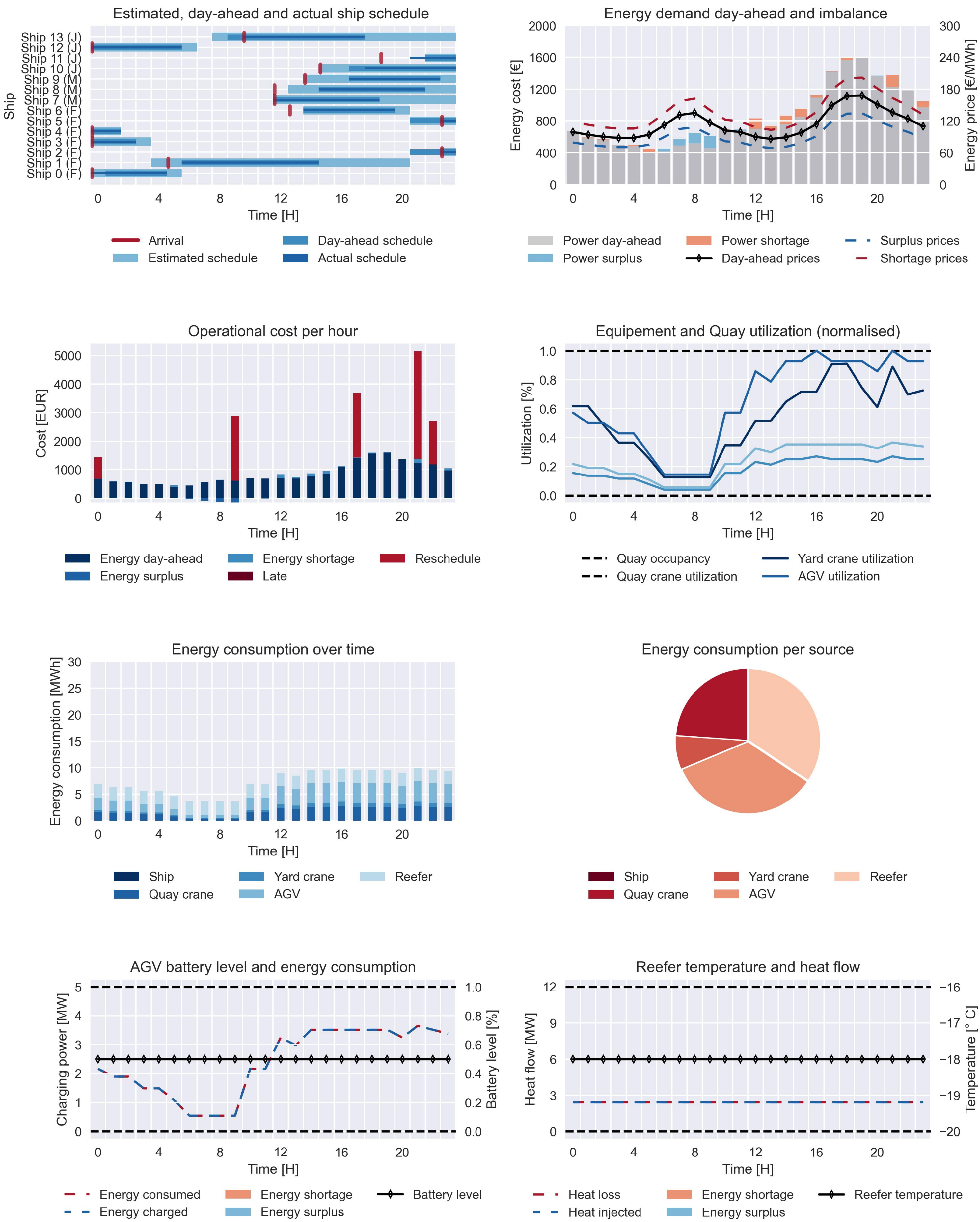
For all the literature found the research aim was stated. Furthermore the energy loads investigated in the paper were found. Lastly to get insight in the dynamics of the loads the time horizon and the time step used in the simulation/optimization were found. This has been defined as the critical time.

Search query	Database	Search date
(”Demand Side Management” OR ”Demand Response” OR ”Demand side flexibility” OR ”Demand flexibility”) AND ”Container Terminal”	Science direct	05-01-2023
(”Demand Side Management” OR ”Demand Response” OR ”Demand side flexibility” OR ”Demand flexibility”) AND (”Container Terminal” OR ”PORT”)	IEEE	06-01-2023
(”Demand Side Management” OR ”Demand Response” OR ”Demand side flexibility” OR ”Demand flexibility”) AND (”Container Terminal”)	SCOPUS	09-01-2023
”electricity price” AND (”Mirco grid OR ”Smart grid”) AND ”Container terminal” NOT (”Demand Side Management” OR ”Demand Response” OR ”Demand side flexibility” OR ”Demand flexibility”)	Science direct	10-01-2023
(”Real-time pricing” OR ”Time-of-use” OR ”critical peak pricing”) AND ”Container Terminal”	Science direct	12-01-2023

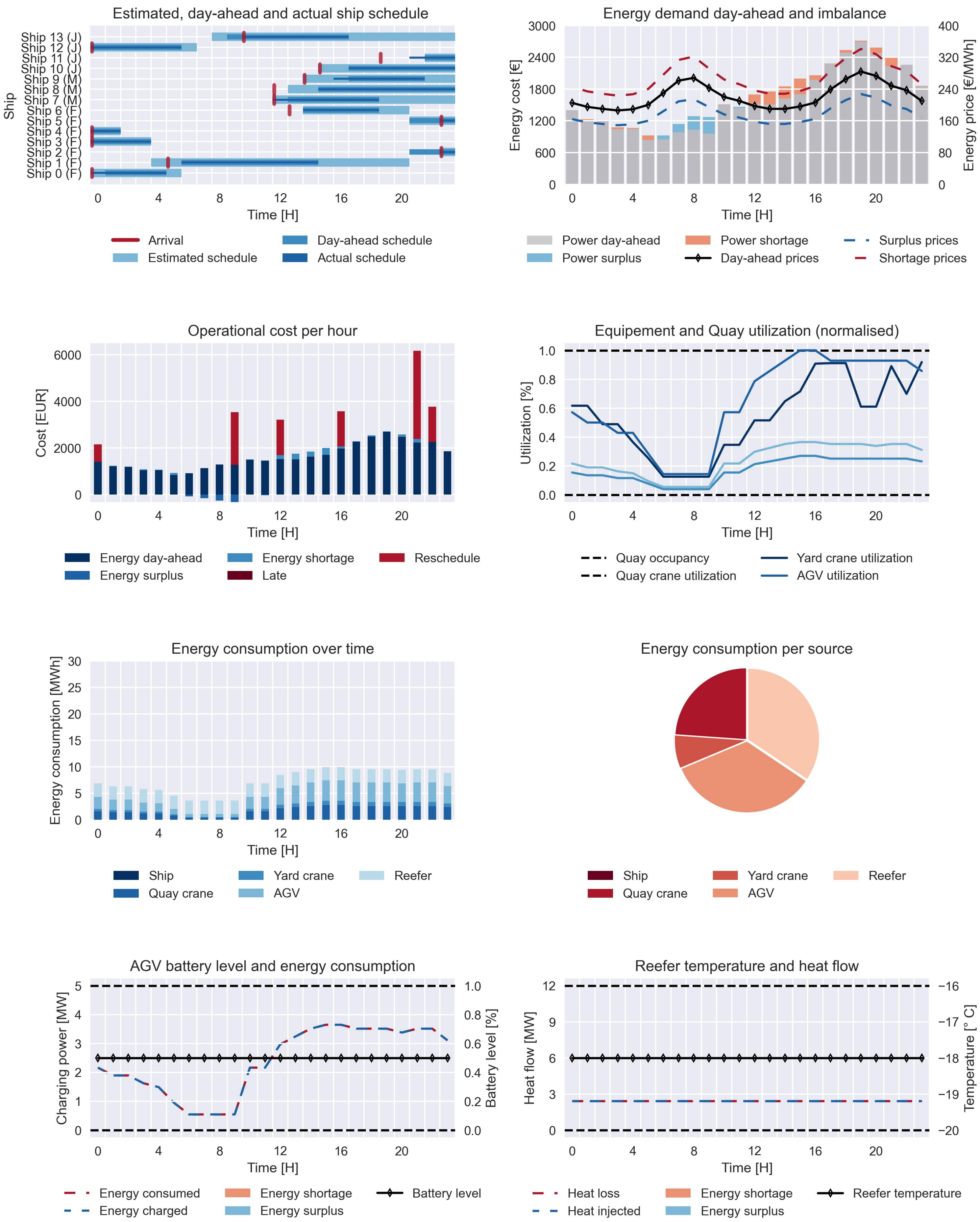
Table B.1: search query

C
Graphs

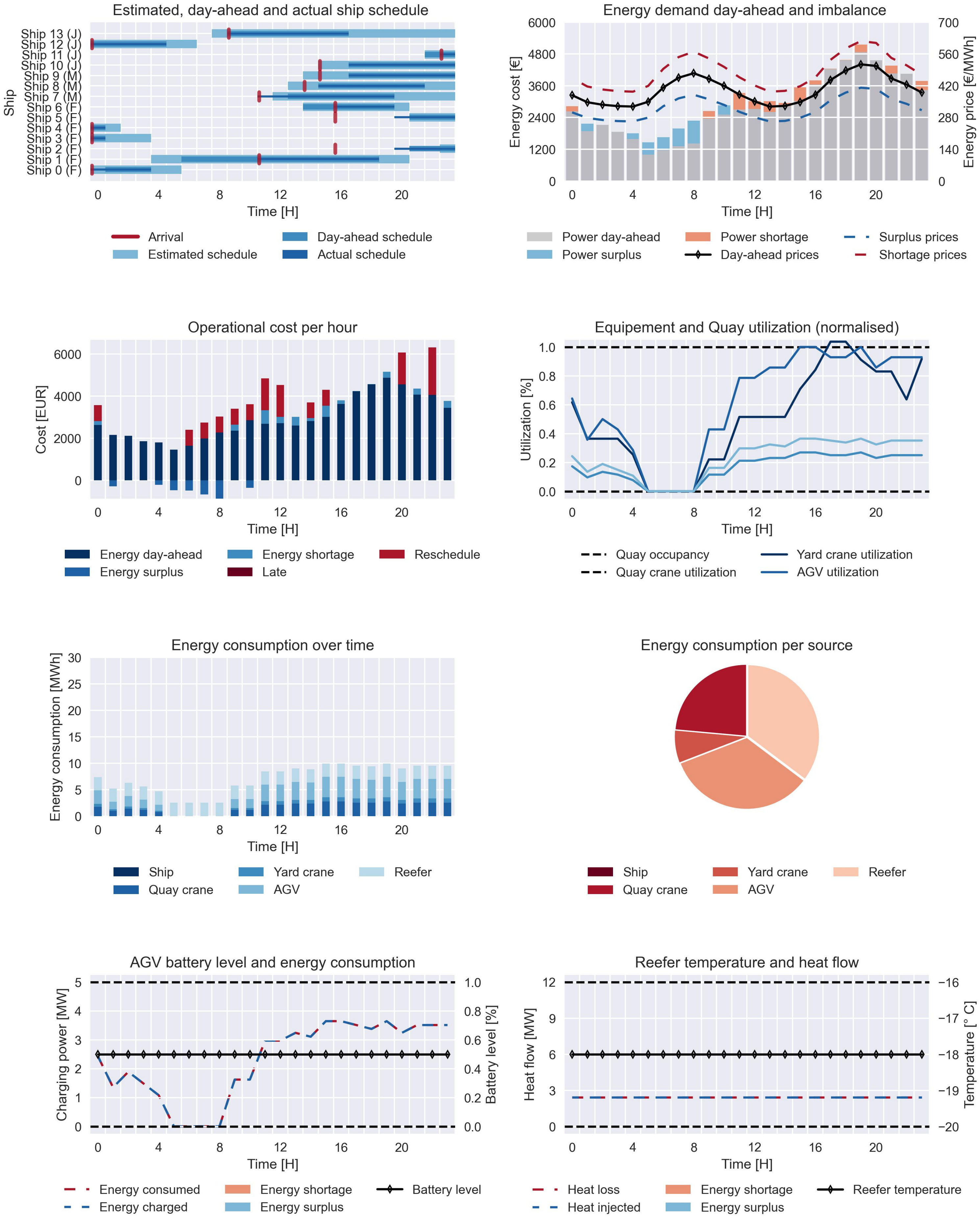
Output results for experiment CP_2022 with instance 0 and scenario scenario_01



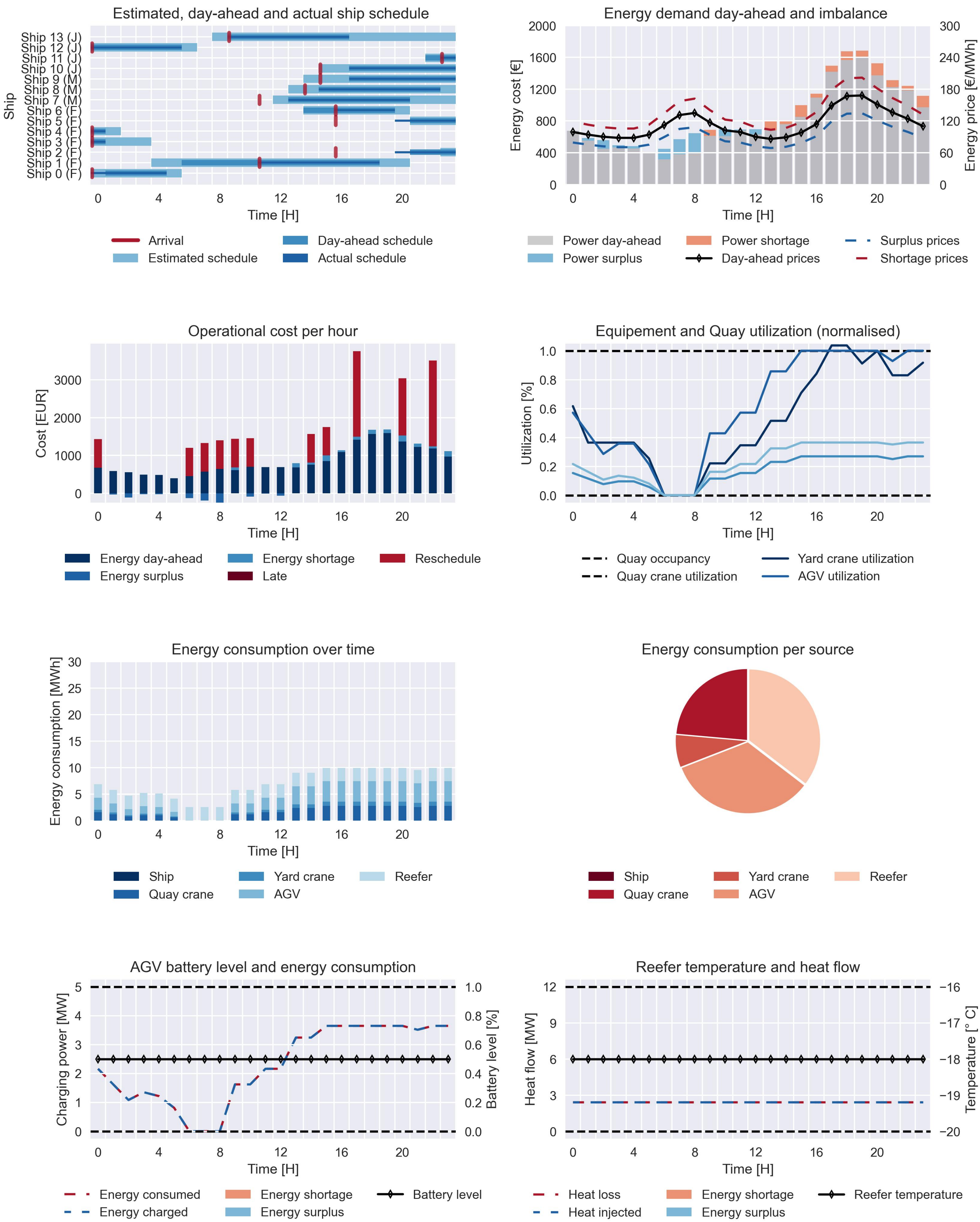
Output results for experiment CP_2022 with instance 0 and scenario scenario_02



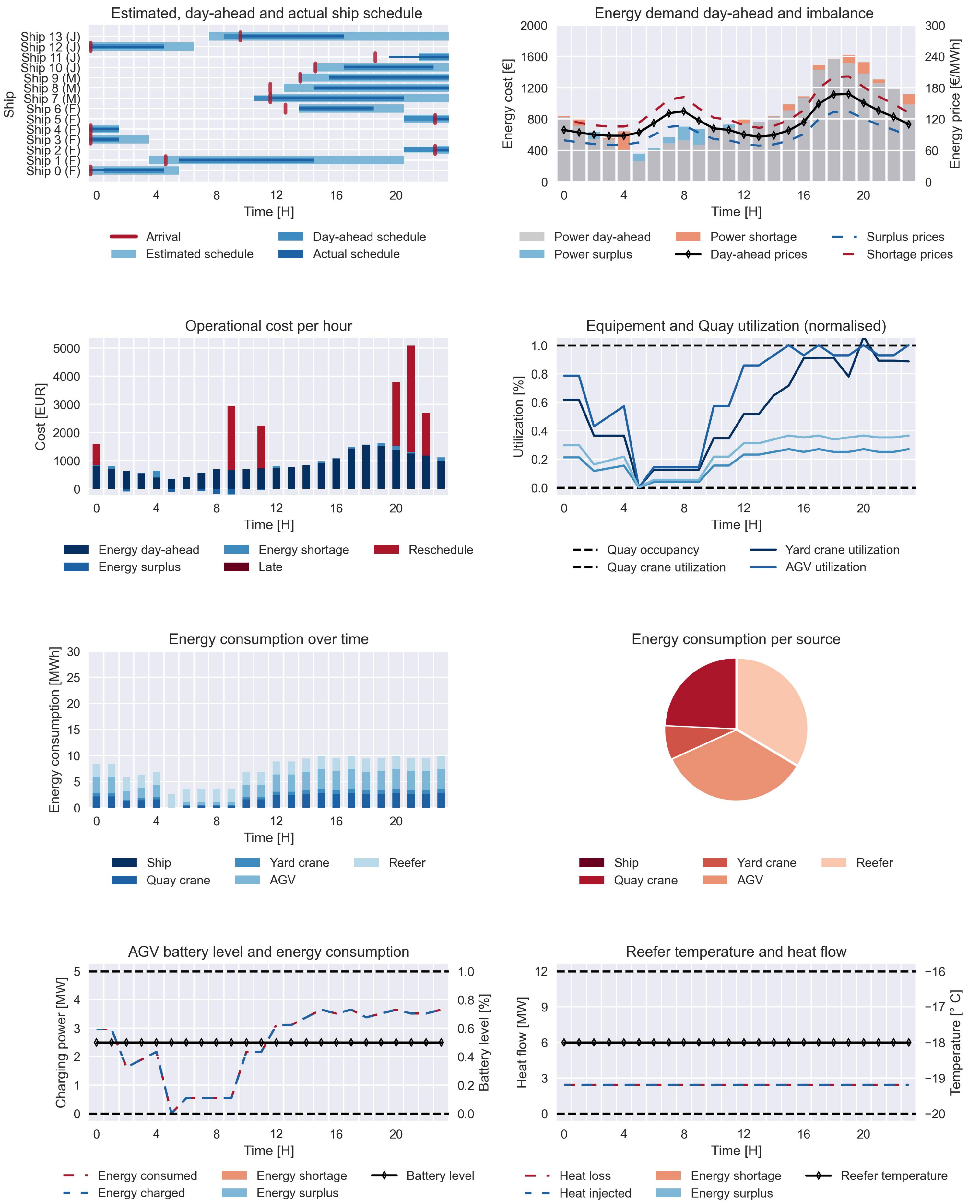
Output results for experiment CP_2022 with instance 0 and scenario scenario_03



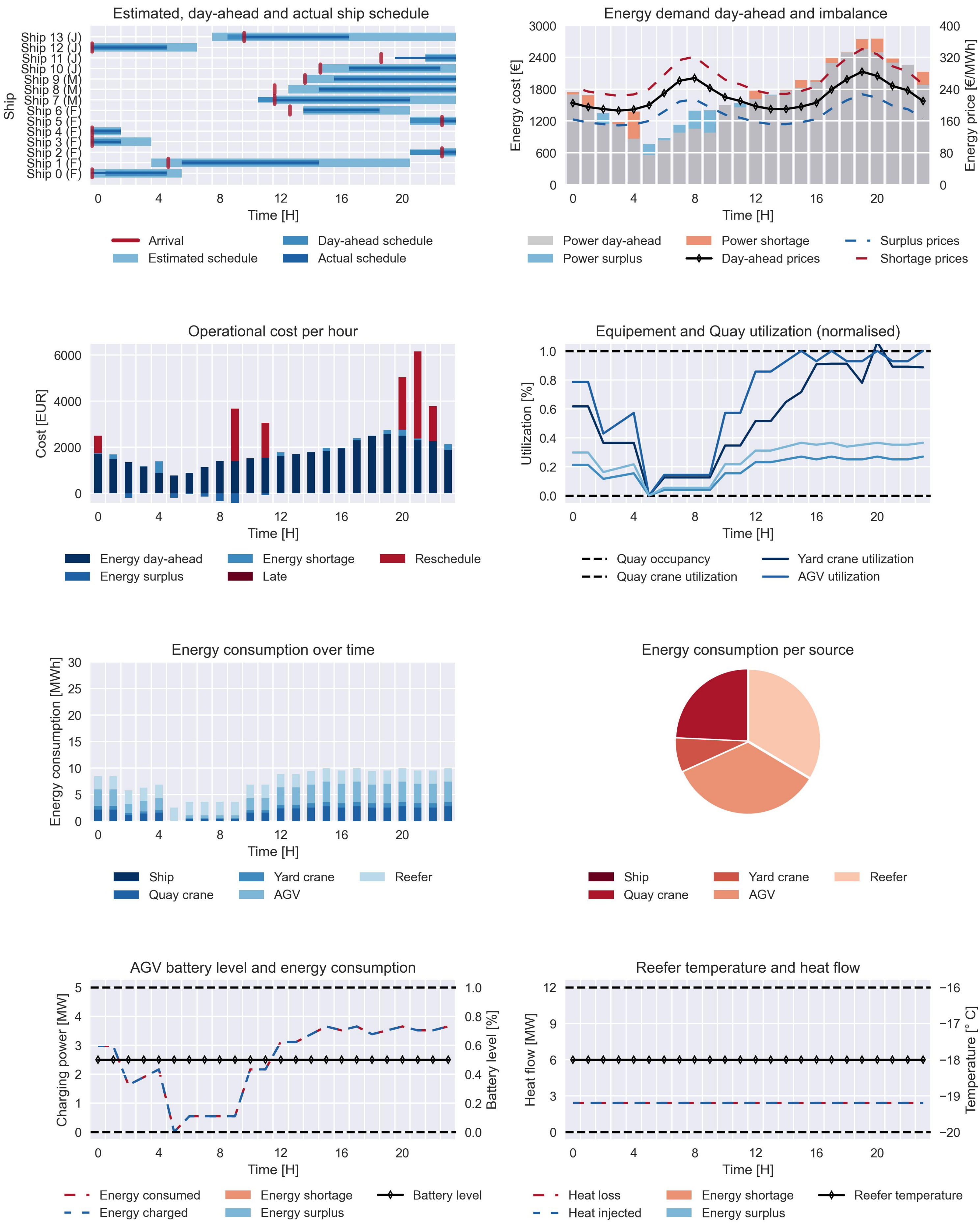
Output results for experiment CP_2022 with instance 0 and scenario scenario_04



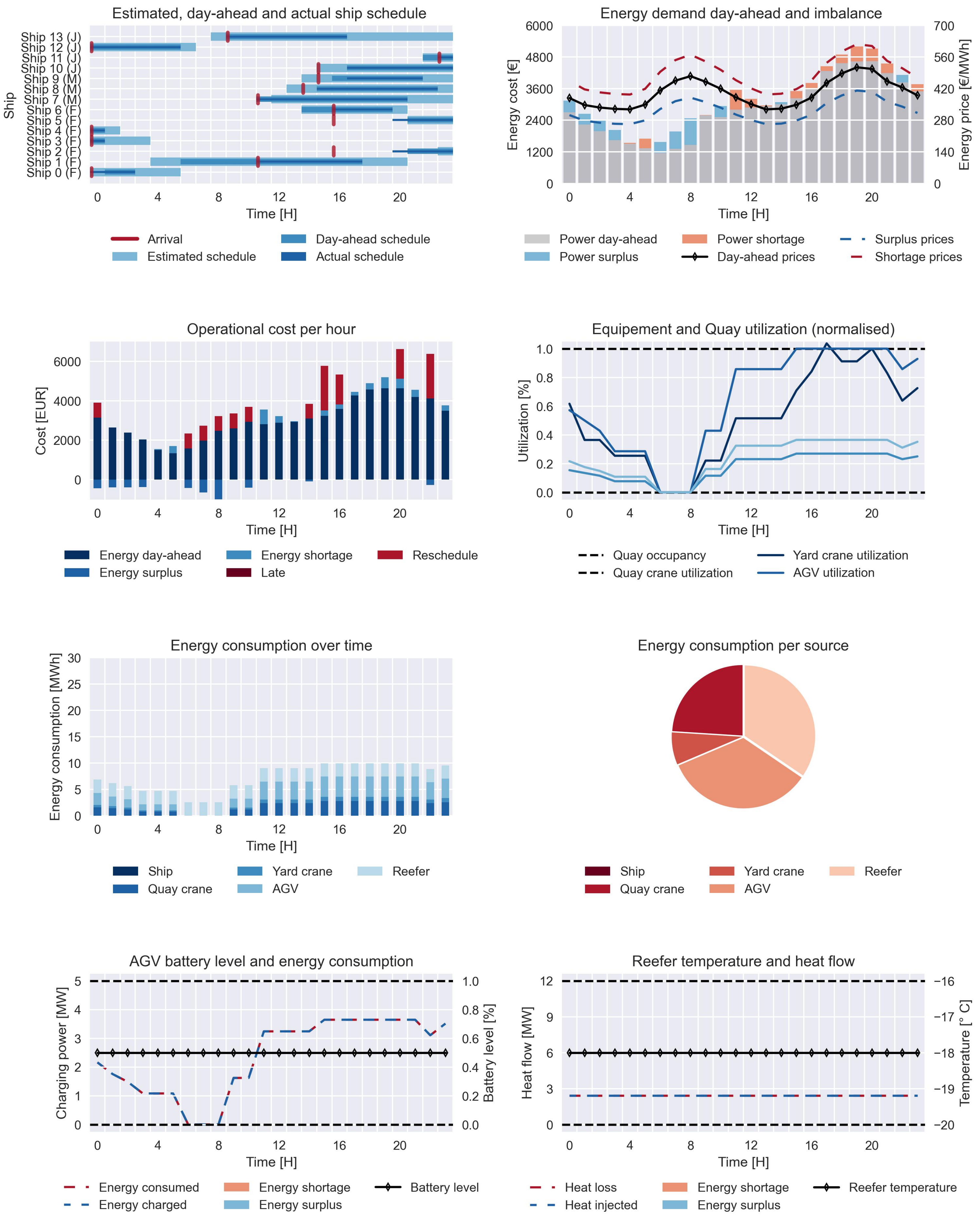
Output results for experiment NP_2022 with instance 0 and scenario scenario_01



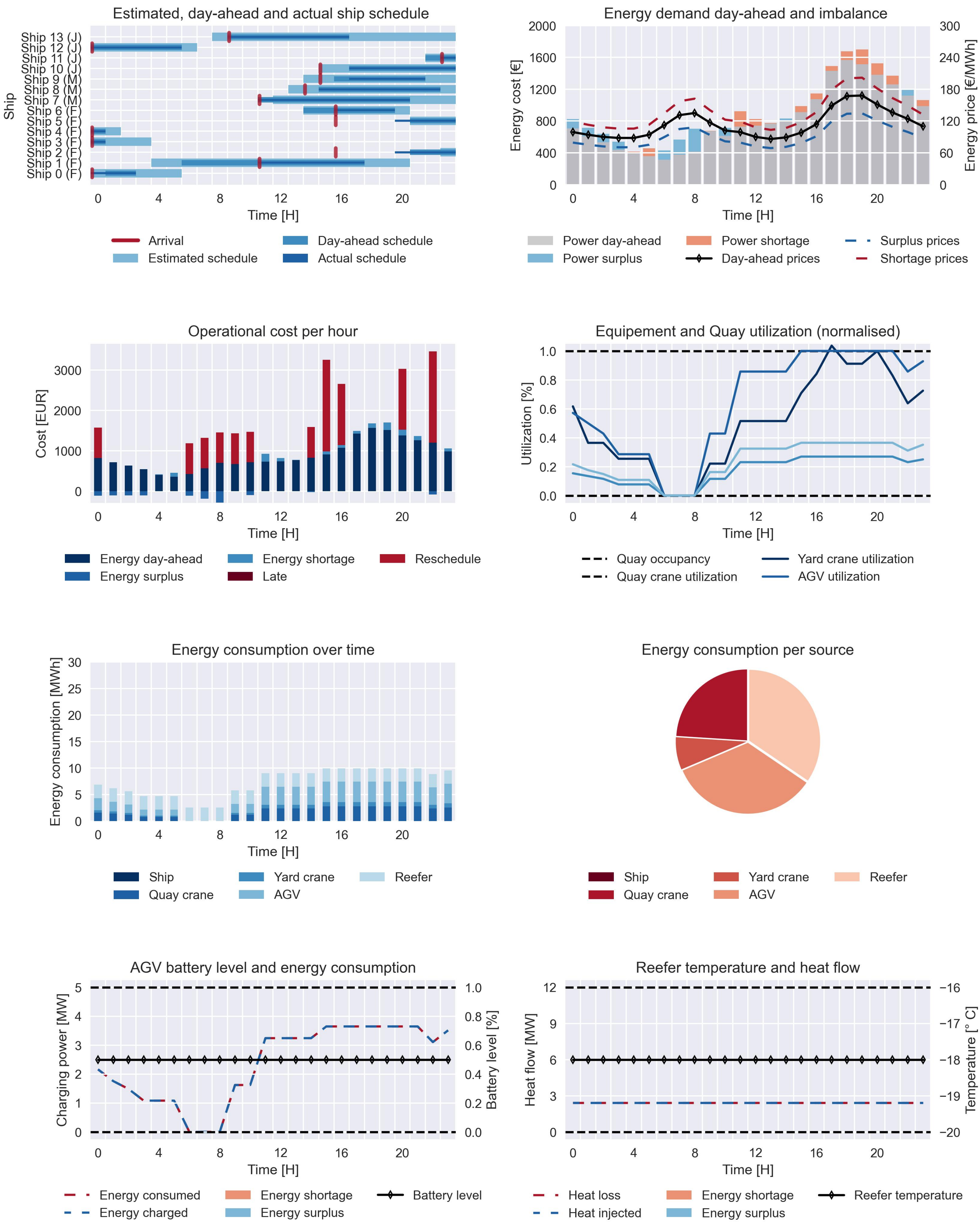
Output results for experiment NP_2022 with instance 0 and scenario scenario_02

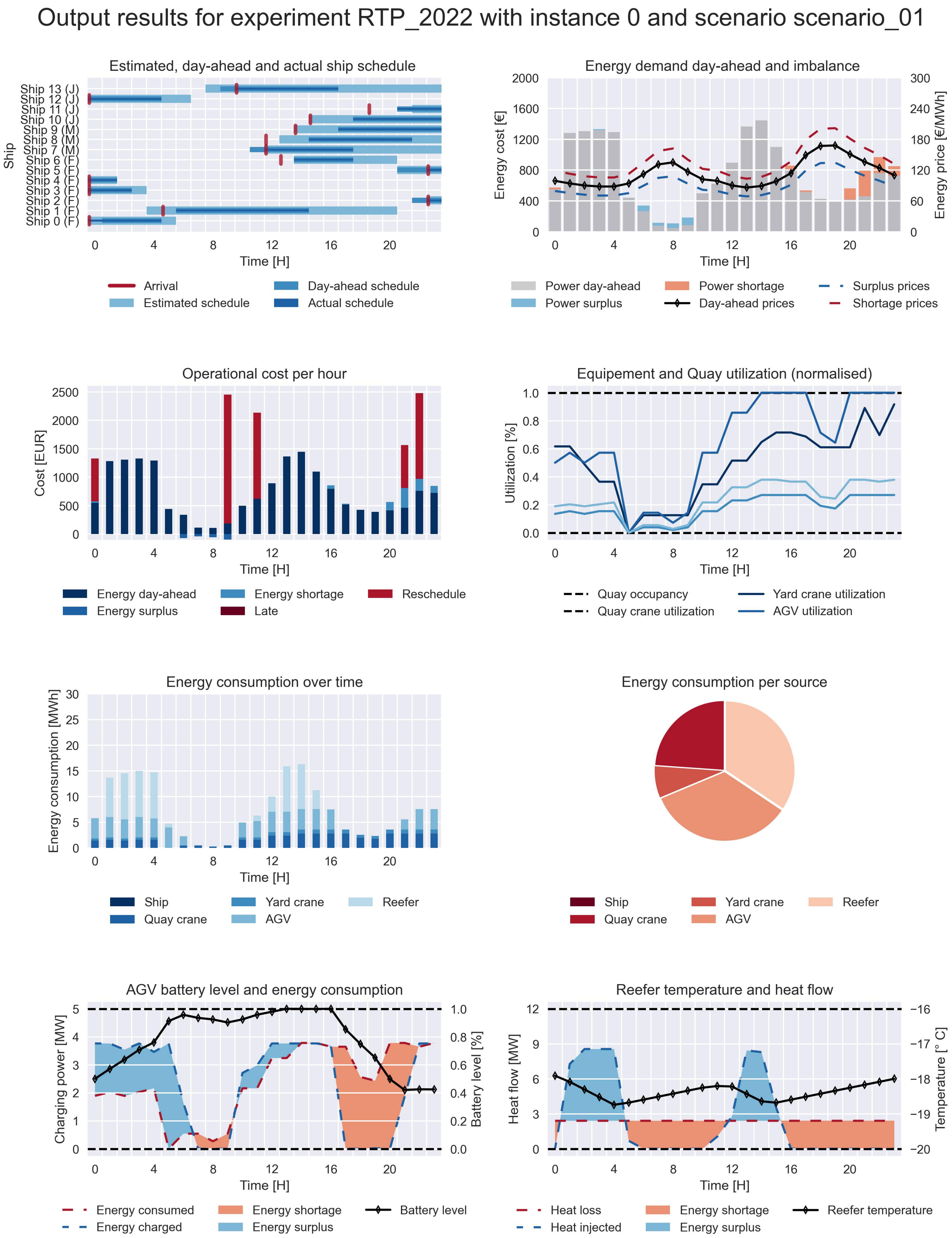


Output results for experiment NP_2022 with instance 0 and scenario scenario_03

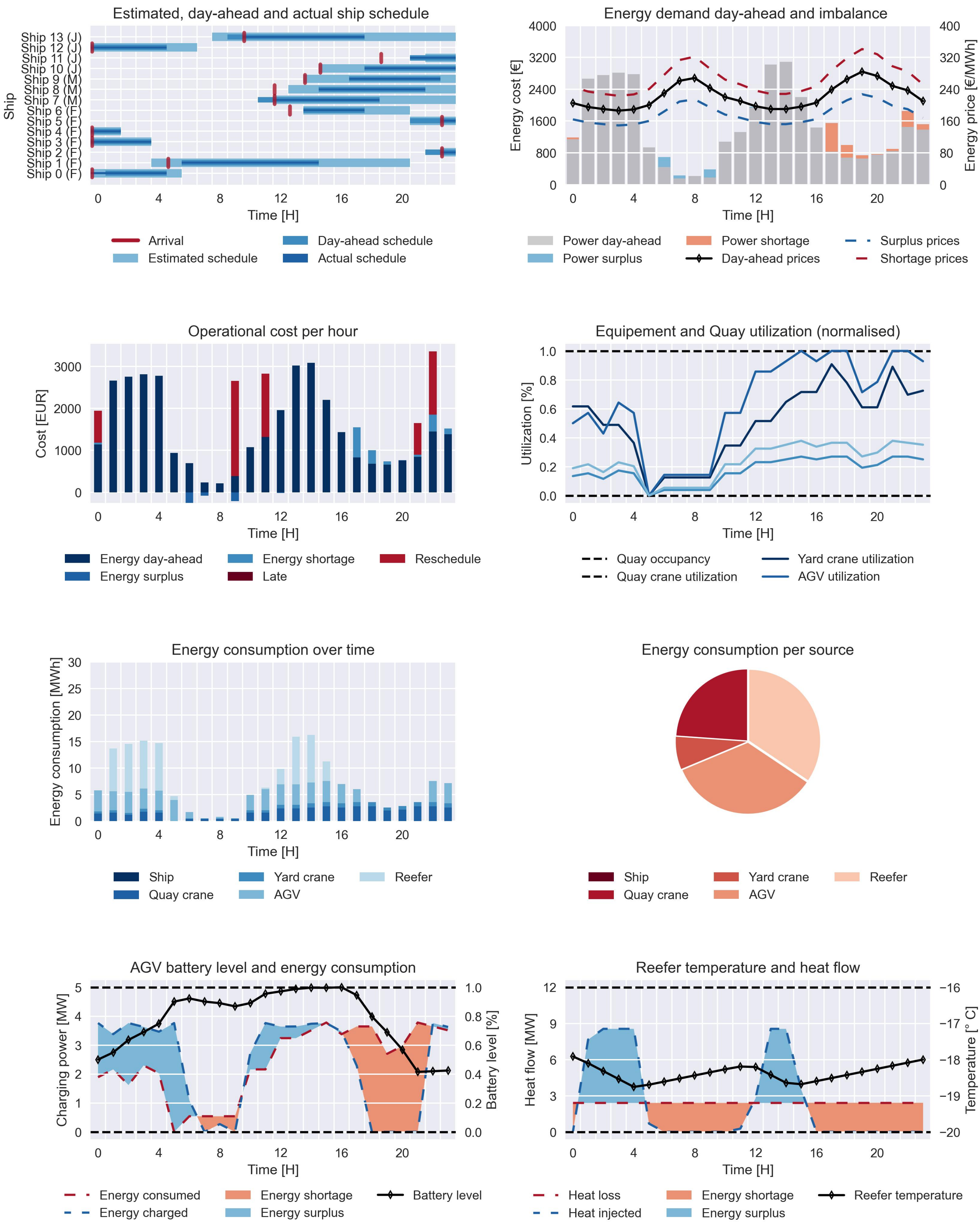


Output results for experiment NP_2022 with instance 0 and scenario scenario_04

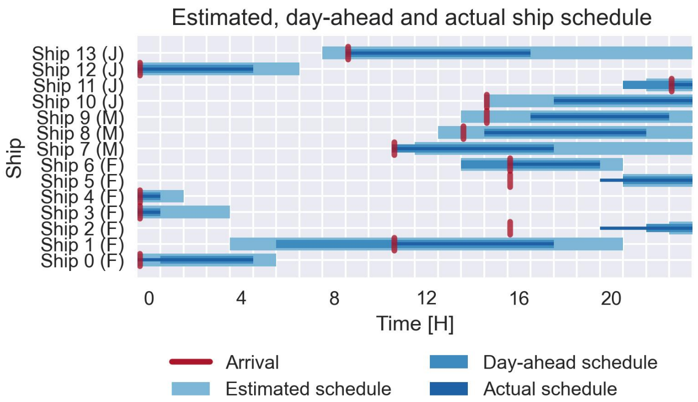


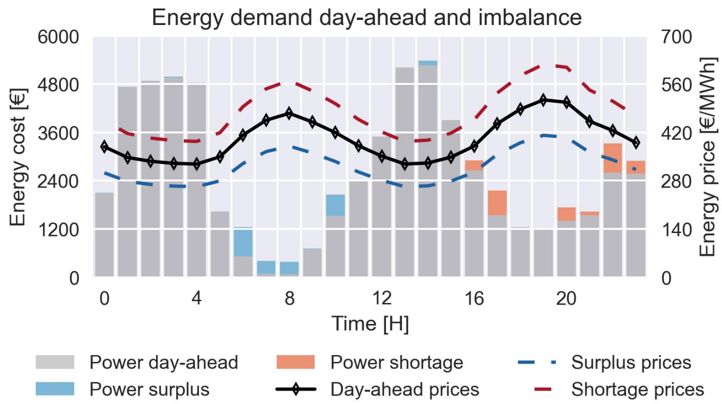

Output results for experiment RTP_2022 with instance 0 and scenario scenario_01
Estimated, day-ahead and actual ship schedule
Ship
Ship 13 (J)
Ship 12 (J)
Ship 11 (J)
Ship 10 (J)
Ship 9 (M)
Ship 8 (M)
Ship 7 (M)
Ship 6 (F)
Ship 5 (F)
Ship 4 (F)
Ship 3 (F)
Ship 2 (F)
Ship 1 (F)
Ship 0 (F)
Time [H]
Arrival
Estimated schedule
Day-ahead schedule
Actual schedule
Energy demand day-ahead and imbalance
Energy cost [€]
Energy price [€/MWh]
Time [H]
Power day-ahead
Power surplus
Power shortage
Day-ahead prices
Surplus prices
Shortage prices
Operational cost per hour
Cost [EUR]
Time [H]
Energy day-ahead
Energy surplus
Energy shortage
Late
Reschedule
Equipement and Quay utilization (normalised)
Utilization [%]
Time [H]
Quay occupancy
Quay crane utilization
Yard crane utilization
AGV utilization
Energy consumption over time
Energy consumption [MWh]
Time [H]
Ship
Quay crane
Yard crane
AGV
Reefer
Energy consumption per source
Ship
Quay crane
Yard crane
AGV
Reefer
AGV battery level and energy consumption
Charging power [MW]
Battery level [%]
Time [H]
Energy consumed
Energy charged
Energy shortage
Energy surplus
Battery level
Reefer temperature and heat flow
Heat flow [MW]
Temperature [° C]
Time [H]
Heat loss
Heat injected
Energy shortage
Energy surplus
Reefer temperature

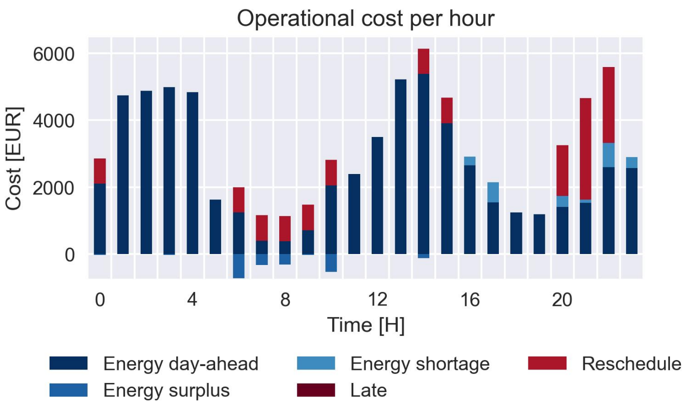
Output results for experiment RTP_2022 with instance 0 and scenario scenario_02

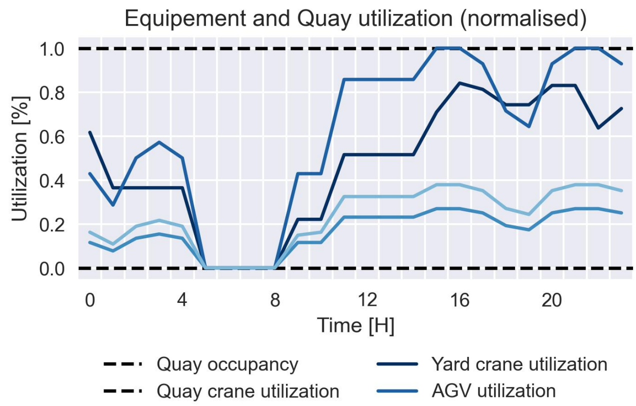


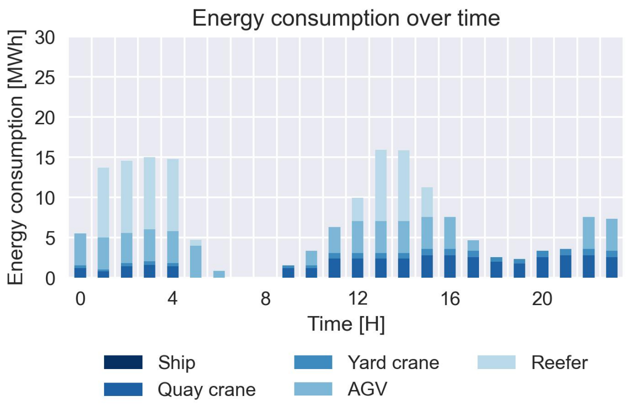
Output results for experiment RTP_2022 with instance 0 and scenario scenario_03

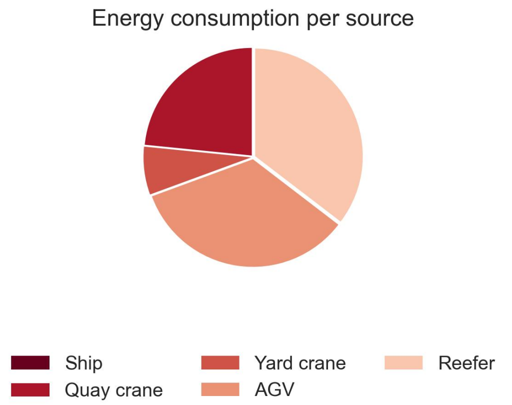


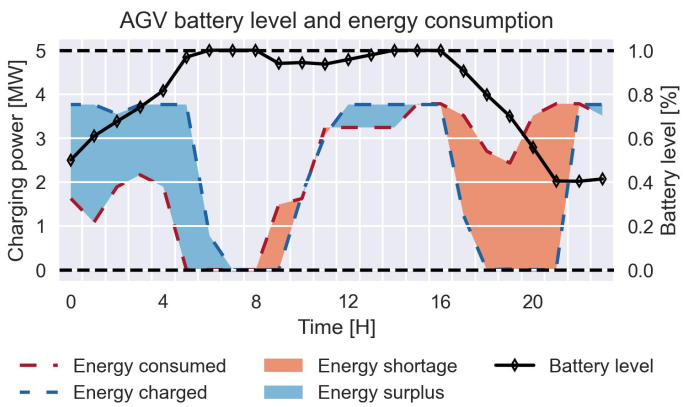


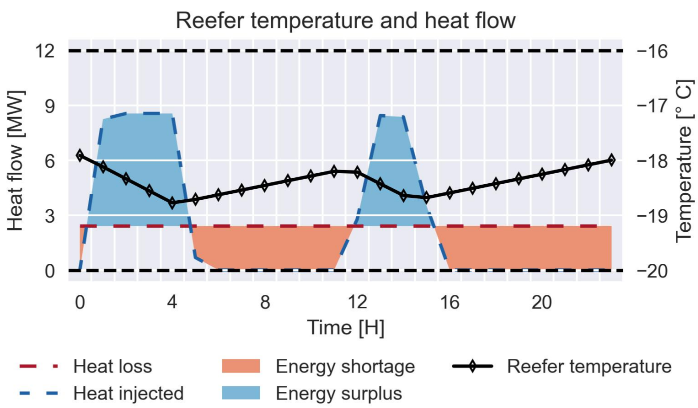




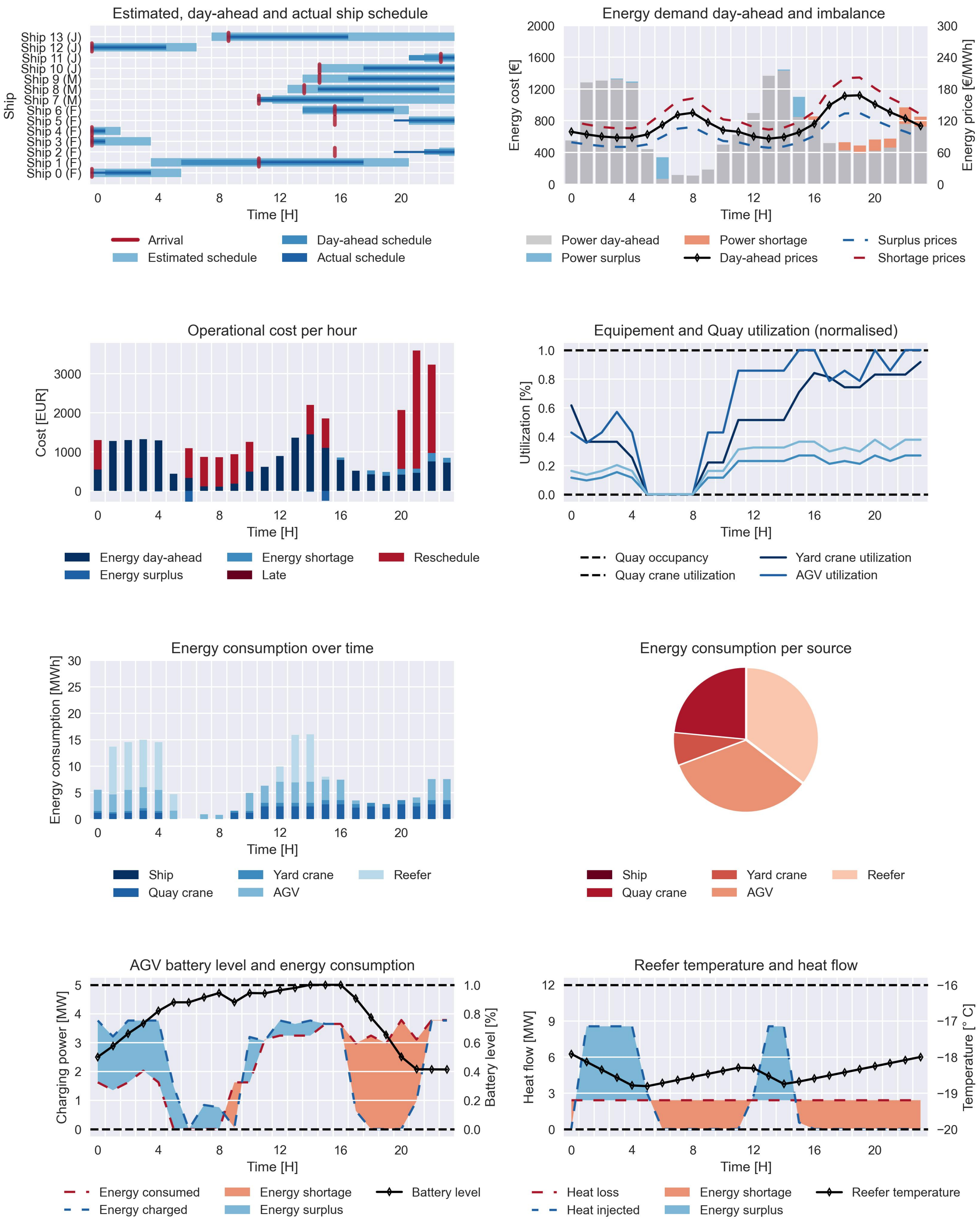




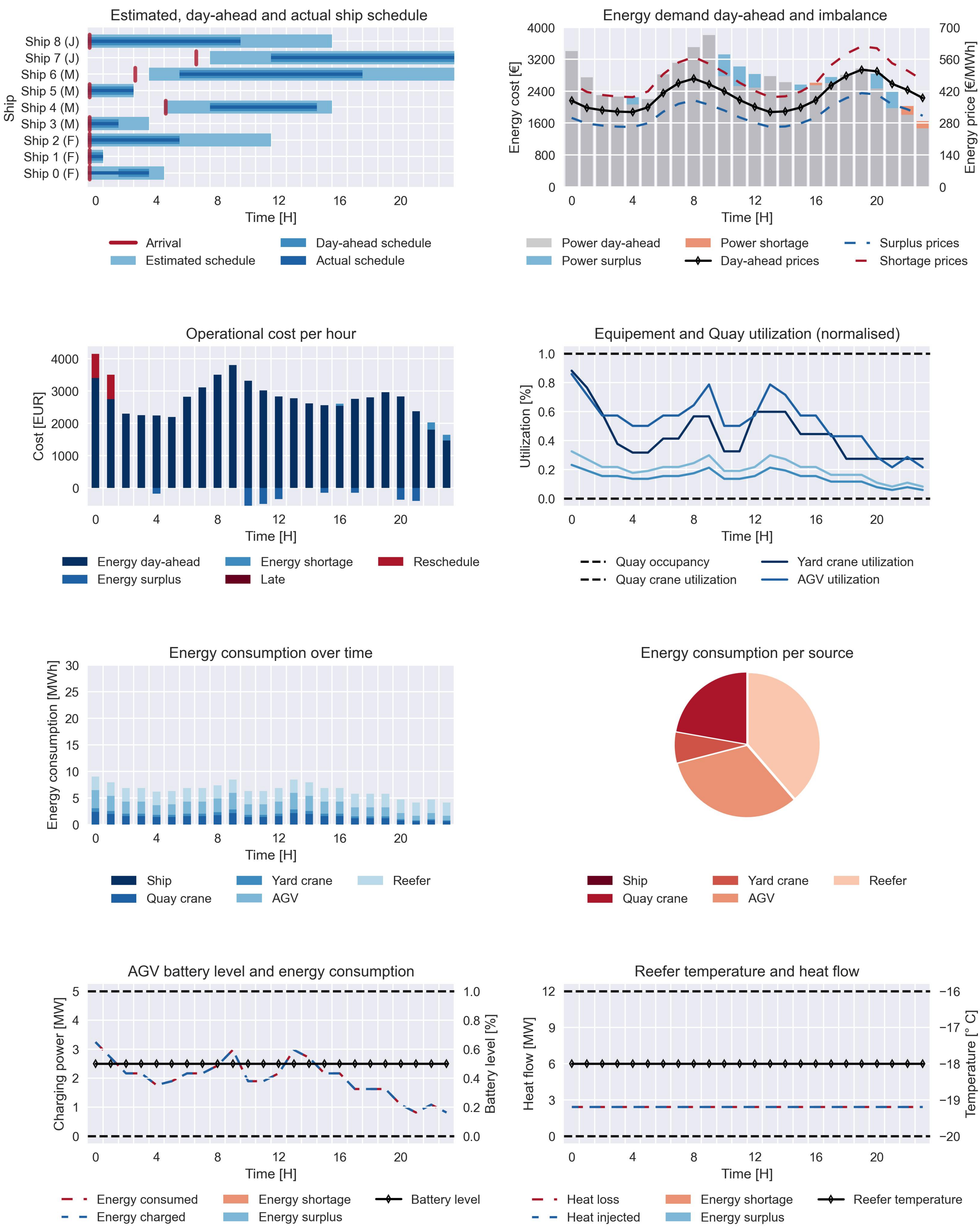




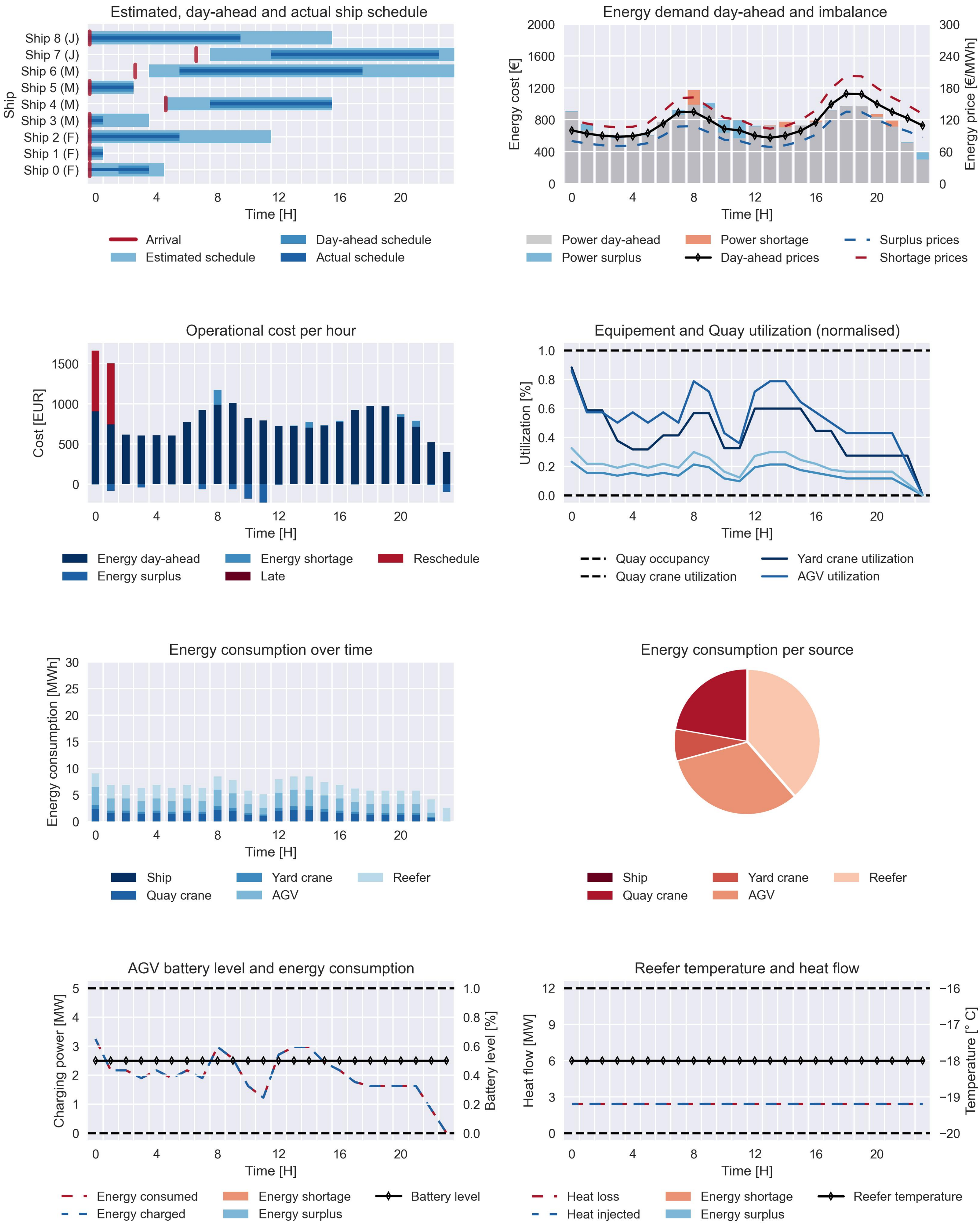
Output results for experiment RTP_2022 with instance 0 and scenario scenario_04



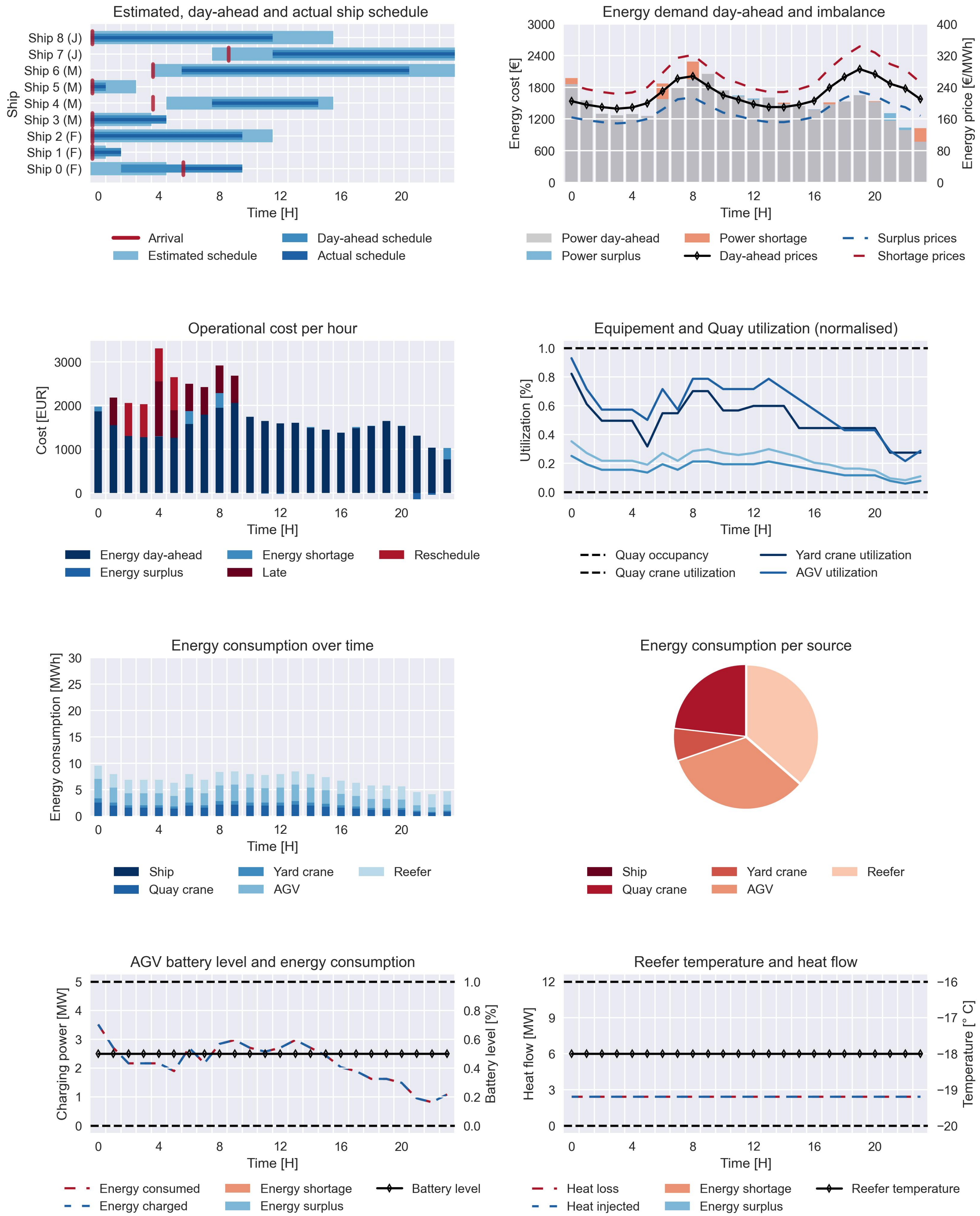
Output results for experiment CP_2022 with instance 7 and scenario scenario_01



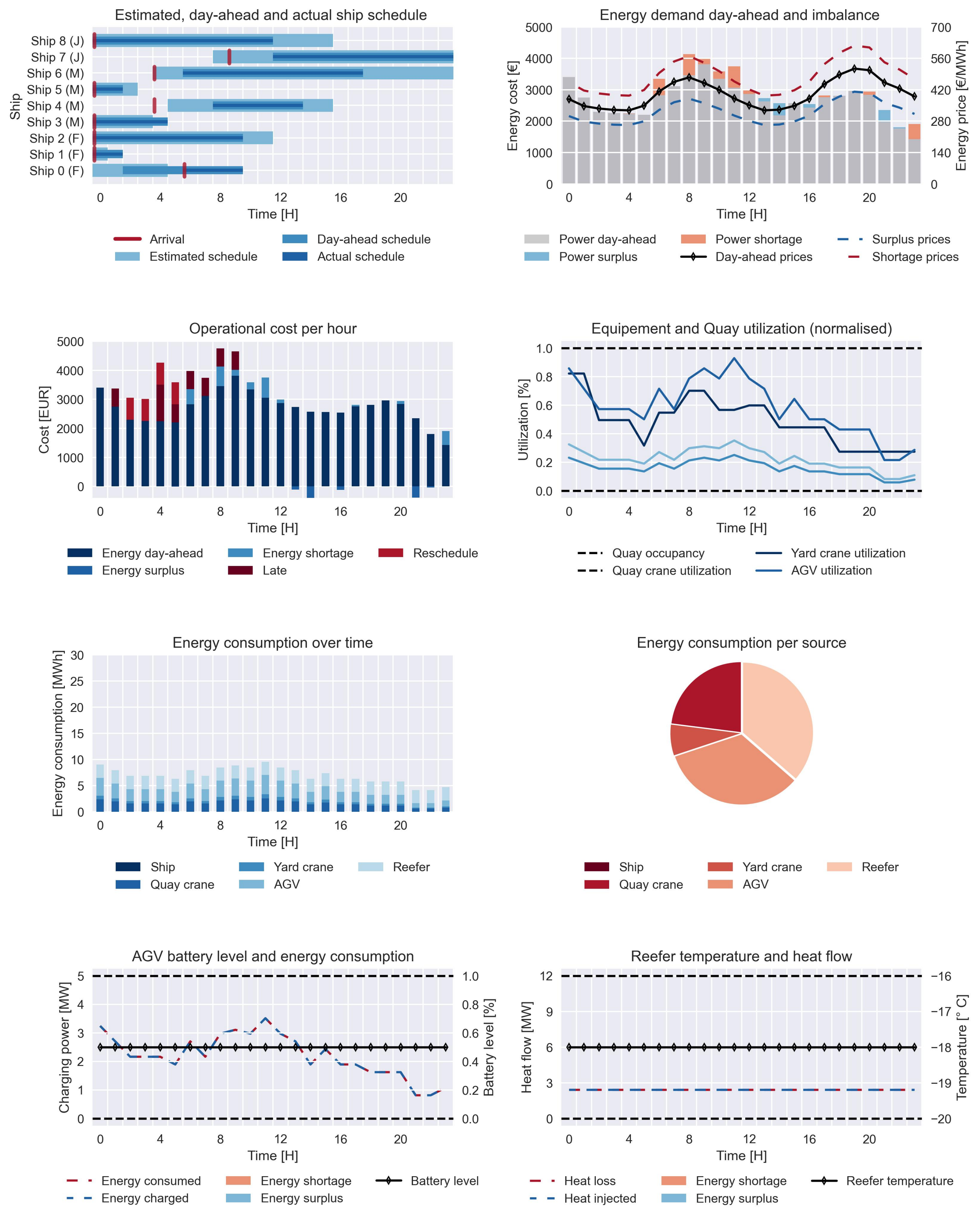
Output results for experiment CP_2022 with instance 7 and scenario scenario_02



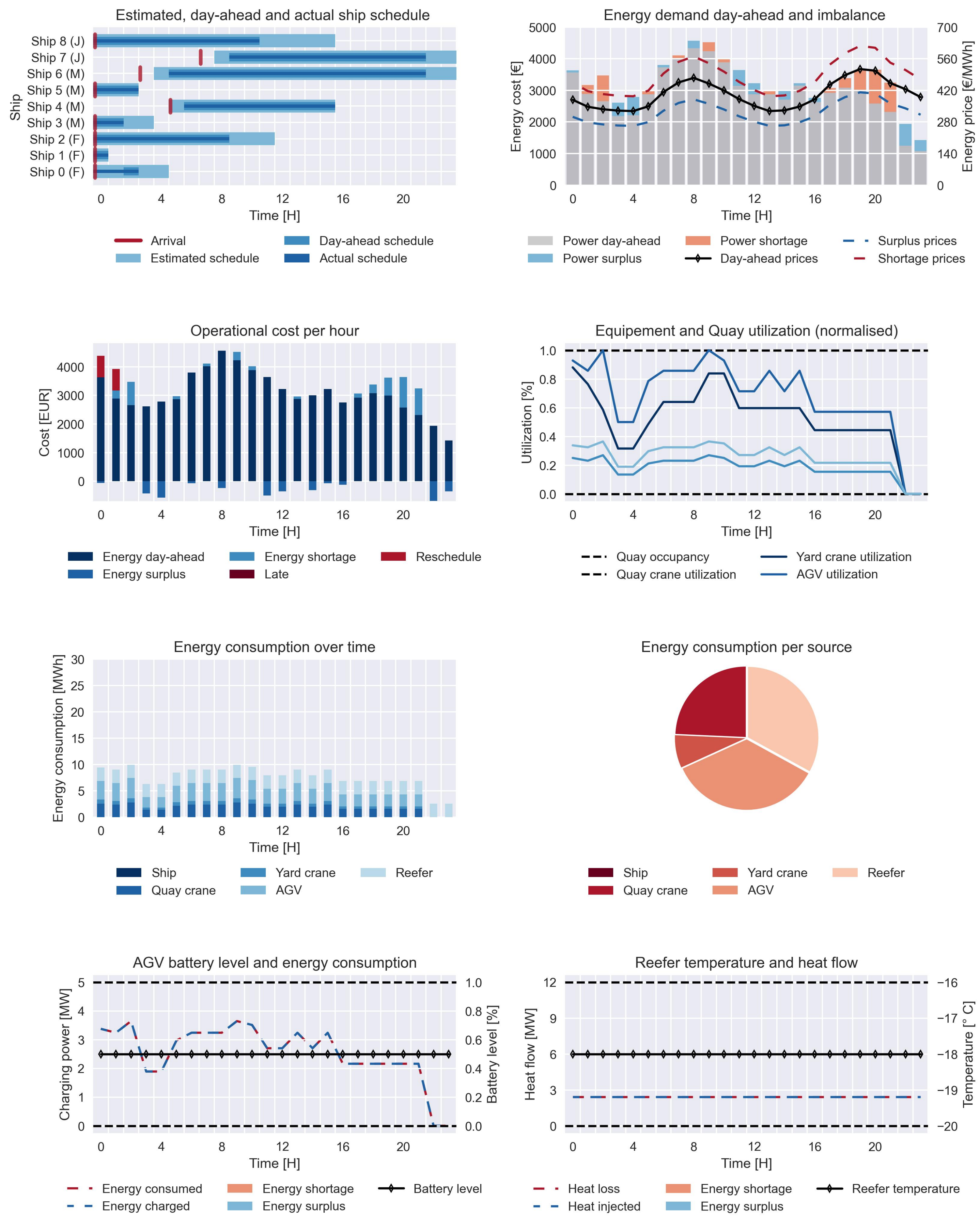
Output results for experiment CP_2022 with instance 7 and scenario scenario_03



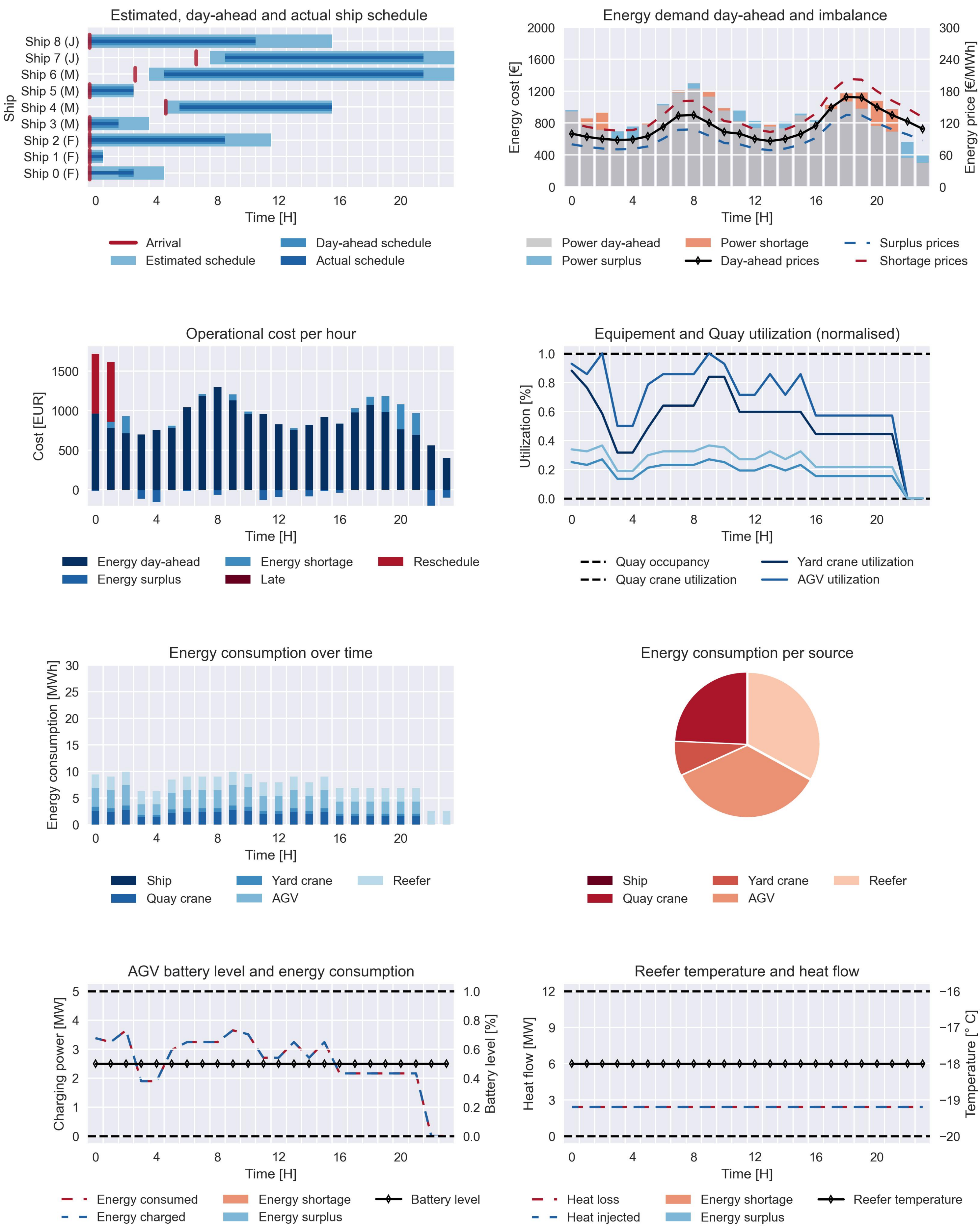
Output results for experiment CP_2022 with instance 7 and scenario scenario_04



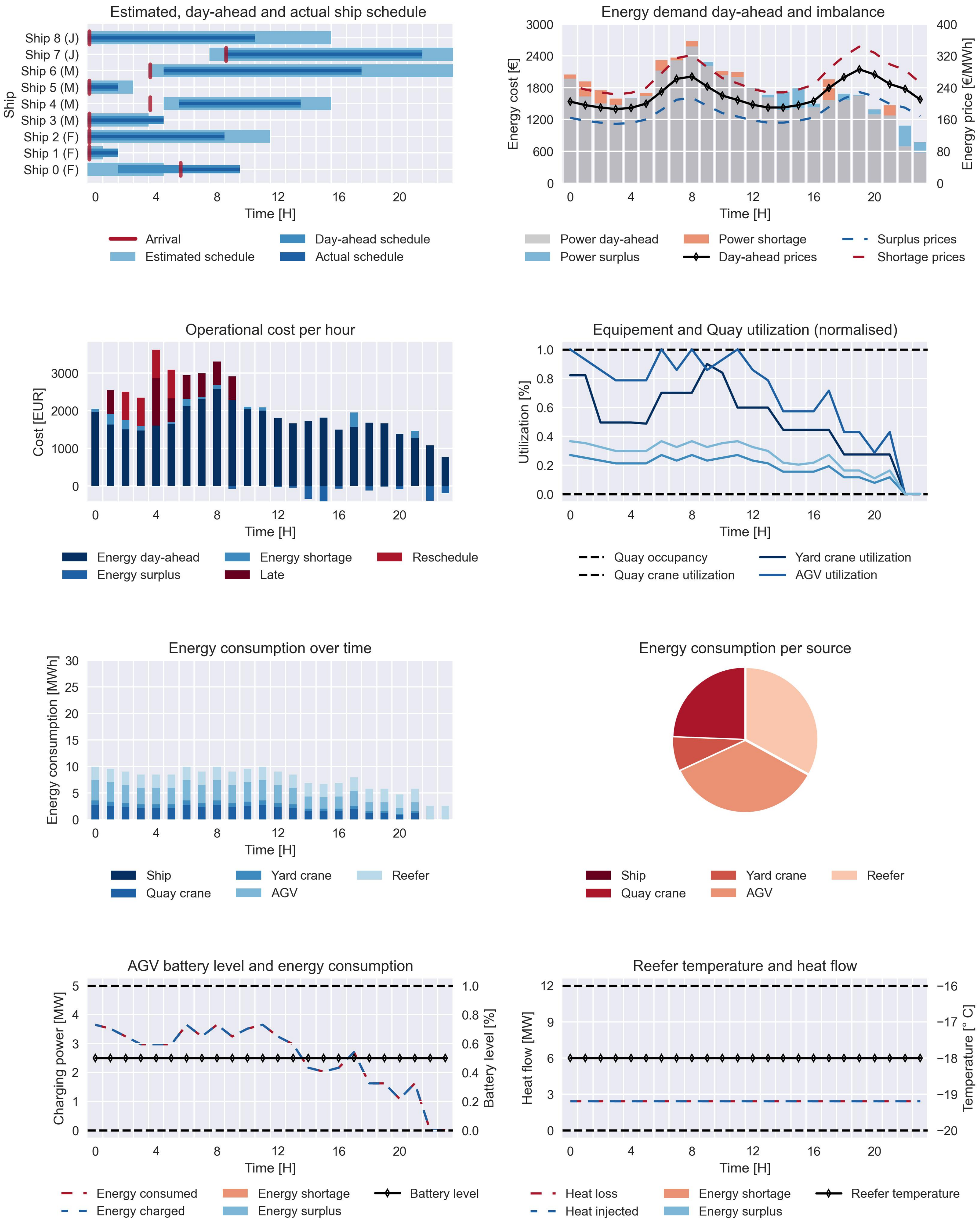
Output results for experiment NP_2022 with instance 7 and scenario scenario_01



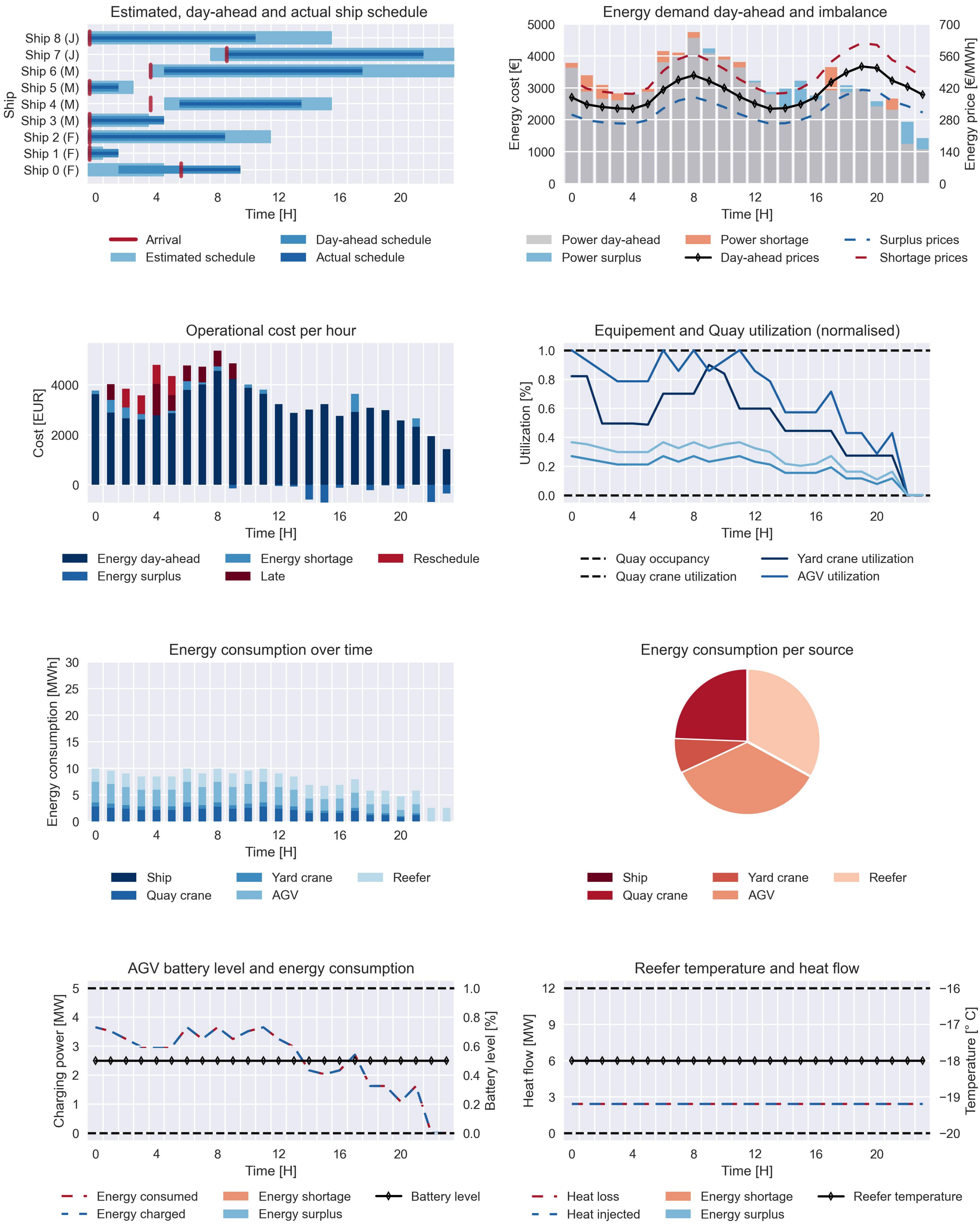
Output results for experiment NP_2022 with instance 7 and scenario scenario_02



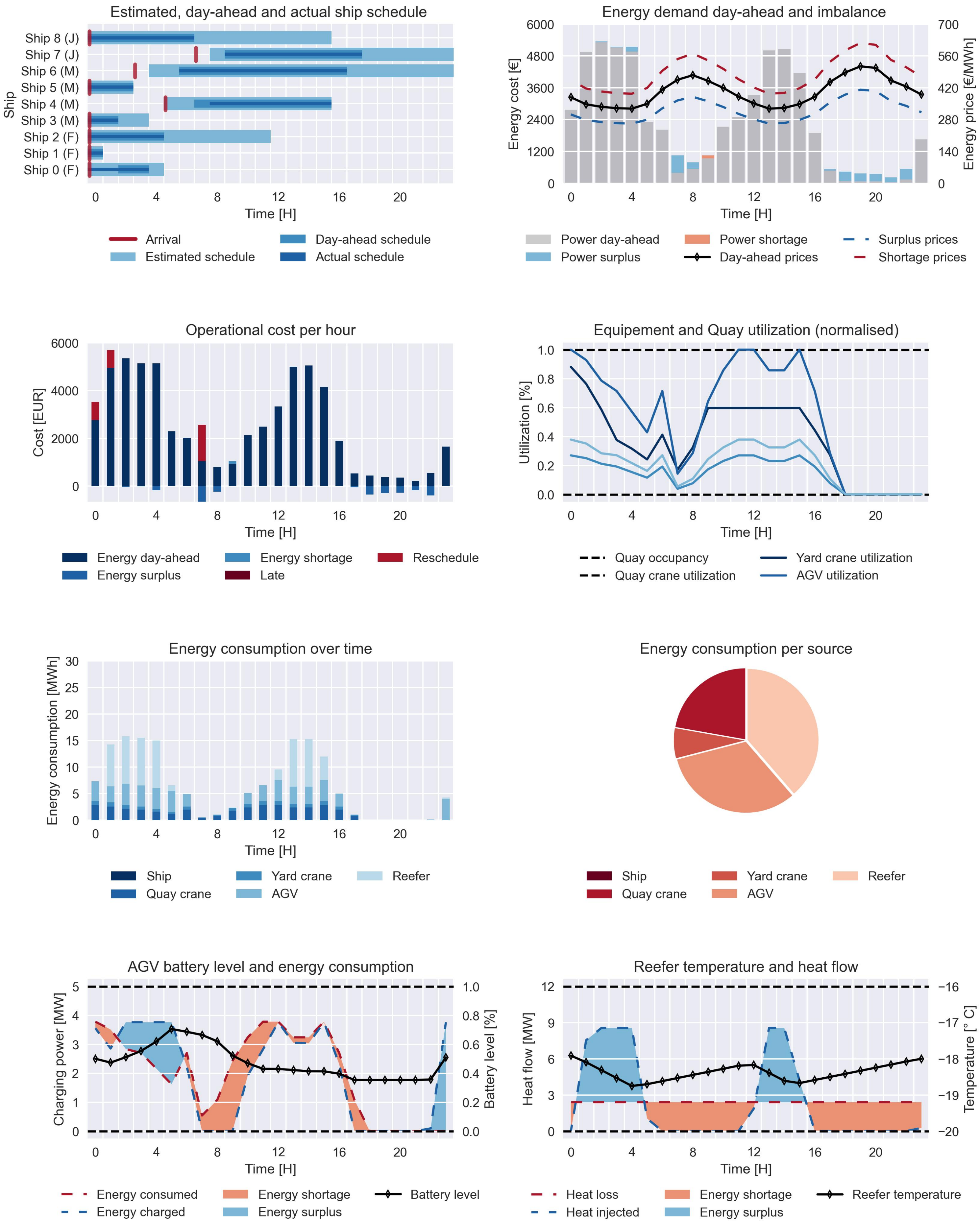
Output results for experiment NP_2022 with instance 7 and scenario scenario_03



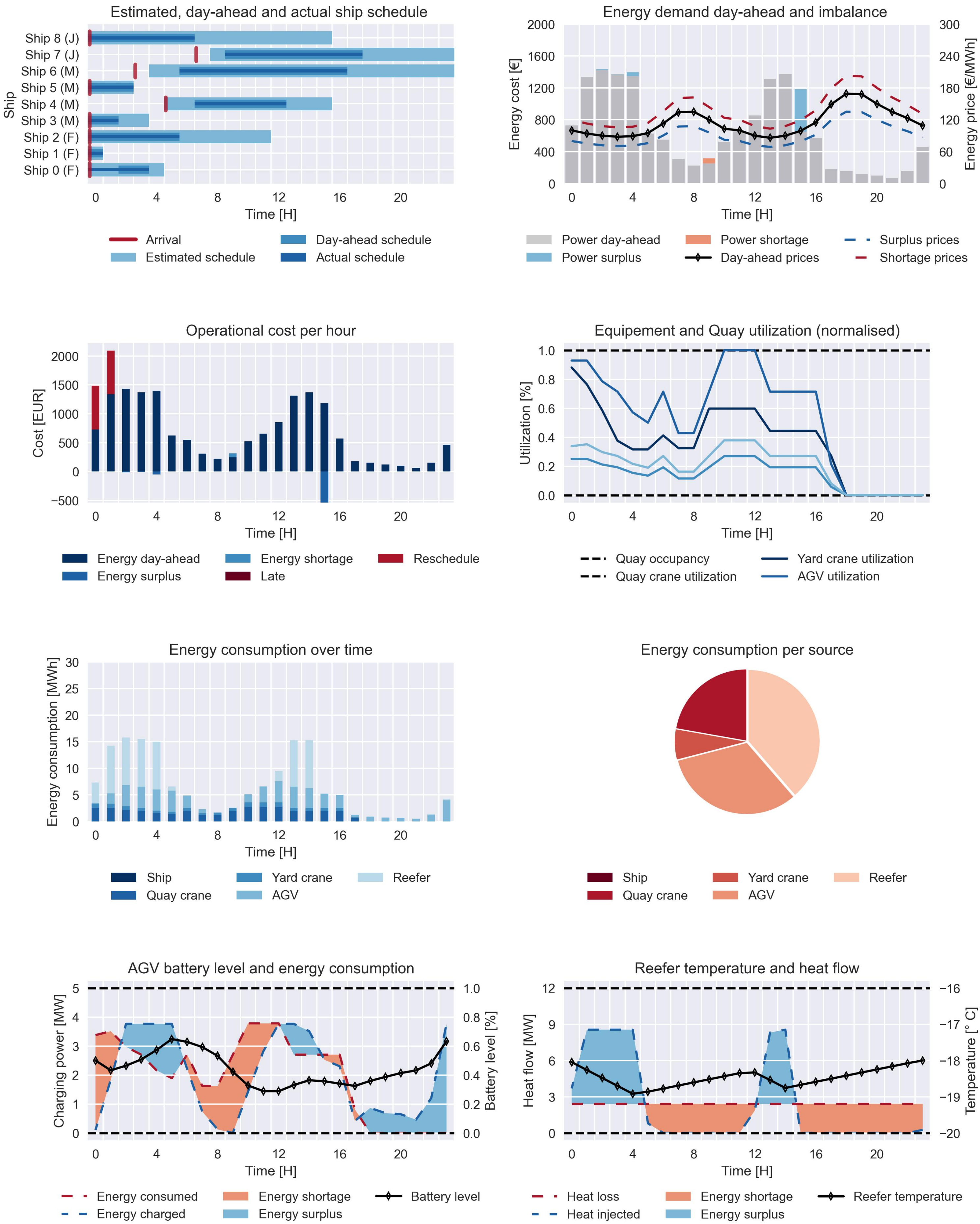
Output results for experiment NP_2022 with instance 7 and scenario scenario_04



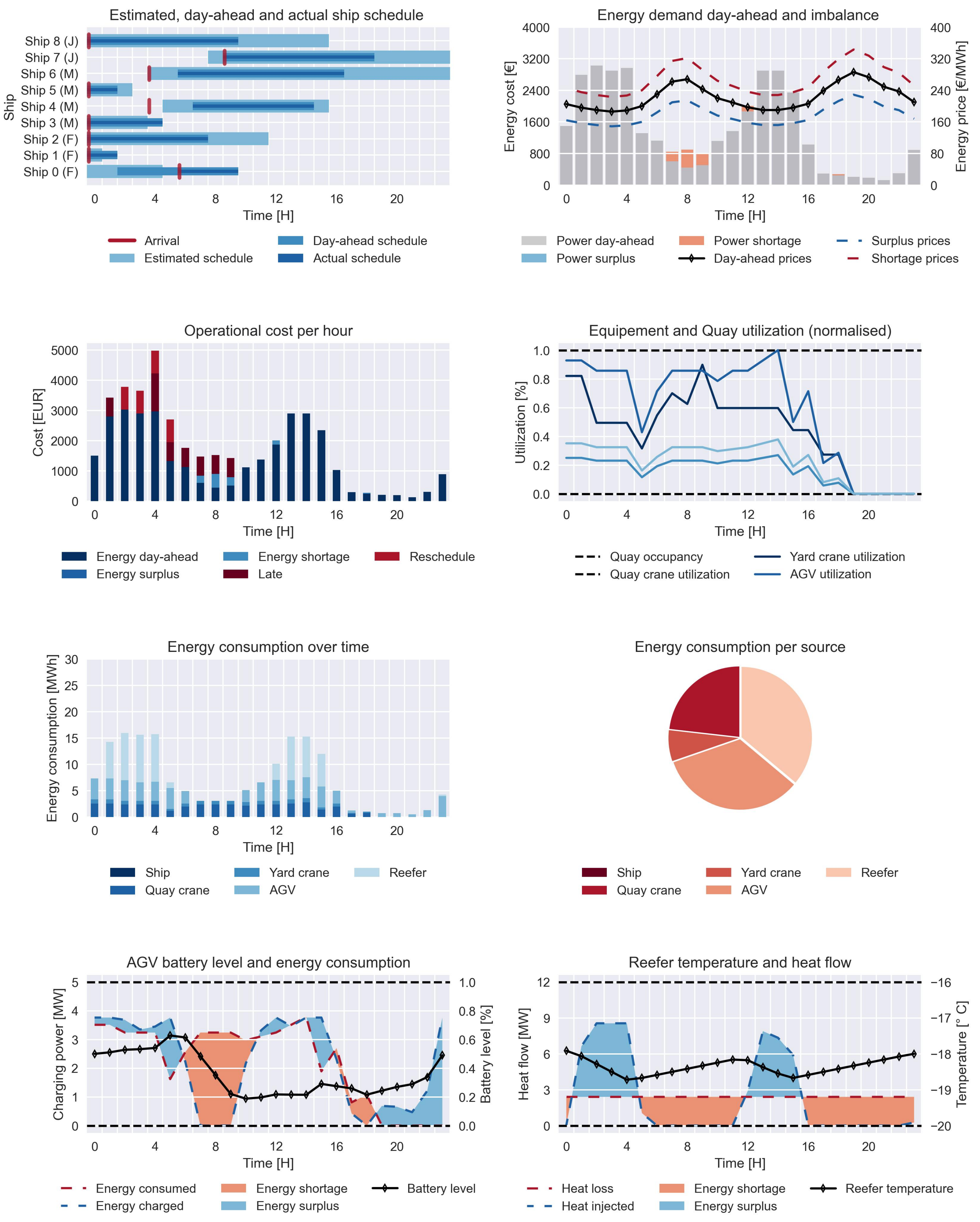
Output results for experiment RTP_2022 with instance 7 and scenario scenario_01



Output results for experiment RTP_2022 with instance 7 and scenario scenario_02



Output results for experiment RTP_2022 with instance 7 and scenario scenario_03



Output results for experiment RTP_2022 with instance 7 and scenario scenario_04